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THE EFFECT OF TRADING VOLUMES ON STOCK RETURNS FOLLOWING LARGE PRICE MOVES

ABSTRACT: *The study analyses the correlation between abnormal trading volumes accompanying large stock price changes and subsequent stock price dynamics. Assuming that abnormal trading volume associated with a large price move may serve as an indication of the extent of the immediate stock price reaction to the underlying company-specific shock, I suggest that large price moves accompanied by relatively high (low) abnormal trading volumes may be followed by price reversals (drifts). Analysing a large sample of major daily stock price moves and defining the latter according to a number of alternative proxies, I document that both large price increases and decreases accompanied by high (low) abnormal trading volumes are followed by significant price reversals (drifts) on each of the next two trading days and over five- and twenty-day intervals following the initial price move, the magnitude of the reversals (drifts) increasing over longer post-event windows. The effect remains significant after accounting for additional company-specific (size, CAPM beta, historical volatility) and event-specific (stock's absolute return on the event day) factors, and is robust to different methods of calculating abnormal returns and to different sample filtering criteria.*

KEY WORDS: *Abnormal Trading Volumes; Behavioural Finance; Large Price Changes; Stock Price Drifts; Stock Price Reversals.*

JEL CLASSIFICATION: G11, G14, G19

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1. INTRODUCTION

It is commonly known that stocks represent a risky category of assets, incorporating both the opportunity of yielding considerable profits and the possibility of bearing painful losses. Stock prices may be affected by a virtually infinite number of different types of news, and sometimes this news may be very influential for a given stock or a group of stocks, resulting in price shocks that may be either positive or negative.

Large stock price changes are the focus of a vast cohort of financial studies, whose main practical goal is to establish, at least as far as possible, when and why stock prices tend to underreact or overreact to the underlying shocks, in order to predict the price dynamics following the initial price changes. The findings in this respect vary as a function of the samples analysed by the authors and the research approaches applied by them. A number of authors (e.g., Zarowin 1989; Bremer and Sweeney 1991; Cooper 1999; Sturm 2003) find that major stock price moves are followed by price reversals, and therefore assert that the former contain some element of overreaction. Another group of studies either does not document any systematic price patterns following large price moves (e.g., Ratner and Leal 1998; Lasfer et al. 2003; Mazouz et al. 2009), or finds some evidence of reversals but concludes that they are economically insignificant and cannot be employed in practice to generate profitable investment opportunities (e.g., Atkins and Dyl 1990; Park 1995; Fehle and Zdorovtsov 2003). The third and probably most influential group of studies (e.g., Pritamani and Singal 2001; Chan 2003; Tetlock 2010; Savor 2012) argues that large stock price changes should be analysed in a wider company-specific context, and concentrates on the role of public information in determining subsequent price patterns. The general conclusion of this literature is that large price moves accompanied by public information releases result in price drifts, indicating that investors tend to underreact to news about fundamentals, while those that are not accompanied by any public news are followed by reversals, suggesting that investors tend to overreact to other shocks that move stock prices, such as shifts in investor sentiment or liquidity shocks.

The present study takes another perspective on the issue of stock price underreactions and overreactions to company-specific shocks, by employing contemporaneous stock trading volumes as a proxy for the magnitude of the immediate stock price reaction to the shocks. The previous literature demonstrates that trading volume results 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. 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 has been fully incorporated in stock price changes, leaving less space for post-event price drifts.

Following the latter strand of literature, I hypothesize that if a company-specific shock, resulting in a large stock price move, is accompanied by an abnormally high trading volume, then it may be an indication that the effect of the shock is more fully (or even excessively) incorporated in the stock price, so that a price reversal may be expected to follow the initial price move. In other words, if the opposite case is considered, I suggest that a large stock price move accompanied by a relatively low abnormal trading volume may result from the fact that, for some reason, investors have not fully reacted to the underlying company-specific shock, so that a residual price reaction may be expected to follow in the form of a price drift.

I analyse daily price data for all the constituents of the S&P 500 Index over the period 1993 to 2017, and define large daily stock price moves according to a number of alternative proxies, based on both raw and market-adjusted stock returns. In line with the first part of the study's hypothesis, I document that both large price increases and decreases accompanied by high abnormal trading volumes are followed by significant price reversals on each of the next two trading days and over five- and twenty-day intervals following the initial price move, the magnitude of the reversals increasing over longer post-event windows. On the other hand, consistent with the second part of the study's hypothesis, I find that both large price increases and decreases accompanied by low abnormal trading volumes are followed by significant price drifts over the same post-event windows, the magnitude of the drifts also increasing over longer post-event windows. This (two-sided) effect of event-day abnormal trading volumes on stock returns following large price moves remains significant after accounting for additional company-specific (size, CAPM beta, historical volatility) and event-specific (stock's absolute return on the event day) factors, and is robust to different methods of calculating abnormal returns and to different sample filtering criteria.

The study logically continues the strand of literature dealing with the effect of stock trading volumes around company-specific events on the subsequent stock returns. Yet its major contribution is that, unlike the previous studies (e.g., Verrecchia 1981; Diamond and Verrecchia 1987; Israeli 2015), I explicitly concentrate on trading volumes around large stock price changes, rather than publicly announced events. Therefore, the results with respect to the subsequent price reversals may be of broader practical importance for stock market investors, since large stock price moves are not always driven by any pre-determined category of company-specific event.

The rest of the paper is structured as follows. Section 2 reviews the literature dealing with large stock price changes and subsequent stock return patterns, as well as the literature concentrating on stock trading volumes. Section 3 defines the study's research hypothesis. Section 4 describes the database and the research design. Section 5 reports the results of the empirical tests. Section 6 concludes and provides a brief discussion.

2. LITERATURE REVIEW

2.1. Stock returns following large price changes

Stock returns following large price changes have been the focus of a vast strand of financial literature. Some of the studies observe stock price reversals following large price moves, and therefore conclude that the latter contain some element of overreaction to unobserved stimuli. Renshaw (1984) and Bremer and Sweeney (1991) find that following daily price declines of at least 10%, stock prices tend to exhibit reversals, significantly outperforming the market as a whole. Zarowin (1989) tests the short-run market overreaction following the approach employed by DeBondt and Thaler (1985, 1987) in their seminal studies of stock price overreactions and reversals. He confirms the evidence regarding the existence of stock market overreaction in the short run. Sturm (2003) documents that negative price shocks tend to serve as a trigger for positive post-event abnormal returns, but this relationship depends on the characteristics of the shocks, which may serve as a proxy for investor confidence. Furthermore, he suggests that post-event reversals are smaller for larger price shocks, supposedly because investors are more likely to attribute the latter to stable causes. Avramov et al. (2006) find that the magnitude of return reversals is positively correlated with stock illiquidity. Frisch et al. (2014) document that large stock price declines are followed by positive stock returns, yet the trading strategy making use of this pattern becomes more risky after the financial crisis of 2008. Angelovska (2016) suggests that irrational behaviour by uninformed investors drives large stock returns, and further finds that the reaction to these large price movements reveals elements of overreaction resulting in short-term price reversal following large price declines

On the other hand, Atkins and Dyl (1990), who also look for excess profits during the first few days after extreme price declines, do not find evidence that would contradict the Efficient Market Hypothesis. They demonstrate that the positive abnormal returns resulting from reversals are not sufficient to generate profitable arbitrage if the bid–ask spreads are taken into consideration. Lehmann (1990) argues that there exist short-term corrections after extremely negative weekly returns, but after accounting for transaction costs these positive returns become economically insignificant. Cox and Peterson (1994) analyse the role of the bid–ask bounce and market liquidity in explaining price reversals. They demonstrate that large one-day price declines are associated with strong selling pressure, which increases the probability that the closing transaction is made at the bid price. Therefore, the reversal documented for the next day arises from the bid–ask bounce. Additionally, they find that the degree of the reversals following large price declines decreases for longer post-event windows, changing their sign (that is, becoming negative) over 4–20 days following the initial price decline. Park (1995) employs the mid-point of bid and ask prices, and detects that predictable variation in stock returns following large price changes is partially driven by the bid–ask bounce. He argues that, controlling for this effect, the short-run price reversals cannot be a source of significant abnormal incomes. Similarly, Hamelink (1999) and Fehle and Zdorovtsov (2003) report significant return patterns after extreme events, but taking the bid–ask spread into account, cannot indicate that there is an overreaction to the company-specific shocks. Ratner and Leal (1998) do not find any evidence of price reversals for emerging markets of Latin America and Asia. Bremer et al. (1997) observe the reversal pattern for the Japanese stock market, but conclude that it cannot be employed to earn arbitrage profits. Their results suggest that the market rapidly absorbs the relevant information, so that stock prices react almost immediately. Lasfer et al. (2003) analyse the daily price behaviour of market indices of both developed and emerging markets, and also do not manage to obtain any significant evidence favouring the existence of price reversals. Mazouz et al. (2009) use three alternative stock-pricing models for calculating abnormal returns following large price moves, and find no evidence in support of overreaction. They even present some evidence of price drifts following positive daily price shocks.

More recently, the emphasis of the research has shifted to the connection between large stock price changes and public information. Pritamani and Singal (2001) investigate a sample of NYSE and AMEX stocks that experienced large price changes and collect daily public news stories on these stocks. They document that stock returns exhibit momentum conditional on a public announcement associated with a large price change, yet unconditional post-event abnormal returns are usually insignificant, and in any case cannot serve as grounds for a profitable investment strategy. Chan (2003) constructs an index of news headlines for a random sample of stocks that have experienced large price changes and finds momentum after price changes accompanied by news. This finding is in line with a number of previous studies demonstrating that investors tend to underreact to news about fundamentals (e.g., Michaely and Womack 1999; Ikenberry and Ramnath 2002; Vega 2006). On the other hand, Chan (2003) detects reversals after price changes unaccompanied by news, especially for loser stocks. These reversals appear to be statistically significant, even after controlling for size and book-to-market value. Moreover, he documents that these effects are stronger among smaller and less liquid stocks. He suggests that these findings may be driven by the fact that some investors react slowly to information, while transaction costs prevent arbitrageurs from eliminating the lag. Larson and Madura (2003) argue that extreme price changes unaccompanied by public (newspaper) announcements provide evidence of overreaction, while large price declines after news being revealed publicly display price continuation. Tetlock (2010) investigates how the presence of public news affects subsequent stock returns, and discovers that reversals are significantly lower after news days. Consistent with Chan (2003), Savor (2012) shows that daily price shocks accompanied by publicly available information (analyst recommendation revisions) are followed by drifts, while those not accompanied by information result in reversals. The drifts are present only when the direction of the large price change corresponds to the direction of the change in analyst recommendations. He interprets these results as investors' underreaction to news about fundamentals and overreaction to other shocks leading to stock price moves (such as shifts in investor sentiment or liquidity shocks). Savor (2012) also asserts that on the one hand analysts can distinguish between these two potential drivers of stock returns, but on the other hand the market does not fully take into consideration the information provided by analysts. Kudryavtsev (2017) documents that both positive and negative large price moves accompanied by opposite-sign contemporaneous changes in the VIX index are followed by significant reversals whose magnitude increases over longer post-event windows, while large stock-price changes taking place on the days when the value of the VIX index moves in the same direction are followed by non-significant price drifts. He attributes this finding to the opposite relation between the direction of changes in the VIX index and contemporaneous investors' mood.

2.2. Stock trading volumes and their connection to stock returns

Prior studies suggest and discuss a number of factors that may explain and drive 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. Continuing Karpoff's line of research, Kim and Verrecchia (1991) define the measure of a market's information asymmetry as the 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, which results in trading activity.

Investors may also trade for portfolio rebalancing reasons, a 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 the drivers of the trading process are investor's expectations of future stock-price returns and exposure to risk in equilibrium conditions . 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 that of stock prices and returns. Early studies on the volume–price relationship 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 in both 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 finds a positive relationship between absolute price changes and contemporaneous volume changes (e.g., Crouch 1970; Epps and Epps 1976; Harris 1983).

More recent studies focus more 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 trading volume is positively correlated with absolute changes in 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) analyse 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 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. Similarly, Tapa and Hussin (2016) document a significant positive contemporaneous relationship between stock returns and trading volumes. Caginalpa and Desantisa (2011) point out that if the stock price is growing but the trading volume is declining, then technical analysts consider stock price growth to be unstable. Remorov (2014) constructs a model of stock price and volume behaviour during market crashes and finds that trading volume is inversely proportional to the square of the stock price in the case of sharp price declines, the result being empirically supported by price and volume data for major recent US stock bankruptcies and market crashes. Bouattour et al. (2016) establish that market turnover is positively related to contemporaneous and past returns, and interpret this finding as evidence of a mixture of the distributions hypothesis and the investor overconfidence hypothesis, suggesting that stock returns help forecast volume.

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 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) analyses 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 price changes have fully incorporated the earnings news, leaving less space for subsequent price drifts.

3. RESEARCH HYPOTHESIS

As discussed in the previous section, there exists a close interdependence between stock prices and returns on the one hand, and stock trading volumes on the other. The present study analyses another aspect of the relationship between these mutually dependent concepts. Namely, it tries to forecast the direction of stock returns following large price moves based on abnormal trading volumes associated with the latter.

I follow the strand of previous literature (e.g., Verrecchia 1981; Diamond and Verrecchia 1987; Israel, 2015) suggesting that higher abnormal trading volumes around company-specific events indicate that the respective stock-price reactions more fully incorporate the new information and are not expected to result in post-event price drifts. In the same spirit, I hypothesize that if, in addition to a large price move, a company-specific shock, either public or unobserved, leads to an abnormally high trading volume, then it may be an indication that the effect of the shock is more fully (or even excessively) incorporated in the stock price, so that a price reversal (or at least, no price drift) may be expected to follow the initial price move. Inversely put, if a large stock price move is accompanied by a relatively low abnormal trading volume, then it may suggest that for some reason investors have not fully reacted to the underlying company-specific shock, so that the residual price reaction should follow in the form of a price drift.

Thus, the study's main hypothesis may be formulated as:

Large daily stock price changes accompanied by relatively high (low) abnormal trading volumes will be followed by price reversals (drifts).

4. DATA DESCRIPTION AND RESEARCH DESIGN

In the framework of the empirical analysis I use the closing daily prices adjusted to dividend payments and stock splits[1] and the daily trading volume data for all the constituents of the S&P 500 Index over the period 1993 to 2017, as recorded

[1] This approach to registering stock prices allows calculating actual daily stock returns based on the changes in the fundamental value of a stock and not arising from technical modifications in the stock's characteristics.

at www.finance.yahoo.com by January 2018[2]. I define large daily stock price changes similarly to Kudryavtsev (2018), employing three alternative proxies and two return thresholds for each of them:

Proxy A: Daily raw stock returns[3] with absolute values exceeding 8% ($\left|SR0_i\right| > 8\%$) and 10% ($\left|SR0_i\right| > 10\%$), where *SR0ᵢ* represents the event-day (Day 0) stock return corresponding to event (large stock price move) *i*: The 10% threshold is commonly used in previous literature (e.g., Shleifer 2000), since it is sufficient to screen out most price movements that do not reflect substantial changes in either fundamentals or investor sentiment. The 8% threshold allows substantially expanding the working sample[4].

Proxy B: Daily raw stock returns with absolute values exceeding three ($\left|SR0_i\right| > 3\sigma_i$) and four standard deviations ($\left|SR0_i\right| > 4\sigma_i$) of the respective stock's daily returns over 250 trading days (approximately a year) preceding the event. This approach is employed in a number of studies (e.g., Pritamani and Singal 2001). The idea is that the same percentage change in the stock price may constitute a large price change for a low-volatility stock, but not for a high-volatility stock.

Proxy C: Daily abnormal stock returns (ARs) with absolute values exceeding 8% ($\left|AR0_i\right| > 8\%$) and 10% ($\left|AR0_i\right| > 10\%$), where $AR0_i$ (Day-0 AR corresponding to event *i*) is calculated using Market Model Adjusted Returns (MMAR)[5] with alpha and beta estimated for the respective stock over 250 trading days preceding event *i*. That is, for each event *i*, for the period of 250 trading days

2 In order to minimize the potential effect of the survivorship bias on the results, I repeat the analysis for: (i) all the constituents of the S&P 500 Index over the period 1993 to 2014 as recorded by January 2015; and (ii) all the constituents of the S&P 500 Index over the period 1993 to 2010 as recorded by January 2011. The results (available upon request from the author) remain similar to those reported in Section 5.

3 Throughout the paper, I use logarithmic returns.

4 For all the three proxies for defining the large stock price moves, I employ a number of additional thresholds. The results for all of these thresholds (available upon request from the author) are qualitatively similar to those reported in Section 5.

5 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.

preceding the event, I regress the respective stock's returns on the contemporaneous market (S&P 500 Index) returns in the following way:

$$SR_{it} = \alpha_i + \beta_i MR_{it} + \varepsilon_{it} \tag{1}$$

where: *SRit* is the stock return on day *t* (*t* runs from –250 to –1) preceding event *i* and *MRit* is the market return on day *t* preceding event *i,* and then use the regression estimates $\widehat{\alpha_i}$ and $\widehat{\beta_i}$ in order to calculate the event-day abnormal stock return for the event *i,* as follows:

$$AR0_i = SR0_i - \left[\widehat{\alpha_i} + \widehat{\beta_i} MR0_i\right] \tag{2}$$

where: *AR0i* is the abnormal stock return on the day of event *i* and *MR0i* is the market return on the day of event *i*.

Similarly to Proxy A, the 10% threshold is widely used in the previous literature (e.g., Atkins and Dyl 1990; Bremer and Sweeney 1991), while the 8% threshold increases the working sample.

In addition, for each large price change I match the respective firm's market capitalization, as recorded on a quarterly basis at http://ycharts.com/, for the closest preceding announcement date.

I include large stock price changes in my working sample if the following conditions are fulfilled: (i) there exists historical trading data for at least 250 trading days before and for 20 days after the event; (ii) market capitalization information is available for the respective stocks; and (iii) the absolute value of the price change does not exceed 50%. The intersection of these filtering rules yields a working sample of the following sizes for the three event definition proxies and according to the second (first) threshold:

- For proxy A: 6,412 (4,024) large price moves, including 2,841 (1,713) increases and 3,571 (2,311) decreases.
- For proxy B: 6,857 (4,202) large price moves, including 3,132 (1,720) increases and 3,725 (2,482) decreases.
- For proxy C: 5,986 (3,851) large price moves, including 2,768 (1,627) increases and 3,218 (2,224) decreases.

Table 1 contains, separately for large stock price increases and decreases defined according to the three alternative proxies, some basic descriptive statistics of the working sample, including the firms' market capitalization for the end of the quarter preceding each large price move, cumulative stock return for one year preceding each large price move, and the standard deviation of the stock's return over the same period.

Table 1: Descriptive statistics for the firms making up the sample and their stocks

Proxy/Threshold	Number of large price moves	Market capitalization, $ millions		Cumulative return over one year preceding the large price move, %		St. Dev. of historical stock returns, %	
		Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Proxy A:							
|SR0i|>8%	*6,412*						
Price increases	2,841	4,840	12,481	5.25	14.52	1.92	0.85
Price decreases	3,571	4,671	12,867	4.61	13.81	1.94	0.86
|SR0i|>10%	*4,024*						
Price increases	1,713	4,564	12,897	5.31	14.68	1.97	0.88
Price decreases	2,311	4,423	13,204	4.72	13.92	1.98	0.88
Proxy B:							
|SR0i|>3σi	*6,857*						
Price increases	3,132	4,887	12,472	5.29	14.46	1.94	0.84
Price decreases	3,725	4,695	12,835	4.68	13.74	1.95	0.85
|SR0i|>4σi	*4,202*						
Price increases	1,720	4,578	12,871	5.34	14.54	1.98	0.87
Price decreases	2,482	4,447	13,174	4.76	13.85	1.98	0.86
Proxy C:							
|AR0i|>8%	*5,986*						
Price increases	2,768	4,824	12,512	5.22	14.57	1.90	0.86
Price decreases	3,218	4,653	12,888	4.58	13.93	1.91	0.87
|AR0i|>10%	*3,851*						
Price increases	1,627	4,545	12,924	5.28	14.75	1.95	0.89
Price decreases	2,224	4,402	13,252	4.69	13.99	1.96	0.90

In order to test the study's research hypothesis, for each event I calculate the respective stock's event-day abnormal trading volume (ATV0) as the difference between the stock's actual Day-0 trading volume and its average trading volume over 250 trading days preceding the event, normalized by the standard deviation of its trading volume over the same estimation window. That is:

$$ATV0_i = \frac{Vol0_i - AvVol(-250,-1)_i}{StDevVol(-250,-1)_i} \quad (3)$$

where: $ATV0_i$ is the abnormal stock trading volume on the day of event *i*; $AvVol(-250,-1)_i$ is the stock's average trading volume over 250 trading days preceding event *i*; and $StDevVol(-250,-1)_i$ is the standard deviation of the stock's trading volume over 250 trading days preceding event *i*.

Table 2 presents the basic descriptive statistics of ATV0 measures.

Table 2: Descriptive statistics of the event-day abnormal trading volumes (ATV0)

Statistical measure	Value
Mean	4.16
Median	3.89
Standard deviation	4.61
Maximum	32.14
Minimum	–0.35
1st decile	0.63
1st quintile	1.52
5th quintile	7.90
10th decile	16.53

Not surprisingly, stock trading volumes on the days of large stock price moves tend to be significantly positive, that is, higher than usual (mean ATV0 equals 4.16). Yet, as also might be expected, the range of abnormal trading volumes associated with large price moves is very wide (minimum ATV0 equals –0.35, while maximum ATV0 reaches 32.14), indicating that the extent of the immediate investors' reactions to company-specific shocks may differ significantly, probably ranging from underreaction to overreaction to the shocks.

5. RESULTS DESCRIPTION

5.1. Stock returns following large price moves: Total sample

First of all, for the total sample of large stock price moves I analyse post-event returns of the stocks that have experienced the price moves. For the period of up to 20 trading days following large stock price increases and decreases, defined according to the three above-mentioned proxies and two thresholds for each of them, and employing the same MMAR approach as described in the previous section, I calculate average ARs, cumulative ARs (CARs), and their statistical significance. Table 3 reports the results, where Day 1 refers to the first trading day after the initial price move.

The results in the table are consistent with most of the previous literature. If the total sample is considered, then positive price moves are followed by non-significant reversals, while negative price moves are followed by either non-significant or marginally significant reversals. The magnitude of the reversals is slightly greater for the time window 1 to 20. All the event-definition proxies and all the thresholds yield similar post-event results. One more noteworthy result is that the magnitude of the post-event reversals appears not to be connected to the magnitude of the initial price shocks.

Table 3: Abnormal stock returns following large stock price increases and decreases: Total sample

Panel A: Large stock price increases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	$\|SR0i\|$>8% (2,841 events)	$\|SR0i\|$>10% (1,713 events)	$\|SR0i\|>3\sigma i$ (3,132 events)	$\|SR0i\|>4\sigma i$ (1,720 events)	$\|AR0i\|$>8% (2,768 events)	$\|AR0i\|$>10% (1,627 events)
1	−0.13 (29.38%)	−0.14 (33.28%)	−0.14 (30.64%)	−0.15 (22.44%)	−0.13 (25.87%)	−0.16 (23.11%)
2	−0.11 (32.07%)	−0.12 (37.64%)	−0.12 (38.55%)	−0.11 (41.52%)	−0.12 (36.41%)	−0.11 (37.61%)
1 to 5	−0.16 (30.87%)	−0.21 (29.61%)	−0.18 (30.01%)	−0.19 (27.16%)	−0.18 (34.29%)	−0.17 (43.65%)
1 to 20	−0.18 (31.92%)	−0.22 (27.30%)	−0.19 (28.66%)	−0.21 (24.34%)	−0.20 (25.37%)	−0.22 (27.99%)

Panel B: Large stock price decreases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	$\|SR0i\|$>8% (3,571 events)	$\|SR0i\|$>10% (2,311 events)	$\|SR0i\|>3\sigma i$ (3,725 events)	$\|SR0i\|>4\sigma i$ (2,482 events)	$\|AR0i\|$>8% (3,218 events)	$\|AR0i\|$>10% (2,224 events)
1	0.18 (22.03%)	0.17 (21.46%)	0.19 (19.21%)	0.18 (20.19%)	0.17 (26.84%)	0.18 (22.54%)
2	0.13 (30.71%)	0.14 (33.42%)	0.13 (34.61%)	0.14 (34.77%)	0.15 (35.54%)	0.14 (34.23%)
1 to 5	0.36 (18.36%)	0.37 (17.28%)	0.41 (15.84%)	0.38 (21.43%)	0.41 (14.73%)	0.42 (12.74%)
1 to 20	0.43 (13.74%)	0.44 (11.47%)	*0.46 (9.74%)	*0.47 (9.67%)	0.43 (12.44%)	*0.46 (9.87%)

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

5.2. The effect of event-day abnormal trading volume on stock returns following large price moves

In order to test if the trading volumes associated with large stock price moves affect the respective stocks' post-event returns, I define subsamples of events with relatively low and relatively high ATV0, as proxied by the 1st and the 5th quintile of ATV0 distribution[6]. Tables 4A, 4B, and 4C comprise average ARs and CARs following large price moves accompanied by low and high ATV0, as well as the respective AR/CAR differences and their statistical significance, for event definition proxies A, B, and C, respectively.

[6] Alternatively, I employ the 1st and the 10th decile of ATV0 distribution as proxies for relatively low and relatively high ATV0. The results of the empirical analysis (available upon request from the author) are qualitatively similar to those reported in Section 5.

Table 4A: Abnormal stock returns following large stock price moves accompanied by low and high ATV0: Proxy A for defining large price moves

Panel A: Large stock price increases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	|*SR0i*|>8%			|*SR0i*|>10%		
	Low ATV0	High ATV0	Difference	Low ATV0	High ATV0	Difference
1	*0.24 (6.53%)	**−0.51 (1.87%)	**0.75 (1.43%)	*0.25 (5.78%)	**−0.52 (1.65%)	**0.77 (1.27%)
2	0.11 (15.38%)	−0.27 (12.08%)	*0.38 (7.58%)	0.11 (14.87%)	−0.26 (13.51%)	*0.37 (7.63%)
1 to 5	**0.77 (1.26%)	***−0.94 (0.69%)	***1.71 (0.02%)	**0.78 (1.14%)	***−0.96 (0.48%)	***1.74 (0.00%)
1 to 20	***1.08 (0.23%)	***−1.42 (0.07%)	***2.50 (0.00%)	***1.10 (0.18%)	***−1.44 (0.02%)	***2.54 (0.00%)
Panel B: Large stock price decreases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	|*SR0i*|>8%			|*SR0i*|>10%		
	Low ATV0	High ATV0	Difference	Low ATV0	High ATV0	Difference
1	*−0.21 (8.12%)	**0.68 (1.23%)	**−0.89 (1.33%)	*−0.20 (8.42%)	**0.66 (1.41%)	**−0.86 (1.65%)
2	−0.07 (25.48%)	*0.29 (8.91%)	*−0.36 (7.88%)	−0.08 (21.74%)	*0.29 (8.98%)	*−0.37 (7.50%)
1 to 5	**−0.62 (1.86%)	***1.11 (0.13%)	***−1.73 (0.00%)	**−0.60 (1.97%)	***1.14 (0.06%)	***−1.74 (0.00%)
1 to 20	***−1.01 (0.19%)	***1.57 (0.02%)	***−2.58 (0.00%)	***−1.00 (0.24%)	***1.62 (0.00%)	***−2.62 (0.00%)

Asterisks denote the significance levels: *$p<0.10$; **$p<0.05$; ***$p<0.01$

Table 4B: Abnormal stock returns following large stock price moves accompanied by low and high ATV0: Proxy B for defining large price moves

Panel A: Large stock price increases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	$\|SR0i\|>3\sigma i$			$\|SR0i\|>4\sigma i$		
	Low ATV0	High ATV0	Difference	Low ATV0	High ATV0	Difference
1	*0.23 (6.84%)	**–0.52 (1.65%)	**0.75 (1.36%)	*0.24 (5.81%)	**–0.53 (1.54%)	**0.77 (1.21%)
2	0.11 (14.35%)	–0.28 (11.68%)	*0.39 (7.27%)	0.10 (16.80%)	–0.27 (12.87%)	*0.37 (7.42%)
1 to 5	**0.76 (1.57%)	***–0.96 (0.62%)	***1.72 (0.00%)	**0.77 (1.23%)	***–0.98 (0.37%)	***1.75 (0.00%)
1 to 20	***1.06 (0.24%)	***–1.45 (0.02%)	***2.51 (0.00%)	***1.08 (0.19%)	***–1.47 (0.00%)	***2.55 (0.00%)
Panel B: Large stock price decreases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	$\|SR0i\|>3\sigma i$			$\|SR0i\|>4\sigma i$		
	Low ATV0	High ATV0	Difference	Low ATV0	High ATV0	Difference
1	*–0.20 (8.25%)	**0.69 (1.17%)	**–0.89 (1.26%)	*–0.20 (8.59%)	**0.68 (1.38%)	**–0.86 (1.61%)
2	–0.08 (21.55%)	*0.31 (7.64%)	*–0.39 (6.49%)	–0.07 (20.89%)	*0.30 (8.60%)	*–0.37 (7.24%)
1 to 5	**–0.61 (1.89%)	***1.14 (0.07%)	***–1.75 (0.00%)	**–0.60 (1.72%)	***1.17 (0.02%)	***–1.77 (0.00%)
1 to 20	***–1.00 (0.20%)	***1.61 (0.00%)	***–2.61 (0.00%)	***–0.99 (0.25%)	***1.68 (0.00%)	***–2.67 (0.00%)

Asterisks denote the significance levels: *p<0.10; **p<0.05; ***p<0.01

Table 4C: Abnormal stock returns following large stock price moves accompanied by low and high ATV0: Proxy C for defining large price moves

Panel A: Large stock price increases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	|*AR0i*|>8%			|*AR0i*|>10%		
	Low ATV0	High ATV0	Difference	Low ATV0	High ATV0	Difference
1	*0.25 (6.23%)	**−0.49 (2.00%)	**0.74 (1.51%)	*0.26 (5.62%)	**−0.50 (1.74%)	**0.76 (1.32%)
2	0.12 (13.81%)	−0.26 (12.45%)	*0.38 (7.42%)	0.11 (14.62%)	−0.25 (13.99%)	*0.36 (7.86%)
1 to 5	**0.78 (1.19%)	***−0.91 (0.73%)	***1.69 (0.04%)	**0.79 (1.10%)	***−0.94 (0.51%)	***1.73 (0.00%)
1 to 20	***1.06 (0.28%)	***−1.39 (0.08%)	***2.45 (0.00%)	***1.08 (0.21%)	***−1.40 (0.03%)	***2.48 (0.00%)
Panel B: Large stock price decreases						
Days relative to event	Average AR/Cumulative ARs following initial price changes, % (2-tailed p-values)					
	|*AR0i*|>8%			|*AR0i*|>10%		
	Low ATV0	High ATV0	Difference	Low ATV0	High ATV0	Difference
1	*−0.22 (7.85%)	**0.66 (1.29%)	**−0.88 (1.46%)	*−0.21 (8.01%)	**0.65 (1.48%)	**−0.86 (1.59%)
2	−0.08 (23.47%)	*0.28 (8.98%)	*−0.36 (7.76%)	−0.09 (20.38%)	*0.27 (9.11%)	*−0.36 (7.67%)
1 to 5	**−0.63 (1.77%)	***1.09 (0.15%)	***−1.72 (0.00%)	**−0.61 (1.85%)	***1.11 (0.08%)	***−1.72 (0.00%)
1 to 20	***−1.02 (0.16%)	***1.54 (0.03%)	***−2.56 (0.00%)	***−1.01 (0.20%)	***1.59 (0.00%)	***−2.60 (0.00%)

Asterisks denote the significance levels: *$p<0.10$; **$p<0.05$; ***$p<0.01$

The results corroborate the study's research hypothesis for large price moves accompanied by both high and low event-day ATV.

First, with all the proxies, both large price increases and decreases accompanied by low ATV0 are followed by significant price drifts. The magnitude of these price drifts increases for longer post-event periods, so that for the post-event window 1 to 20, average CARs following low-ATV0 large price increases reach 1.08%, 1.06%, and 1.06% for the lower threshold, according to proxies A, B, and C, respectively, while average CARs following low-ATV0 large price decreases equal −1.01%, −1.00%, and −1.02%, according to proxies A, B, and C, respectively, all the CARs being highly statistically significant.

Second, with all the proxies, both large price increases and decreases accompanied by high ATV0 are followed by significant price reversals. The magnitude of the latter also increases for longer post-event periods, and for the post-event window 1 to 20, average CARs following high-ATV0 large price increases equal −1.42%, −1.45%, and −1.39% for the lower threshold, according to proxies A, B, and C, respectively, while average CARs following high-ATV0 large price decreases are even more pronounced and equal 1.57%, 1.61%, and 1.54%, according to proxies A, B, and C, respectively, all the CARs again being highly statistically significant.

The bottom line of this battery of results is that the post-event AR/CAR differences between the low- and high-ATV0 events are highly significant and for the post-event window 1 to 20 reach 2.50%, 2.51%, and 2.45% following large price increases, and –2.58%, –2.61%, and –2.56% following large price decreases for the lower threshold, according to proxies A, B, and C, respectively.[7]

Overall, the results in this subsection demonstrate that abnormal trading volumes associated with large daily price changes may serve as a useful tool for predicting the direction of subsequent stock returns.

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7 As a robustness check, I repeat the analysis employing two additional sample-filtering criteria. Namely, I alternatively exclude from the working sample: (i) overlapping price moves, defined as those that took place for the same stock within a 20-trading-days window; and (ii) price moves for the stocks whose prices prior to the moves were lower than ten dollars. The results (available upon request from the author) are qualitatively similar, representing an additional support for the existence of the event-day ATV effect on stock returns following large price moves.

5.3. Multifactor analysis

Having detected the event-day ATV effect on stock returns following large price changes, I now check its persistence controlling for additional company-specific and event-specific factors. To do so, separately for large price increases and decreases, for the windows 1, 1 to 5, and 1 to 20 following the events, and according to all the proxies and thresholds, I run the following cross-sectional regressions:

$$AR_{it} / CAR_{it} = \beta_0 + \beta_1 ATV0_i + \beta_2 MCap_i + \beta_3 Beta_i + \beta_4 SRVolat_i + \beta_5 \left|SR0\right|_i + \varepsilon_{it} \quad (4)$$

where: *ARit/CARit* is the abnormal/cumulative abnormal stock return following event *i* for post-event window *t* (Days 1, 1 to 5, or 1 to 20); *ATV0i* is the abnormal Day-0 stock trading volume corresponding to event *i*, calculated according to formula (3); *MCapi* is the natural logarithm of the firm's market capitalization corresponding to event *i*, normalized in the cross-section; *Betai* is the estimated CAPM beta for event *i*, calculated over the Days –250 to –1 and normalized in the cross-section; *SRVolati* is the standard deviation of stock returns over the Days –250 to –1 corresponding to event *i*, normalized in the cross-section; and |*SR0*|*i* is the absolute Day-0 stock return representing event *i*.

Tables 5, 6, and 7 report the regression coefficients for post-event windows 1, 1 to 5, and 1 to 20, respectively, providing additional support for the study's research hypothesis.

First, with all the proxies and for all the post-event windows, the regression coefficients on *ATV0* are significantly negative (positive) following large price increases (decreases). These results suggest once again that the higher the trading volume associated with a large price move, the more fully the effect of the underlying company-specific shock incorporated in the company’s stock price, and the higher the probability that the initial price move will be followed by a more pronounced price reversal.

Table 5: Multifactor regression analysis of ARs/CARs following large stock price increases and decreases: Dependent variable – Stock AR for Day 1 following the event

Panel A: Large stock price increases						
Explanatory variables	Coefficient estimates, % (2-tailed p-values)					
	|*SR0i*|>8% (2,841 events)	|*SR0i*|>10% (1,713 events)	|*SR0i*|>3σ*i* (3,132 events)	|*SR0i*|>4σ*i* (1,720 events)	|*AR0i*|>8% (2,768 events)	|*AR0i*|>10% (1,627 events)
Intercept	***–0.09 (0.45%)	***–0.10 (0.38%)	***–0.10 (0.34%)	***–0.11 (0.33%)	***–0.10 (0.41%)	***–0.11 (0.35%)
ATV0	**–0.16 (2.14%)	**–0.17 (1.94%)	**–0.17 (1.76%)	**–0.18 (1.64%)	**–0.17 (1.74%)	**–0.16 (2.35%)
MCap	**0.22 (2.62%)	**0.23 (2.28%)	**0.21 (2.58%)	**0.23 (2.20%)	**0.22 (2.66%)	**0.23 (2.43%)
Beta	*–0.10 (8.56%)	*–0.11 (7.51%)	*–0.09 (9.10%)	–0.07 (11.75%)	*–0.10 (8.17%)	*–0.09 (8.69%)
SRVolat	*–0.14 (6.28%)	*–0.13 (6.38%)	*–0.12 (6.49%)	*–0.12 (6.74%)	*–0.11 (6.58%)	*–0.13 (6.00%)
|SR0|	–0.04 (34.19%)	–0.05 (30.46%)	–0.04 (33.42%)	–0.03 (38.81%)	–0.02 (48.82%)	–0.03 (41.35%)
Panel B: Large stock price decreases						
Explanatory variables	Coefficient estimates, % (2-tailed p-values)					
	|*SR0i*|>8% (3,571 events)	|*SR0i*|>10% (2,311 events)	|*SR0i*|>3σ*i* (3,725 events)	|*SR0i*|>4σ*i* (2,482 events)	|*AR0i*|>8% (3,218 events)	|*AR0i*|>10% (2,224 events)
Intercept	***0.14 (0.00%)	***0.15 (0.00%)	***0.14 (0.00%)	***0.13 (0.02%)	***0.14 (0.00%)	***0.14 (0.00%)
ATV0	**0.19 (1.61%)	**0.18 (1.85%)	**0.20 (1.52%)	**0.21 (0.09%)	**0.18 (1.73%)	**0.19 (1.69%)
MCap	**–0.20 (3.12%)	**–0.19 (3.47%)	**–0.21 (2.87%)	**–0.21 (2.99%)	**–0.20 (3.19%)	**–0.19 (3.57%)
Beta	0.07 (16.58%)	0.08 (11.57%)	0.06 (18.96%)	*0.08 (9.87%)	*0.09 (9.21%)	0.07 (12.18%)
SRVolat	**0.18 (4.22%)	**0.19 (4.02%)	*0.16 (5.24%)	**0.17 (4.82%)	**0.19 (4.00%)	**0.18 (4.27%)
|SR0|	0.03 (36.87%)	0.02 (43.17%)	0.03 (32.07%)	0.03 (36.09%)	0.01 (54.18%)	0.02 (42.34%)

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

Table 6: Multifactor regression analysis of ARs/CARs following large stock price increases and decreases: Dependent variable – Stock CAR for Days 1 to 5 following the event

Panel A: Large stock price increases						
	Coefficient estimates, % (2-tailed p-values)					
Explanatory variables	|*SR0i*|>8% (2,841 events)	|*SR0i*|>10% (1,713 events)	|*SR0i*|>3*σi* (3,132 events)	|*SR0i*|>4*σi* (1,720 events)	|*AR0i*|>8% (2,768 events)	|*AR0i*|>10% (1,627 events)
Intercept	***−0.11 (0.15%)	***−0.10 (0.17%)	***−0.10 (0.14%)	***−0.11 (0.18%)	***−0.12 (0.04%)	***−0.11 (0.10%)
ATV0	***−0.40 (0.00%)	***−0.41 (0.00%)	***−0.42 (0.00%)	***−0.41 (0.00%)	***−0.39 (0.00%)	***−0.40 (0.00%)
MCap	***0.24 (0.84%)	***0.25 (0.77%)	**0.23 (1.17%)	***0.24 (0.96%)	**0.23 (1.30%)	**0.22 (1.64%)
Beta	*−0.11 (8.41%)	*−0.12 (7.46%)	−0.10 (10.57%)	*−0.12 (8.60%)	*−0.11 (9.02%)	*−0.10 (9.49%)
SRVolat	*−0.17 (6.57%)	*−0.18 (5.98%)	*−0.19 (5.52%)	*−0.18 (5.81%)	*−0.20 (5.23%)	*−0.19 (5.85%)
|SR0|	−0.03 (35.69%)	−0.02 (42.19%)	−0.04 (31.43%)	−0.05 (26.48%)	−0.03 (36.46%)	−0.04 (33.34%)
Panel B: Large stock price decreases						
	Coefficient estimates, % (2-tailed p-values)					
Explanatory variables	|*SR0i*|>8% (3,571 events)	|*SR0i*|>10% (2,311 events)	|*SR0i*|>3*σi* (3,725 events)	|*SR0i*|>4*σi* (2,482 events)	|*AR0i*|>8% (3,218 events)	|*AR0i*|>10% (2,224 events)
Intercept	***0.27 (0.00%)	***0.28 (0.00%)	***0.28 (0.00%)	***0.29 (0.00%)	***0.30 (0.00%)	***0.31 (0.00%)
ATV0	***0.39 (0.00%)	***0.38 (0.00%)	***0.40 (0.00%)	***0.40 (0.00%)	***0.39 (0.00%)	***0.40 (0.00%)
MCap	***−0.25 (0.61%)	***−0.24 (0.86%)	***−0.24 (0.72%)	***−0.25 (0.68%)	**−0.22 (1.87%)	***−0.25 (0.74%)
Beta	*0.09 (8.81%)	*0.10 (8.27%)	*0.10 (7.92%)	*0.08 (9.36%)	*0.10 (7.82%)	*0.08 (9.68%)
SRVolat	**0.21 (1.35%)	**0.20 (1.74%)	**0.20 (1.60%)	**0.22 (1.07%)	***0.23 (0.95%)	**0.21 (1.46%)
|SR0|	0.03 (37.91%)	0.04 (29.81%)	0.03 (35.53%)	0.03 (36.80%)	0.04 (26.83%)	0.04 (28.94%)

Table 7: Multifactor regression analysis of ARs/CARs following large stock price increases and decreases: Dependent variable – Stock CAR for Days 1 to 20 following the event

Panel A: Large stock price increases						
Explanatory variables	Coefficient estimates, % (2-tailed p-values)					
	$\lvert SR0i \rvert>8\%$ (2,841 events)	$\lvert SR0i \rvert>10\%$ (1,713 events)	$\lvert SR0i \rvert>3\sigma i$ (3,132 events)	$\lvert SR0i \rvert>4\sigma i$ (1,720 events)	$\lvert AR0i \rvert>8\%$ (2,768 events)	$\lvert AR0i \rvert>10\%$ (1,627 events)
Intercept	***–0.13 (0.00%)	***–0.12 (0.02%)	***–0.13 (0.00%)	***–0.14 (0.00%)	***–0.15 (0.00%)	***–0.14 (0.00%)
ATV0	***–0.60 (0.00%)	***–0.61 (0.00%)	***–0.61 (0.00%)	***–0.59 (0.00%)	***–0.61 (0.00%)	***–0.62 (0.00%)
MCap	***0.28 (0.12%)	***0.27 (0.24%)	***0.28 (0.10%)	***0.26 (0.37%)	***0.28 (0.14%)	***0.27 (0.31%)
Beta	*–0.13 (5.78%)	*–0.12 (6.25%)	*–0.14 (5.20%)	*–0.13 (5.93%)	*–0.13 (5.54%)	*–0.14 (5.39%)
SRVolat	**–0.20 (4.05%)	**–0.19 (4.63%)	**–0.21 (3.84%)	**–0.18 (4.87%)	**–0.19 (4.46%)	**–0.18 (4.92%)
$\lvert SR0 \rvert$	–0.04 (32.51%)	–0.03 (40.07%)	–0.03 (38.04%)	–0.04 (34.59%)	–0.04 (30.16%)	–0.02 (56.62%)

Panel B: Large stock price decreases						
Explanatory variables	Coefficient estimates, % (2-tailed p-values)					
	$\lvert SR0i \rvert>8\%$ (3,571 events)	$\lvert SR0i \rvert>10\%$ (2,311 events)	$\lvert SR0i \rvert>3\sigma i$ (3,725 events)	$\lvert SR0i \rvert>4\sigma i$ (2,482 events)	$\lvert AR0i \rvert>8\%$ (3,218 events)	$\lvert AR0i \rvert>10\%$ (2,224 events)
Intercept	***0.32 (0.00%)	**0.33 (0.00%)	***0.33 (0.00%)	***0.34 (0.00%)	***0.32 (0.00%)	***0.33 (0.00%)
ATV0	***0.65 (0.00%)	***0.64 (0.00%)	***0.65 (0.00%)	***0.65 (0.00%)	***0.66 (0.00%)	***0.67 (0.00%)
MCap	***–0.29 (0.08%)	***–0.28 (0.13%)	***–0.27 (0.21%)	***–0.28 (0.10%)	***–0.26 (0.29%)	**–0.28 (0.17%)
Beta	*0.10 (7.96%)	*0.09 (8.51%)	*0.09 (8.26%)	*0.12 (6.76%)	*0.11 (7.28%)	*0.10 (8.09%)
SRVolat	**0.23 (3.85%)	**0.22 (4.08%)	**0.23 (3.72%)	**0.24 (3.70%)	**0.23 (3.51%)	**0.22 (4.18%)
$\lvert SR0 \rvert$	0.05 (27.49%)	0.04 (32.63%)	0.03 (34.27%)	0.05 (29.46%)	0.04 (30.44%)	0.03 (39.58%)

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

In addition, the results indicate that for all the post-event windows following large price increases (decreases), the regression coefficients on *MCap* are significantly positive (negative), the regression coefficients on *Beta* are negative (positive) and marginally significant, and the regression coefficients on *SRVolat* are significantly negative (positive), suggesting that post-event ARs following large price increases (decreases) tend to be lower (higher) for low capitalization, high-beta, and highly volatile stocks. A potential explanation for these results may be that investors possess less fundamental information on these groups of stocks and subsequently tend to overreact to the respective company-specific shocks, which in turn may lead to post-event price reversals. The coefficients on |*SR0*| are non-significant, demonstrating that post-event stock returns do not depend on the magnitude of the initial shocks.

Overall, the results in this subsection indicate that the event-day ATV effect on stock returns following large price changes remains significant if other company-specific and event-specific factors are accounted for, and also if the actual values of the event-day ATVs are considered, instead of categorizing the events as low- and high-ATV.

6. CONCLUDING REMARKS

In the present study I analysed the effect of abnormal trading volumes accompanying large stock price changes on subsequent price dynamics. Assuming that the event-day abnormal trading volume serves as an indication of the extent of the stock price reaction to the underlying company-specific shock, I suggested that large price moves accompanied by relatively high (low) abnormal trading volumes may be followed by price reversals (drifts).

The results of the empirical analysis supported my research hypothesis. Analysing a large sample of major daily stock price moves and defining the latter according to a number of alternative proxies, based on both raw and abnormal stock returns and on both absolute and relative (scaled by the respective stock's volatility) return thresholds, I documented that both large price increases and decreases accompanied by high (low) abnormal trading volumes are followed by significant price reversals (drifts) on each of the next two trading days and over five- and twenty-day intervals following the initial price move, the magnitude of the reversals (drifts) increasing over longer post-event windows. This (two-sided) effect of event-day abnormal trading volumes on stock returns following large price moves remained significant after accounting for additional company-specific (size, CAPM beta, historical volatility) and event-specific (stock's absolute return on the event day) factors. The results were robust to different return thresholds, both higher and lower, to different methods of adjusting returns, such as market-adjusted returns, market-model excess returns, and Fama-French three-factor model excess returns, and to different sample filtering criteria.

To summarize, at least in a perfect stock market with no commissions, the strategy based on buying (selling short) stocks after large price increases (decreases) accompanied by low abnormal trading volume and/or after large price decreases (increases) accompanied by high abnormal trading volume looks promising. 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. Moreover, this result may even possess broader practical importance, compared to the findings of the previous literature (e.g., Verrecchia 1981; Diamond and Verrecchia 1987; Israeli 2015) dealing with the effect of stock trading volumes around company-specific events on the subsequent stock returns, since large stock price moves are not always driven by any predetermined category of company-specific events. Potential directions for further research could include expanding the analysis to other stock exchanges, employing additional, including cross-sectional, proxies for calculating abnormal trading volume, and performing a separate analysis for the periods of bull and bear markets.

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