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Research article

Availability heuristic and reversals following large stock price changes: evidence from the FTSE 100

Diogo Matos[1], Luís Pacheco[2,*] and Júlio Lobão[1]

[1] School of Economics and Management, University of Porto, Porto, Portugal
[2] Department of Economics and Management, Portucalense University, REMIT, IJP (Portucalense Institute for Legal Research), Porto, Portugal

* **Correspondence:** Email: luisp@upt.pt.

Abstract: This paper examines if investors exhibited evidence of the availability heuristic in their investment decisions when significant price changes occurred in the British stock market during the 2010–2018 period. We raise the hypothesis that if a significant stock price move takes place on a day when the stock market index also undergoes a significant change (either positive or negative), then the magnitude of that shock may be increased by the availability of positive investment or negative outcomes. We applied three different proxies for large stock price changes which yielded a robust sample of events for this study. We found no significant evidence of the availability heuristic. In addition, we also found no significant evidence of price overreaction for both price decreases and increases. Inversely, we found robust results that suggest randomness in the behavior of stock prices in this period, thus supporting the efficiency of financial markets and opposing the results from similar studies carried out in the United States.

Keywords: large stock price changes; United Kingdom; overreaction; behavioral finance; availability heuristic; market efficiency

JEL Codes: G14, G41

1. Introduction

In the world of financial research, many debates have arisen regarding the efficiency of capital markets. On one side, many authors presented strong evidence in favor of the random walk hypothesis (Fama, 1965; Fama & French, 1996; Jensen, 1968). On the other side, the emergence of price models in the 1960s marked an important point where a considerable number of researchers endorsed the predictability of prices (Jegadeesh, 1990; Lo & MacKinlay, 1988).

In particular several authors provided empirical results evidencing that stock prices overreact and are followed by mean reversion, usually at three to five year horizons (De Bondt & Thaler, 1985, 1987; Hong & Stein, 1999; Jegadeesh & Titman, 1993; Lee & Swaminathan, 2000). Considering this effect, some possible behavioral explanations for these phenomena were also presented (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999).

In this paper we explore the behavior of stock prices after significant 1-day price moves. Considering this short-time approach, most of the empirical evidence provides support for the overreaction hypothesis (Jegadeesh, 1990; Lehmann, 1990; Lo & MacKinlay, 1988, 1990). However, there are also those who did not find evidence of stock price reversals (Lasfer et al., 2003; Mazouz et al., 2009, 2012), or find that the reversals are not pronounced enough to profit from abnormal returns (Atkins & Dyl, 1990; Brown et al., 1988; Cox & Peterson, 1994; Lehmann, 1990; Watts, 1978).

Behavioral biases have been found to influence investors' decisions and to impact financial prices (Chen et al., 2017; Gavrilakis & Floros, 2021; Hirshleifer, 2001). For example, the presence of overconfident investors in financial markets has been presented as a major explanation for the excessive volatility of prices and the formation of speculative bubbles (Chuang & Lee, 2006; Scheinkman & Xiong, 2003). Also, the tendency of investors to "anchor" to salient price levels has been related to the underreaction of prices to information (George & Hwang, 2004). In our research we focus on the impact of the availability bias on investors' decisions after a 1-day extreme return. According to this heuristic, people are inclined to estimate frequencies or probabilities by the ease with which related instances or associations could be brought to their minds (Tversky & Kahneman, 1973, 1974) and will be proxied by the sign of the general stock market index return on the event day. Following Kudryavtsev (2018), we examine if large stock price increases (decreases) that occur on a day where the return on the market index is positive (negative) will suffer from extreme reversals on the following trading days. In other words, we aim to understand if price overreaction to company-specific shocks is augmented by the general market movement on the day of the large price change.

Focusing on the period between 2010 and 2018, we study the United Kingdom stock market, using data from the FTSE 100 Share Index. The choice of the UK stock market for our analysis is motivated by the economic importance thereof. In fact, London hosts the largest European stock market, with a market capitalization of U$3.8 trillion as of December 2021 and the FTSE 100 Share index tracks the performance of London's top 100 shares. Also, albeit its importance, there is a lack of recent studies about the presence of anomalies in the London Exchange Market. Thus, by presenting empirical evidence for this market we contribute to the academic knowledge in the field of Behavioral Finance, in particular with regard to the availability bias.

The paper is structured as follows: Section 2 offers a review of existing literature. In section 3, we discuss the methodology used, and in section 4 the relevant data and results are presented and discussed. In section 5 we apply a set of robustness tests to our data, while in the last section we present the key conclusions arising from the results of this study.

2. Literature review

2.1. Concept of market efficiency

The concept of efficiency is crucial to the finance world. Theoretically, a market is efficient if, on average, it is not possible to make significant profits taking as basis generally available public information. In efficient markets, only insiders can make money (Fama, 1970; Tobin, 1984).

The Random walk theory supports the Efficient Markets Hypothesis (EMH) in finance and suggests that stock price moves have the same distribution and are independent of each other. It undertakes the hypothesis that the past movement or trend of a stock price or market cannot be used to predict its future movement. It is important to note that the EFH does not exclude minor abnormal returns, before fees and expenses. To make sense, the concept of market efficiency has to allow minor market inefficiencies. There is evidence stating that markets cannot reach full efficiency in the strong form, but there is firm support for the weak and semi-strong forms, and even for versions of strong form efficiency that focus on the performance of professional investment managers (Dimson & Mussavian, 1998).

Regarding previous market efficiency studies in the United Kingdom, Chan et al. (1997) analyzed eighteen European stock indices (including the UK) and suggested that all are individually efficient. Furthermore, Worthington & Higgs (2004) tested random walks and weak-form market efficiency in European equity markets and concluded on the presence of random walks in daily returns in the United Kingdom.

However, many market participants try to benefit from collecting and studying information, since, otherwise, if all information gathering and analysis stopped, market prices could not react to the new information (Fama, 1970; Grossman & Stiglitz, 1980). Furthermore, the degree of market efficiency has a bearing on market structure. Markets with fewer participants, higher transaction costs, and less ease of information gathering tend to be less efficient, which gives active management an edge in less efficient markets and passive investing an edge in more efficient markets (Menkhoff et al., 2006). The U.S. stock market is one of the most efficient in the world given the number of investors, its liquidity, and diversification. In turn, the British Stock market is among the highest efficient markets in Europe.

Despite the strong support for efficiency there are some examples of consistent success. For example, albeit most fund managers are not able to beat the market consistently (Fama & French, 2010), literature shows that funds who beat the market in the past tend to do well in the future, which shows persistence in performance (Hendricks et al., 1993). If there are indeed people beating the market, there is a consequent underperformance from the counterparty (Fama, 1998). It is possible to argue that the success of some investors is only possible due to the behavior predictability of individual investors who commit errors that are being continuously exploited. In practical terms, we can state that there are frictions within investing (like investor's irrationality for example) that limit market efficiency.

Taking it into account, many anomalies emerged in several empirical studies that led to the growth of a significant debate between those who believe in market efficiency and those that do not. Two of the major identified anomalies are momentum and overreaction, playing a vital role in the finance community as they expose serious inconsistencies in the EMH.

2.2. Overreaction and reversals

Several authors provided empirical evidence in which stock returns following large price changes were analyzed. Most concluded that stock prices exhibit reversals following large price moves, usually at three to five year horizons, thus supporting the theory of overreaction (DeBondt & Thaler, 1985, 1987; Hong & Stein, 1999; Jegadeesh & Titman, 1993; Lee & Swaminathan, 2000).

Starting with DeBondt & Thaler (1985), using monthly return data of the New York Stock Exchange (NYSE) common stocks between 1926 and 1982, the authors found that the looser portfolio of 35 stocks outperformed the market by, on average, 19.6%, thirty-six months after the portfolio formation. Additionally, both Barberis et al. (1998) and Hong & Stein (1999) provided models that identify price momentum in the short/medium term and overreaction in the long term, supporting both DeBondt & Thaler (1985) and Jegadeesh & Titman (1993). Also, Lee & Swaminathan (2000) provided a "Momentum Life Cycle hypothesis", where they found that firms with high past turnover ratios that exhibit many glamour characteristics earn lower future returns. Moreover, they also found that price momentum effects reverse over the next five years, and high-volume winners experience faster reversals.

Regarding longer time horizons in markets outside the U.S., it is important to mention the study presented by MacDonald & Power (1993) who found that mean reversion applies to the UK. Also, Campbell & Limmack (1997) found evidence of reversals in the abnormal returns of winner and loser portfolios considering a period of 2 up to 5 years, providing support to the "winner-loser" effect in the UK stock market. Moreover, this effect was also found in 18 countries (the United Kingdom included) by Balvers et al. (2000) and Baytas & Cakici (1999).

In the short term, there is also empirical evidence suggesting that prices suffer from reversals. Lo & MacKinlay (1988, 1990) and Lehmann (1990) found evidence of market inefficiency in the way that there are systematic tendencies for "current 'winners' and 'losers' in one week to experience sizeable return reversals over the subsequent week in a way that reflects apparent arbitrage profits".

The main variable employed to explain the short-term overreaction was information on trading activity. Particularly, Conrad et al. (1994), applying a variant of Lehmann's (1990) contrarian trading strategy, showed that return reversals for relatively small NASDAQ stocks decrease with trading volume and that high-transaction securities experience price reversals, which is consistent with the findings of Cooper (1999) who found that return reversals for larger NYSE stocks increase with trading volume.

More recently, Kudryavtsev (2017) found that both positive and negative large price moves accompanied by the opposite-sign contemporaneous changes in the VIX index are followed by significant reversals on the next two trading days. Dyl et al. (2019) found that small stocks with lower institutional ownership are more likely to experience reversals following a large one-day price drop or increase, and Piccoli et al. (2017) analyzed 663 U.S. extreme events and found statistically and economically significant support for the overreaction hypothesis.

Still, regarding the research made by Dyl et al. (2019), the authors also concluded that markets underreact to news about a firm's fundamentals and overreact to non-information-based price movements. There is considerable empirical evidence linking large stock price changes and the public (published) information. The results by Dyl et al. (2019) are consistent with findings from previous studies showing that firm-specific information has a significant effect on price continuations, and that prices overreact when there are no specific news (Chan, 2003; Larson & Madura, 2003; Pritamani & Singal, 2001; Savor, 2012).

Moreover, it is important to mention that several earlier studies have concluded that estimated abnormal returns are indeed predictable, based on previously announced earnings, as prices do not fully reflect the implications of current earnings for future earnings. This phenomenon is known as the post-earnings announcement drift (Bernard & Thomas, 1989, 1990; Joy et al., 1977; Rendleman et al., 1982; Watts, 1978). Later, Chan (2003) studied this anomaly through the construction of an index of news headlines for a random subset of stocks that have experienced large price moves and found momentum after the news, which is in line with the studies suggesting the phenomenon of underreaction, like those by Ikenberry & Ramnath (2002) or Michaely & Womack (1999), and reversals after no firm-specific news. This phenomenon happens either because investors are slow to respond to valid information, causing drifts, or because investors overreact to price shocks, causing excess trading volume and volatility, which leads to reversals. Tetlock (2010) found that public news predicts substantially lower ten-day reversals of daily stock returns and higher ten-day volume-induced momentum in daily returns, which supports the theory of underreaction to news.

Despite the evidence in favor of the overreaction in the short-term and the underreaction to news from investors, there is also some evidence against these two phenomena in the sense that authors did not detect such reversals following large price changes, or that the reversals are excessively small to try to benefit from arbitrage opportunities.

Firstly, concerning studies showing the presence of reversals with lack of opportunity of abnormal profits, it is important to mention Watts (1978), who found that stock prices are predictable after the announcement of quarterly earnings, but abnormal returns are absorbed by transaction costs, which is in line with the conclusions from Lehmann (1990) and Atkins & Dyl (1990). Also, Brown et al. (1988) found positive abnormal returns in the 60 days following the event for both positive and negative shocks, but these returns simply reflect the increase in risk following the event, thus supporting the EMH. However, Corrado & Jordan (1997) argued that the 2.5% event threshold of Brown et al. (1988) was too low, thus generating too many events. By using a much larger event filter of 10% price change, the authors achieved findings consistent with the overreaction hypothesis.

Later, Cox & Peterson (1994) discovered significant reversals, more pronounced amongst smaller stocks. However, these reversals vanish through time and much of the reversal is attributable to the bid-ask bounce. Besides the bid-ask bounce, the small remaining recovery works as an indicator of compensation to short-term suppliers of liquidity who would otherwise not trade. This is also in line with Park (1995) and observable in the Tokyo Stock Exchange (Bremer et al., 1997) and on the French Stock Exchange (Hamelink, 2003).

However, some authors did not detect reversals following large price changes. Lasfer et al. (2003) focused on price behavior using daily market indexes from 40 stock exchanges in which the British Stock Market is included, and found evidence of return continuation, which is in line with Mazouz et al. (2009) who reached the same conclusion for the United Kingdom.

Continuing to consider markets outside the U.S., Ajayi & Mehdian (1994) found evidence on the British stock market that the average price changes following negative events are positive and those following positive events are positive or at least non-negative. Amini et al. (2010), documented strong evidence for price reversals after large price changes in the London Stock Exchange and trend continuation after small price changes. Mazouz et al. (2012), and in line with their previous study already mentioned in this paper (Mazouz et al., 2009), using updated yearly stocks of the FTSE All Share Index concluded that stocks with large positive stocks will be followed by positive abnormal returns, consistent with price continuation.

2.3. The availability heuristic

Many empirical studies in the field of Behavioral Finance attempted to explain price patterns taking as a basis a certain heuristic. Examples of this are Barberis et al. (1998), who argued that momentum and overreaction may be caused by investors' representativeness bias and conservatism. Others like Daniel et al. (1998) argued that some investors may suffer overconfidence and self-attribution bias. In this section we will develop the Availability Heuristic, presenting an overview of literature related thereto.

The availability heuristic states that people may estimate frequencies or probabilities by the ease with which related instances or associations could be brought to their minds (Tversky & Kahneman, 1973, 1974). Under this heuristic, 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. The same authors argued that "recent occurrences are likely to be relatively more available than earlier experiences" (p. 1127), and hence concluded that people calculate probabilities by overweighting recent information as opposed to processing all relevant information.

There is some empirical evidence regarding the availability heuristic and its impact on investors. Shiller (1998) concluded that investor attention to the several categories of investments, e.g. stocks versus bonds, seems to be affected by different waves of public attention. Moreover, major crashes in financial markets seem to be a phenomenon of attention, as a significant number of investors seem to follow certain market trends. This is consistent with the findings of Barber & Odean (2008), in which they conclude that individual investors are net buyers of attention-grabbing stocks (stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns) and Lee (1992), who suggests that small investors make their "buy decisions" based on attention-drawing events despite the direction of the news. In addition, Ganzach (2000) suggested a model concerning unfamiliar assets in which people base their judgments of risk and return on a global attitude toward them, where an asset globally perceived as good will be deemed to have both high return and low risk.

More recently, Lee et al. (2008) analyzed growth forecast behavior about two subsets of economic agents: analysts who generate observable forecasts, and managers who make investment decisions. They found 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. This will lead to firms overinvesting in expansion periods and underinvesting in contraction periods. The availability heuristic is found to exert other impacts on financial prices. For example, Chen et al. (2017) analyzed the Taiwanese stock market to conclude that the heuristic provides an explanation for the fact that higher risk-adjusted returns are observed in that market during the month of January (the January effect).

Regarding the impact of the availability heuristic, it is imperative to mention the research made by Kliger & Kudryavtsev (2010) and Kudryavtsev (2018, 2019). The first article analyzed the effect of the availability heuristic on investors' reactions to analyst recommendation revisions. The authors found that positive (negative) stock price reactions to analyst recommendation upgrades are stronger when accompanied by positive (negative) stock market index returns. This is dubbed as the "outcome availability effect" and is explained by the higher availability of positive (negative) outcomes on days of market index rises (declines). Kudryavtsev (2018, 2019) analysed the heuristic on investors when there are major positive (negative) stock price moves. His conclusions state that when the stock market index rises (falls), the magnitude of the stock price moves is amplified by the availability of positive (negative) investment outcomes. In both cases, the availability heuristic causes price overreaction to the initial company-specific shock, resulting in a subsequent price reversal.

In turn, Baker & Wurgler (2006) concluded that "when sentiment is estimated to be high, stocks attractive to activists like small and high volatility stocks, extreme growth stocks, and distressed stocks, tend to earn relatively low subsequent returns. However, considering low sentiment, these cross-sectional patterns attenuate or completely reverse" (p. 1677), meaning that these stocks are disproportionately sensitive to broad waves of investor sentiment.

Additionally, Kliger & Kudryavtsev (2010) documented that the "effect of the sign of day 0 market returns on stock price reactions to company-specific news is more pronounced for small, more volatile and high-beta stocks" (p. 62), which is consistent with Kudryavtsev (2018), who suggested that large price moves of low market capitalization and more volatile stocks are more affected by the availability heuristic, with the post-event price reversals for these stocks being more pronounced.

Finally, Kahn (2015), Fachrudin et al. (2017) and Gavrilakis & Floros (2021) have recurred to surveys to conclude that the availability heuristic has a significant impact on the investment decisions of individual investors located in Pakistan, Indonesia, and Greece, respectively.

In sum, the debate in the literature continues, justifying the motivation of the present paper to study the presence of the availability heuristic and reversals following large stock price changes and to confront the obtained results with the scant previous literature.

3. Data description and methodology

This paper will focus on the London Stock Exchange. Consistent with Amini et al. (2010) and Mazouz et al. (2009, 2012), the sample contains constituents of the FTSE 100 at September 2020, with the data retrieved from Thomson Reuters and comprehending the period from January 2010 to December 2018. Additionally, as the FTSE 100 will be the proxy for the general market index in Great Britain, the daily values of this index will also be extracted from the same source in the same interval. We also used the Orbis database by Bureau Van Dijk to extract the underlying market capitalization of the companies under analysis.

Consistent with Kudryavtsev (2018), we will define three different proxies with two return thresholds for them to define our sample.

Starting with proxy I, it will be comprised of daily stock returns with absolute values exceeding 8% ($|SR0i| > 8\%$) and 10% ($|SR0i| > 10\%$), where SR0i represents the event day stock return corresponding to the large stock price move. The 10% threshold was used due to previous literature about large price changes (Shleifer, 2000; Mazouz et al., 2009, 2012; Larson & Madura, 2003; Kudryavtsev, 2018). The 8% threshold provides a larger sample.

With regard to proxy II, we define a large change when daily stock returns show absolute values exceeding 3 ($|SR0i| > 3\sigma i$) and 4 ($|SR0i| > 4\sigma i$) standard deviations of the corresponding stock's daily returns over 250 trading days preceding the event. Notice that 250 days constitute approximately one year. This is consistent with Pritamani & Singal (2001) and Kudryavtsev (2018), who state that what constitutes a significant price change is different for high-volatility and low-volatility stocks (a 10% change for a high-volatility stock may be a non-event whereas a 5% change for a low volatility stock may be a relevant event).

Finally, proxy III is comprised of daily abnormal stock returns (ARs) with absolute values exceeding 8% and 10% ($|AR0i| > 8\%$ and $|AR0i| > 10\%$), where the AR0i is calculated using Market

Model Adjusted Returns. The beta of the stock is estimated considering the 250 trading days preceding event *i*. The 10% threshold is consistent with the literature from Atkins & Dyl (1990), Bremer & Sweeney (1999), Dyl et al. (2019), Kudryavtsev (2018) and Park (1995), while the 8% threshold increases the sample in analysis.

There is some criticism in employing absolute rather than relative edges. For example, Piccoli et al. (2017) state that the one-size-fits-all threshold (in our case, 8% and 10%) biases the sample towards illiquid stocks since such major shocks are more easily found in less liquid securities (Cox & Peterson, 1994). Additionally, the sentiment of a surprise to an outcome is not only attributed to the magnitude of the event, but also to the way it contrasts with common expectations. This is the reason for using proxy II.

However, it also has its advantages in comparison with relative edges. For example, return volatility is not exogenous, reflecting the industry in which a firm operates and the degree to which investor sentiment or liquidity shocks affect trading activity in the stock (Kudryavtsev, 2018). If we did not use absolute returns, we would lose a lot of stock returns with higher volatilities and they are also important to this study.

Considering all these factors and the proxies previously defined, we excluded all the stock returns that did not have data for at least the 250 trading days before and 20 days after the event, stock returns for which their respective market capitalization information was not available, and stocks with absolute value of the price changes exceeding 50%.

In Table 1, we present the sample sizes for the different proxies and thresholds.

Table 1. Total large price moves.

Total Observations						
Days Relative to the Event	**$\|SR0_i\|$ > 8%**	**$\|SR0_i\|$ > 10%**	**$\|SR0_i\|$ > 3σi**	**$\|SR0_i\|$ > 4σi**	**$\|AR0_i\|$ > 8%**	**$\|AR0_i\|$ > 10%**
Increases	417	170	1266	398	268	130
Decreases	344	173	1363	456	200	102
Total	**761**	**343**	**2629**	**854**	**468**	**232**

To understand if the availability effect is reflected on stock returns following large price moves, and consistent with Kliger & Kudryavtsev (2010) and Kudryavtsev (2018), the total sample will be divided by the sign of the market index corresponding to the day of the event (Day 0).

Our hypothesis will be tested as follows:

H0: stock returns are not affected by the availability of positive or negative investment outcomes.

H1 (increases): reversals are more pronounced, the more available the positive investment outcomes on the day of the event, as reflected by positive contemporaneous MR0.

H1 (decreases): reversals are more pronounced, the more available the negative investment outcomes on the day of the event, as reflected by positive contemporaneous MR0.

In addition, after performing our general test we will divide our sample into high and low volatility stocks as well as into high and low market capitalization stocks, to control these variables. High (low) volatility stocks will be the ones with volatility above (below) the average volatility of the sample. As for high and low market capitalization, we decided to apply the following threshold: 10bn€ or higher for large stocks; 9.99bn€ or less for smaller stocks.

To conclude, we will run a regression consistent with Kudryavtsev (2018) for additional firm-specific and event-specific factors. This regression will be applied separately for increases and decreases, for the windows 1, 1–5, and 1–20 following the events, for all of the proxies and thresholds:

$$AR_{it} = \gamma_0 + \gamma_1 MR0\_dum_i + \gamma_2 MCap_i + \gamma_3 beta_i + \gamma_4 SR\_volat_i + \gamma_5 |\mathrm{SRO}|_i + \gamma_6 ABVOL0_i + \varepsilon_i \quad (1)$$

where,

AR_{it}: abnormal return following the event i for post-event interval t (days 1, 1–5 and 1–20);

$MR0\_dum_i$: dummy variable that takes the value 1 if the market return corresponding to day 0 for the event "i" is positive, and 0 otherwise;

$MCap_i$: the natural logarithm of the firm's market capitalization corresponding to event i, normalized in the cross-section;

$beta_i$: estimated CAPM beta for event i, calculated over days −250 to −1, normalized in the cross-section;

SR_volat_i: the standard deviation of stock returns over days −250 to −1 corresponding to event i, normalized in the cross-section;

$|\mathrm{SRO}|_i$: the absolute day 0 stock return representing event i;

$ABVOL0_i$: the abnormal day 0 stock trading volume corresponding to event i, normalized in the cross-section;

Firstly, to understand the best model to run our regression analysis, a Hausman Test will be applied. Furthermore, to validate the statistical inference in the presence of heteroscedasticity, we will use White's robust estimator. A covariance analysis will also be performed on the independent variables to assure that they do not suffer from multicollinearity, that is, they are independent of each other, which is a key basis for a well-fitted model.

4. Results description

4.1. Stock returns following large price moves: total sample

Firstly, we computed the abnormal returns (ARs) following the large stock price change for day 1 (the first trading day after the initial price change), day 2 (the second trading day after the initial price change), the average return from days 1 to 5, and average return from days 1 to 20. These abnormal returns were calculated using the market model adjusted returns.

Table 2 presents average ARs for increases and decreases for all the defined proxies as well as their statistical significance.

Table 2. Stock returns following large price moves—total sample.

Panel A: Large stock price increases						
Average AR following initial price changes. % (2-tailed p values)						
Days Relative to the Event	|SR0í| > 8% (417 Events)	|SR0í| > 10% (170 Events)	|SR0í| > 3σi (1266 Events)	|SR0í| > 4σi (398 events)	|AR0í| > 8% (268 Events)	|AR0í| > 10% (130 Events)
AR Day 1	0.07% (70.62%)	−0.24% (47.24%)	−0.14% (3.34%)**	0.03% (83.14%)	−0.44% (19.56%)	−0.08% (85.92%)
AR Day 2	0.16% (29.38%)	0.17% (55.63%)	0.06% (30.57%)	0.10% (36.76%)	0.20% (40.90%)	0.31% (32.01%)
Average AR 1–5 Days	−0.11% (15.90%)	0.06% (58.16%)	−0.12% (0.01%)***	−0.06% (26.79%)	−0.13% (23.99%)	0.16% (28.22%)
Average AR 1–20 Days	0.09% (1.80%)**	0.20% (0.18%)***	−0.01% (48.26%)	0.01% (69.42%)	0.15% (0.26%)***	0.25% (28.22%)
Panel B: Large stock price decreases						
Average AR following initial price changes. % (2-tailed p values)						
Days Relative to the Event	|SR0í| > 8% (344 Events)	|SR0í| > 10% (173 Events)	|SR0í| > 3σi (1363 Events)	|SR0í| > 4σi (456 events)	|AR0í| > 8% (200 Events)	|AR0í| > 10% (102 Events)
AR Day 1	−0.43% (5.84%)*	−0.79% (4.19%)**	−0.05% (45.01%)	−0.33% (3.02%)**	−0.44% (19.56%)	−0.77% (17.99%)
AR Day 2	0.23% (23.61%)	0.02% (94.15%)	0.06% (32.83%)	0.10% (36.76%)	0.20% (40.90%)	0.19% (59.10%)
Average AR 1−5 Days	−0.05% (50.16%)	−0.26% (4.69%)**	0.02% (39.67%)	−0.06% (26.79%)	−0.13% (23.99%)	−0.29% (11.56%)
Average AR 1−20 Days	0.09% (1.59%)**	0.06% (28.53%)	0.03% (1.33%)**	0.01% (69.42%)	0.02% (75.24%)	0.03% (70.69%)

Notes: We calculated 2-tailed p values being p-value < 0,05 and these are presented between parentheses.
The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

The results show no evidence of significant reversals either for increases and decreases, with average ARs very close to 0. For increases, the prices seem to behave randomly. For decreases, the average abnormal returns in the next days of the events are mostly negative, which indicates evidence of price continuation. So, stock price increases and decreases are followed either by positive or negative abnormal returns, which is contrary to most of the literature analyzed. Although some authors who performed studies in the United Kingdom (Lasfer et al., 2003; Mazouz et al., 2009) did not find support in favor of the overreaction, they did find strong support for price continuation in their research.

Concluding, these results appear to follow a random walk, which is consistent with the Efficiency Markets Theory already addressed in this paper, and particularly with Worthington & Higgs (2004), who also studied the behavior of daily prices and found that the United Kingdom is among the countries of their study who “satisfy the most stringent random walk criteria” (p. 59).

4.2. Availability effect on stock returns following large price moves

In this sub-section, we perform the main test of this paper. In Tables 3, 4 and 5 we present average ARs following large price moves divided by the sign of the market on the day of the event (MR0). We also present the statistical significance of the average ARs, as well as the statistical significance of our test, which is performed by computing differences in average ARs taking into consideration MR0.

Regarding price increases, both proxies I and III (Tables 3 and 5) show evidence of price continuation independently from the sign of the market, which is contrary to the findings of Kliger & Kudryavtsev (2010) and Kudryavtsev (2018), but consistent with the findings of Lasfer et al. (2003). Considering decreases, when analyzing proxy I, the results indicate randomness in price behavior. If we consider MR < 0, there is evidence of reversals for AR 2 and AR 1–20, while for MR > 0 the reversals only occur at AR1 and AR 1–20 and our hypothesis testing lacks statistical significance, thus suggesting that we have to accept the null hypothesis, evidencing that stock returns are not affected by the availability of positive or negative investment outcomes. The results are similar for proxy III (Table 5).

Concerning proxy II (Table 4), considering MR > 0, there is mainly evidence of price reversal, whereas in the case of MR < 0 there is evidence of price continuation, which is more consistent with the availability hypothesis (except when considering AR Day 1), although the results lack statistical significance for the 2 and 1–20 day window. Therefore, the results from proxy II are more consistent with Kliger & Kudryavtsev (2010) and Kudryavtsev (2018).

In conclusion, we have not found evidence of the availability heuristic, which is contrary to the findings of Kliger & Kudryavtsev (2010) and Kudryavtsev (2018). Additionally, we also find some cases of price continuation, which is consistent with the findings of Cox & Peterson (1994), Lasfer et al. (2003), Mazouz et al. (2009). Prices behave almost like "wandering series" (Kendall & Hill, 1953), thus supporting the EMH.

Table 3. Large price changes (|SR0*i*|)—divided by the MR0 sign.

Panel A: Large stock price increases						
Average AR following initial price changes. % (2-tailed p values)						
	|SR0*i*| > 8%			|SR0*i*| > 10%		
Days Relative to the Event	MR > 0 (344 Events)	MR < 0 (73 Events)	Difference	MR > 0 (136 Events)	MR < 0 (34 Events)	Difference
AR Day 1	0.28% (15.21%)	−0.90% (10.15%)	1.17% (4.39%)**	−0.02% (96.07%)	−1.11% (12.32%)	1.09% (17.46%)
AR Day 2	0.08% (62.83%)	0.54% (14.56%)	−0.46% (26.06%)	0.17% (61.27%)	0.17% (75.89%)	−0.01% (99.22%)
Average AR 1–5 Days	−0.16% (6.81%)*	0.10% (61.09%)	−0.26% (36.94%)	0.04% (72.22%)	0.14% (65.39%)	−0.10% (76.29%)
Average AR 1–20 Days	0.08% (5.00%)*	0.14% (18.30%)	−0.06% (58.01%)	0.20% (0.43%)	0.20% (21.07%)	0.01% (97.06%)
Panel B: Large stock price decreases						
Average AR following initial price changes. % (2-tailed p values)						
	|SR0*i*| > 8%			|SR0*i*| > 10%		
Days Relative to the Event	MR > 0 (42 Events)	MR < 0 (302 Events)	Difference	MR > 0 (22 Events)	MR < 0 (151 Events)	Difference
AR Day 1	0.12% (87.85%)	−0.51% (3.16%)**	0.63% (44.42%)	1.30% (24.63%)	−1.10% (0.81%)***	2.40% (4.92%)**
AR Day 2	−0.66% (30.06%)	0.35% (8.06%)*	−1.01% (13.17%)	−1.35% (7.47%)*	0.22% (40.24%)	−1.57% (5.03%)*
Average AR 1–5 Days	−0.10% (57.50%)	−0.05% (58.83%)	−0.05% (79.64%)	−0.16% (54.88%)	−0.27% (5.86%)*	0.11% (71.08%)
Average AR 1–20 Days	0.03% (77.84%)	0.10% (1.36%)**	−0.07% (55.97%)	0.08% (52.10%)	0.08% (18.97%)	−0.16% (25.44%)

Notes: We calculated 2-tailed p values being p-value < 0.05 and these are presented between parentheses.
The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 4. Large price changes (σí)—divided by the MR0 sign.

Panel A: Large stock price increases						
Average AR following initial price changes. % (2-tailed p values)						
	|SR0*i*| > 3σi			|SR0*i*| > 4σi		
Days Relative to the Event	MR > 0 (1051 Events)	MR < 0 (215 Events)	Difference	MR > 0 (305 Events)	MR < 0 (93 Events)	Difference
AR Day 1	−0.07% (30.76%)	−0.49% (1.26%)	0.42% (4.40%)**	0.18% (23.31%)	−0.46% (9.88%)*	0.64% (4.37%)**
AR Day 2	0.03% (65.80%)	0.20% (16.54%)	−0.17% (26.13%)	−0.08% (43.90%)	0.20% (26.24%)	−0.28% (17.35%)
Average AR 1–5 Days	−0.14% (0.00%)***	0.01% (92.78%)	−0.15% (6.24%)*	−0.16% (1.62%)**	0.05% (64.79%)	−0.21% (9.85%)*
Average AR 1–20 Days	−0.01% (44.67%)**	0.00% (98.27%)	−0.01% (76.99%)	−0.03% (23.12%)	0.03% (44.93)	−0.06% (20.73%)
Panel B: Large stock price decreases						
Average AR following initial price changes. % (2-tailed p values)						
	|SR0*i*| > 3σi			|SR0*i*| > 4σi		
Days Relative to the Event	MR > 0 (211 Events)	MR < 0 (1152 Events)	Difference	MR > 0 (87 Events)	MR < 0 (369 Events)	Difference
AR Day 1	0.06% (72.81%)	−0.07% (34.13%)	0.13% (47.59%)	0.11% (64.67%)	−0.44% (1.62%)	0.54% (6.61%)*
AR Day 2	−0.18% (23.06%)	0.10% (11.22%)	−0.28% (8.55%)*	−0.30% (16.18%)	0.19% (12.21%)	−0.50% (4.75%)**
Average AR 1–5 Days	0.07% (21.32%)	0.01% (65.94%)	0.06% (35.59%)	0.05% (56.34%)	−0.08% (16.24%)	0.14% (21.70%)
Average AR 1–20 Days	0.04% (9.63%)*	0.02% (4.73%)**	0.02% (46.12%)	0.03% (44.08%)	0.00% (95.44%)	0.03% (50.17%)

Notes: We calculated 2-tailed p values being p-value < 0,05 and these are presented between parentheses.
The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 5. Large price changes (|AR0i|)—divided by the MR0 sign.

Panel A: Large stock price increases						
Average AR following initial price changes. % (2-tailed p values)						
	|AR0*i*| > 8%			|AR0*i*| > 10%		
Days Relative to the Event	MR > 0 (167 Events)	MR < 0 (101 Events)	Difference	MR > 0 (83 Events)	MR < 0 (47 Events)	Difference
AR Day 1	0.39% (21.65%)	−0.95% (3.14%)**	1.34% (1.33%)**	0.38% (43.30%)	−0.89% (26.48%)	1.27% (17.29%)
AR Day 2	0.21% (43.91%)	0.11% (72.86%)	0.10% (80.34%)	0.35% (36.58%)	0.23% (65.46%)	0.11% (86.41%)
Average AR 1–5 Days	0.10% (34.25%)	0.02% (91.83%)	0.08% (67.50%)	0.09% (55.43%)	0.28% (37.05%)	−0.20% (56.87%)
Average AR 1–20 Days	0.19% (0.23%)***	0.09% (29.95%)	0.10% (33.55%)	0.21% (2.92%)**	0.31% (4.13%)**	−0.11% (54.07%)
Panel B: Large stock price decreases						
Average AR following initial price changes. % (2-tailed p values)						
	|AR0*i*| > 8%			|AR0*i*| > 10%		
Days Relative to the Event	MR > 0 (76 Events)	MR < 0 (124 Events)	Difference	MR > 0 (27 Events)	MR < 0 (75 Events)	Difference
AR Day 1	0.45% (35.80%)	−0.99% (3.11%)**	1.44% (3.20%)**	1.06% (28.34%)	−1.43% (4.00%)**	2.49% (4.01%)**
AR Day 2	−0.21% (61.65%)	0.46% (12.48%)	−0.67% (19.68%)	−0.51% (52.61%)	0.44% (24.13%)	−0.95% (26.68%)
Average AR 1–5 Days	0.07% (64.56%)	−0.26% (10.68%)	0.33% (13.43%)	−0.04% (87.92%)	−0.37% (9.80%)	0.33% (36.63%)
Average AR 1–20 Days	0.00% (99.02%)	0.03% (65.07%)	−0.03% (80.25%)	0.12% (59.22%)	0.00% (99.61%)	0.12% (61.31%)

Notes: We calculated 2-tailed p values being p-value < 0.05 and these are presented between parentheses. The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

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

In line with the approach followed by Kudryavtsev (2018), we will divide our sample by the sign of the market (MR0) into two different groups: low and high market capitalization stocks, and low and high volatility stocks.

4.3.1. Market capitalization

Tables 6, 7, and 8 refer to proxy I, II, and III, respectively. For each of the event proxies, we split the samples of events into two equal parts by the firms' market capitalization (high and low) reported on the day. The mentioned tables present the average post-event ARs, by the sign of market on the day of the event (MR0), as well as the respective AR differences and their statistical significance, for high and low market capitalization firms.

Starting with increases we can observe randomness in average ARs. Considering proxies I and III, we can state that for low capitalization firms' prices there seems to be evidence of price continuation. For large caps, there is evidence of price reversals when the sign of the market on the day of the event was positive and continuation when MR < 0, which shows evidence of availability heuristic, although the differences lack statistical significance. This effect is also observable for proxy II, while in proxy III this evidence is not as strong as in the previous situations. These results are surprising in the way that according to previous literature large capitalization firms tend to present more stable post-event abnormal returns, even though these reversals are not very far from 0.

Table 6. Large price changes (|SR0i|)—Divided by Market Cap.

Panel A: Large stock price increases						
Average AR following initial price changes for high/low market capitalization firms. %						
	|SR0*i*| > 8%			|SR0*i*| > 10%		
Days Relative to the Event	MR > 0 (117/227 Events)	MR < 0 (12/61 Events)	Difference	MR > 0 (42/94 Events)	MR < 0 (7/27 Events)	Difference
AR Day 1	0.12% /0.36%	−1.18% /−0.84%	1.30% /1.20%*	−1.15%** /0.49%	−0.90% /−1.17%	−0.25% /1.66%*
AR Day 2	−0.54%* /0.40%**	0.45% /0.56%	−0.99%** /−0.16%	−0.42% /0.43%	0.30% /0.14%	−0.72% /0.29%
Average AR 1–5 Days	−0.18% /−0.15%	0.52% /0.02%	−0.69% /−0.17%	−0.01% /0.07%	0.68% /0.01%	−0.69% /0.06%
Average AR 1–20 Days	0.02% /0.11%**	0.22% /0.12%	−0.20% /−0.02%	0.10% /0.25%***	0.11% /0.22%	−0.01% /0.03%
Panel B: Large stock price decreases						
Average AR following initial price changes for high/low market capitalization firms. %						
	|SR0*i*| > 8%			|SR0*i*| > 10%		
Days Relative to the Event	MR > 0 (14/28 Events)	MR < 0 (102/200 Events)	Difference	MR > 0 (5/17 Events)	MR < 0 (53/98 Events)	Difference
AR Day 1	−0.52% /0.44%	−0.42% /−0.56%*	−0.10% /1.00%	0.59% /1.51%	−0.98% /−1.16%**	1.57% /2.67%*
AR Day 2	−1.03% /−0.47%	−0.15% /0.61%***	−0.88% /−1.09%	−0.29% /−1.67%*	−0.18% /0.43%	−0.12% /−2.10%**
Average AR 1–5 Days	−0.04% /−0.13%	−0.19% /0.03%	−0.15% /−0.15%	0.17% /−0.26%	−0.45% /−0.18%	0.62% /−0.08%
Average AR 1–20 Days	0.01% /0.04%	−0.04% /0.13%**	−0.03% /−0.09%	−0.06% /−0.09%	−0.06% /0.16%*	0.00% /−0.25%

Notes: The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

Considering the decreases, the pattern of randomness is also verified. When analyzing proxy I, we can observe mainly price continuation, except for small stocks when considering the sign of the market as negative mainly in the 8% threshold. In addition, in proxy II when considering MR < 0, there is evidence of price reversal for AR 2, more pronounced for small-capitalization firms. This is consistent with Baker & Wurgler (2006), but is an isolated example, as the rest of the observations are very diverse. In proxy III this case is also applicable for the 8% and 10% threshold, while for the other observations the behavior is also inconsistent.

Thus, we observe a certain standard of randomness when analyzing stock size, which is consistent with the results of previous tests presented in this paper. In some isolated cases, we can find evidence of size effect and availability heuristic, but with low statistical significance. When considering a higher window (1–5 and 1–20) there is evidence that average post-event ARs are very close to 0, which means that the market corrects the residual reversals and continuations observed when considering lower post-event windows.

Table 7. Large price changes (σi)—divided by market cap.

Panel A: Large stock price increases						
Average AR following initial price changes for high/low market capitalization firms. %						
	|SR0*i*| > 3σi			|SR0*i*| > 4σi		
Days Relative to the Event	MR > 0 (438/613 Events)	MR < 0 (73/142 Events)	Difference	MR > 0 (110/195 Events)	MR < 0 (26/67 Events)	Difference
AR Day 1	−0.17%* /0.00%	−0.42% /−0.53%**	0.25% /0.53%*	0.03% /0.26%	−0.20% /−0.56%*	0.24% /0.82%**
AR Day 2	−0.06% /0.09%	−0.04% /0.32%	−0.02% /−0.24%	−0.11% /−0.07%	0.37%* /0.13%	−0.48%* /−0.20%
Average AR 1–5 Days	−0.12%*** /−0.16%***	0.06% /−0.02%	−0.18% /−0.14%	−0.13% /−0.18%**	−0.30% /−0.05%	−0.42% /−0.13%
Average AR 1–20 Days	−0.02% /0.00%	0.01% /−0.01%	−0.03% /0.00%	−0.07%** /−0.01%	0.09% /0.01%	0.16%* /−0.02%
Panel B: Large stock price decreases						
Average AR following initial price changes for high/low market capitalization firms. %						
	|SR0*i*| > 3σi			|SR0*i*| > 4σi		
Days Relative to the Event	MR > 0 (95/116 Events)	MR < 0 (478/674 Events)	Difference	MR > 0 (40/47 Events)	MR < 0 (153/216 Events)	Difference
AR Day 1	−0.06% /0.16%	−0.17% /−0.01%	0.10% /0.16%	0.13% /0.09%	−0.52%** /−0.38%	0.64%* /0.47%
AR Day 2	−0.31% /−0.08%	0.11% /0.09%	−0.42%* /−0.17%	−0.18% /−0.41%	0.07% /0.28%	−0.25% /−0.69%*
Average AR 1–5 Days	0.13%* /0.02%	−0.03% /0.04%	0.16%* /−0.02%	0.20%* /−0.07%	−0.14% /−0.04%	0.33%** /−0.02%
Average AR 1–20 Days	0.05% /0.04%	0.00% /0.04%***	0.06% /−0.01%	0.09% /−0.01%	−0.04% /0.03%	0.13%* /−0.04%

Notes: The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 8. Large price changes (|AR0i|)—divided by market cap.

Panel A: Large stock price increases						
Average AR following initial price changes for high/low market capitalization firms. %						
	|AR0*i*| > 8%			|AR0*i*| > 10%		
Days Relative to the Event	MR > 0 (39/128 Events)	MR < 0 (25/76 Events)	Difference	MR > 0 (83 Events)	MR < 0 (47 Events)	Difference
AR Day 1	−0.40% /0.63%*	−0.57% /−1.08%**	0.17% /1.71%***	2.20%* /0.95%*	−0.21% /−1.07%	−1.99% /2.02%*
AR Day 2	0.07% /0.26%	−0.15% /0.19%	0.22%* /0.06%	1.63%* /0.06%	0.09% /0.27%	1.54% /−0.21%
Average AR 1–5 Days	−0.02%* /0.14%	0.11% /−0.01%	−0.13%* /0.15%	0.37% /0.02%	1.07% /0.07%	−0.71% /−0.04%
Average AR 1–20 Days	0.16% /0.20%***	−0.01% /0.12%	0.17% /0.08%	0.22% /0.20%**	−0.35% /0.30%	0.14% /−0.10%
Panel B: Large stock price decreases						
Average AR following initial price changes for high/low market capitalization firms. %						
	|AR0*i*| > 8%			|AR0*i*| > 10%		
Days Relative to the Event	MR > 0 (28/48 Events)	MR < 0 (35/89 Events)	Difference	MR > 0 (8/19 Events)	MR < 0 (24/51 Events)	Difference
AR Day 1	0.05% /0.69%	−1.24% /−0.89%*	1.29% /1.57%*	−0.02% /1.51%	−1.43% /−1.43%*	1.42% /2.94%**
AR Day 2	−0.20% /−0.22%	0.28% /0.52%	−0.48% /−0.74%	−0.59% /−0.98%	0.28% /0.51%	0.31% /−1.49%
Average AR 1–5 Days	0.32% /−0.08%	−0.64%* /−0.11%	0.96%** /0.03%	0.05% /−0.08%	−0.67% /−0.24%	0.71% /0.15%
Average AR 1–20 Days	0.02% /−0.02%	−0.13% /0.09%	0.15% /−0.11%	0.08% /0.13%	−0.07% /0.03%	0.15% /0.10%

Notes: The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

4.3.2. Volatility

After analyzing the behavior of prices for different groups of stocks, we will now analyze high and low volatile stocks also divided by the sign of the market (MR0). Tables 9, 10, and 11 refer to, respectively, proxy I, II, and III.

When analyzing increases, there is evidence of price continuation for high volatility firms and price reversals for low volatility firms for proxy I, with no significant differences considering the sign of the market. For proxy II the effect is similar for the "3σi" threshold. For the "4σi" threshold, the results exhibit augmented reversals for high volatility firms when the sign of the market on the day of the event was positive, and price continuation when the sign of the market was the opposite. This is consistent with the findings of Baker & Wurgler (2006) and with the availability heuristic by

Kudryavtsev (2018). For proxy III we do not find these effects, as we only find signs of reversals for low volatility stocks considering MR < 0.

Table 9. Large price changes (|SR0i|)—divided by volatility.

Panel A: Large stock price increases						
Average AR following initial price changes for high-/low-volatility stocks. %						
	|SR0*i*| > 8%			|SR0*i*| > 10%		
Days Relative to the Event	MR > 0 (180/164 Events)	MR < 0 (24/49 Events)	Difference	MR > 0 (42/94 Events)	MR < 0 (7/27 Events)	Difference
AR Day 1	0.65%** /−0.14%	−0.53% /−1.08%**	1.18% /0.94%*	0.19% /−0.27%	−0.47% /−1.56%**	0.66% /1.29%
AR Day 2	0.05% /0.12%	1.18% /0.23%	−1.14% /−0.11%	0.43% /−0.15%	−0.02% /0.31%	0.45% /−0.46%
Average AR 1–5 Days	0.09% /−0.43%***	0.67% /−0.17%	−0.58% /−0.26%	0.19% /−0.14%	0.50% /−0.11%	−0.31% /−0.03%
Average AR 1–20 Days	0.21% /−0.07%*	0.59%** /−0.08%	−0.37% /0.01%	0.40%*** /−0.03%	0.61%* /−0.09%	−0.21% /0.06%
Panel B: Large stock price decreases						
Average AR following initial price changes for high-/low-volatility stocks. %						
	|SR0*i*| > 8%			|SR0*i*| > 10%		
Days Relative to the Event	MR > 0 (13/29 Events)	MR < 0 (108/194 Events)	Difference	MR > 0 (5/17 Events)	MR < 0 (53/98 Events)	Difference
AR Day 1	0.30% /0.04%	0.01% /−0.80%***	0.29% /0.84%	0.65% /1.67%	0.29% /−2.04%***	0.36% /3.71%***
AR Day 2	−2.22%* /0.04%	0.35% /0.35%*	−2.57%** /−0.32%	−3.26%* /−0.27%	0.41% /0.18%	−3.66%** /−0.45%
Average AR 1–5 Days	−0.53% /0.10%	0.15% /−0.16%*	−0.68% /0.25%	−0.75% /0.17%	0.12% /−0.47%***	−0.87% /0.64%**
Average AR 1–20 Days	−0.25% /0.15%*	0.30%* /−0.02%	−0.55% /0.17%*	−0.43%** /0.12%	0.40% /−0.09%*	−0.83%*** /0.20%

Notes: The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

For proxy I and III there is evidence of price reversals for low volatility firms when considering MR > 0 and high volatility firms when considering MR < 0, while for proxy II post-event ARs follow a random path for high and low volatility firms. The pronounced reversals observable for high volatility firms when considering MR < 0 are consistent with the findings of Kudryavtsev (2018), but the rest of the observations do not exhibit a correlation between the volatility effect and the availability heuristic.

Table 10. Large price changes (σi)—divided by volatility.

Panel A: Large stock price increases						
Average AR following initial price changes for high-/low-volatility stocks. %						
	|SR0*i*| > 3σi			|SR0*i*| > 4σi		
Days Relative to the Event	MR > 0 (466/585 Events)	MR < 0 (79/136 Events)	Difference	MR > 0 (122/183 Events)	MR < 0 (37/56 Events)	Difference
AR Day 1	−0.03% /−0.10%	−0.93%** /−0.24%	0.90%* /0.14%	0.36% /0.05%	−0.59% /−0.38%	0.95% /0.43%
AR Day 2	0.09% /−0.02%	0.49% /0.03%	−0.40% /−0.06%	−0.20% /−0.01%	0.08% /0.27%	−0.28% /−0.28%
Average AR 1–5 Days	−0.26%*** /−0.05%*	−0.03% /−0.03%	−0.23% /−0.07%	−0.36%** /−0.02%	0.10% /0.01%	−0.46%* /−0.04%
Average AR 1–20 Days	0.00% /−0.02%	0.03% /0.03%	−0.03% /0.00%	−0.06% /−0.01%	0.07% /0.01%	−0.12% /−0.02%
Panel B: Large stock price decreases						
Average AR following initial price changes for high-/low-volatility stocks. %						
	|SR0*i*| > 3σi			|SR0*i*| > 4σi		
Days Relative to the Event	MR > 0 (54/157 Events)	MR < 0 (448/704 Events)	Difference	MR > 0 (21/66 Events)	MR < 0 (155/214 Events)	Difference
AR Day 1	−0.20% /0.15%	−0.32%* /0.08%	0.12% /0.06%	0.30% /0.04%	−0.89%** /−0.11%	1.20% /0.15%
AR Day 2	−0.55% /−0.05%	0.19% /0.04%	−0.74% /−0.10%	−1.10%* /−0.05%	0.59%** /−0.09%	−1.69%*** /0.04%
Average AR 1–5 Days	−0.02% /0.10%	−0.03% /0.04%*	0.01% /0.06%	−0.09% /0.10%	−0.21% /0.01%	0.11% /0.09%
Average AR 1–20 Days	0.04% /0.05%	0.06%** /0.00%	−0.02% /0.05%	0.05% /0.03%	0.03% /−0.02%	0.02% /0.05%

Notes: The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 11. Large price changes (|AR0i|)—divided by volatility.

Panel A: Large stock price increases						
Average AR following initial price changes for high-/low-volatility stocks. %						
	|AR0*i*| > 8%			|AR0*i*| > 10%		
Days Relative to the Event	MR > 0 (90/77 Events)	MR < 0 (33/68 Events)	Difference	MR > 0 (83 Events)	MR < 0 (47 Events)	Difference
AR Day 1	0.89%* /0.39%	−1.54% /−0.67%*	2.42%** /1.06%	0.75% /0.06%	−0.30% /−1.32%	1.05% /1.38%
AR Day 2	0.26%/ 0.21%	0.55% /−0.10%	−0.28% /0.32%	0.79% /−0.04%	0.77% /−0.16%	0.02% /0.12%
Average AR 1–5 Days	0.18% /0.10%	0.18% /−0.06%	0.00% /0.16%	0.12% /0.05%	0.83% /−0.12%	−0.70% /0.17%
Average AR 1–20 Days	0.34%*** /0.19%***	0.34% /−0.03%	0.00% /0.22%	0.45% /−0.01%	0.83% /−0.07%	−0.38% /0.06%
Panel B: Large stock price decreases						
Average AR following initial price changes for high-/low-volatility stocks. %						
	|AR0*i*| > 8%			|AR0*i*| > 10%		
Days Relative to the Event	MR > 0 (27/49 Events)	MR < 0 (42/82 Events)	Difference	MR > 0 (8/19 Events)	MR < 0 (24/51 Events)	Difference
AR Day 1	1.12% /0.08%	−0.07% /−1.46%**	1.19% /1.54%*	0.32% /1.73%	0.15% /−2.22%**	0.17% /3.96%***
AR Day 2	−0.37% /−0.13%	0.68% /0.34%	−1.05% /−0.46%	−0.88% /−0.17%	0.88% /0.22%	−1.77% /−0.39%
Average AR 1–5 Days	−0.03% /0.12%	0.01% /−0.40%**	−0.04% /0.52%**	−0.22% /0.12%	0.03% /−0.58%**	−0.25% /0.69%*
Average AR 1–20 Days	−0.10% /0.05%	0.20% /−0.06%	−0.30% /0.11%	0.11% /0.13%	0.19% /−0.09%	−0.08% /0.22%

Notes: The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

To conclude, following on from what was previously stated when analyzing for firms' market capitalization, the results provided by the general test performed earlier in this paper are not affected by the volatility effect, meaning that there is no clear correlation between high and low volatility stocks and the average post-event ARs for all the proxies.

4.3.3. Multifactor regression

The Hausman Test yielded very high p-values, meaning the acceptance of the null hypothesis and, therefore, the estimation of our regression through the random-effects model. As referred before, to validate the statistical inference in the presence of heteroscedasticity, we used White's robust estimator. In addition, our covariance analysis showed a very low correlation between the variables, meaning the absence of multicollinearity problems in our estimated models.

Table 12. Large price changes—AR 1.

Panel A: Large stock price increases						
Average AR following initial price changes. % (2-tailed p values)						
Days Relative to the Event	|SR0í| > 8% (417 Events)	|SR0í| > 10% (170 Events)	|SR0í| > 3σi (1266 Events)	|SR0í| > 4σi (398 Events)	|AR0í| > 8% (268 Events)	|AR0í| > 10% (130 Events)
Intercept	−0.008 (33.78%)	−0.023 (6.38%)*	−0.007 (5.03%)*	−0.002 (74.38%)	−0.012 (8.57%)*	−0.013 (35.06%)
MRO_dum	0.009 (12.29%)	0.013 (14.03%)	0.005 (1.64%)**	0.007 (4.00%)**	0.012 (3.11%)**	0.013 (19.34%)
MCap	−0.001 (44.84%)	−0.008 (3.92%)**	−0.002 (5.93%)*	−0.002 (28.31%)	−0.004 (15.79%)	−0.007 (17.25%)
beta	0.002 (50.66%	0.002 (73.75%	0.001 (48.23%)	−0.000 (95.32%)	−0.005 (21.26%)	0.004 (50.40%)
SR_Volar	0.005 (9.95%)*	0.002 (75.58%)	−0.002 (20.85%)	0.004 (22.83%)	−0.001 (78.31%)	0.000 (95.68%)
|SR0|	0.011 (82.93%)	0.068 (31.13%)	0.023 (57.80%)	−0.032 (54.52%)	0.029 (58.45%)	0.029 (67.30%)
ABVOL0	0.000 (97.19%)	0.004 (32.49%)	0.000 (67.97%)	0.002 (23.15%)	0.002 (42.96%)	0.002 (64.64%)
Panel B: Large stock price decreases						
Average AR following initial price changes. % (2-tailed p values)						
Days Relative to the Event	|SR0í| > 8% (344 Events)	|SR0í| > 10% (173 Events)	|SR0í| > 3σi (1363 Events)	|SR0í| > 4σi (456 Events)	|AR0í| > 8% (200 Events)	|AR0í| > 10% (102 Events)
Intercept	0.016 (19.43%)	0.025 (21.45%)	0.010 (21.76%)	0.017 (14.26%)	0.017 (30.56%)	0.026 (33.14%)
MRO_dum	0.008 (44.76%)	0.025 (11.09%)	0.001 (58.68%)	0.004 (35.96%)	0.004 (53.06%)	0.016 (22.13%)
MCap	−0.003 (16.06%)	−0.004 (17.21%)	−0.002 (4.88%)**	−0.003 (9.34%)	−0.004 (24.96%)	−0.006 (34.59%)
beta	0.006 (15.12%)	0.004 (50.95%)	0.001 (32.70%)	−0.002 (45.39%)	0.005 (14.67%)	0.006 (52.28%)
SR_Volar	−0.001 (61.90%)	0.001 (87.34%)	0.001 (64.07%)	0.006 (14.41%)	−0.017 (18.42%)	−0.003 (70.93%)
|SR0|	−0.185 (21.57%)	−0.237 (16.78%)	−0.155 (26.89%)	−0.219 (16.40%)	−0.179 (26.36%)	−0.223 (26.81%)
ABVOL0	0.001 (62.46%)	0.002 (36.99%)	0.000 (64.88%)	0.000 (66.40%)	−0.001 (70.74%)	−0.000 (80.76%)

Notes: We calculated 2-tailed p values being p-value < 0,05 and these are presented between parentheses.

The asterisks denote 2-tailed p values: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 12 presents the ARs for post-event day 1 (the results of the estimation for large stock price changes for the remaining post-event days are available upon request).

Our results show regression coefficients on MR0_dum very close to 0 with very low statistical significance, meaning that the impact of the sign of the market on stock price reactions on the following days after the event is very low. Therefore, from our regression, we find no evidence in support of our research hypothesis.

In addition, analyzing the regression coefficients for all the other variables, we conclude that all of them are not statistically significant, meaning that their impact on post-event ARs is not significant. Thus, these results are consistent with the previous tests performed in this paper.

5. Robustness tests

To perform the robustness tests to our research, we will apply two additional sample filtering criteria, which are consistent with the work by Kudryavtsev (2018). Firstly, we will adjust our sample considering overlapping price moves. In short, if we detect that the sample has 2 large price changes within a 20-trading day window, both changes will be excluded from the sample. Secondly, we will exclude from our sample events in which the stock prices are below 10€. This approach is consistent with Cox & Peterson (1994) and Park (1995), because of the bid-ask prices. In addition, it is also consistent with the work done in the United States by Kliger & Kudryavtsev (2010) and Kudryavtsev (2018). An additional third filter will also be applied to control for Brexit impacts on the results. When analyzing the data for the UK, we concluded that a large portion of the events was verified in 2016. This year coincides with the announcement of the results of the Brexit referendum. Due to space limitations, the results from these three analyses will be briefly presented, but the numerical tables with the complete results are available from the authors upon request.

5.1. Overlapping prices excluded

Taking into account the exclusion of overlapping price moves, the results show significant evidence of price reversals for large stock price increases for all of the proxies, which is different from what was stated before in this paper and is consistent with the findings for the United States by Kudryavtsev (2018). More specifically, looking at proxy II we find significant evidence of the availability heuristic when considering the "4σi" threshold, as in all of the windows of analysis we observe augmented reversals with MR > 0 with statistical significance, as our p-values are very low, and we reject the null hypothesis. In addition, in the other proxies, this effect is also observable in some cases, but with lower statistical significance. As for decreases, we observe mainly price continuation for proxy I, more pronounced when considering MR > 0. For proxy III we observe several price continuation and reversals for different post-event windows, with no statistical significance for differences computed, which is consistent with the general test performed. However, for proxy II there is support for the overreaction, as reversals are observed in almost all the windows considered. In addition, if we consider the "3σi" threshold, we find evidence of the availability heuristic hypothesis as the reversals are more pronounced when considering MR < 0, although we must consider that the differences are not very profound. In proxy I, we also observe that prices that suffer from reversals are more pronounced for MR < 0, and for those that suffer from continuation, the continuation is less pronounced for MR < 0, which can be also seen as a sign of the availability heuristic.

5.2. Stock prices below 10€ excluded

Here the results are slightly different from the general test performed and are more consistent with the ones that emerged from the previous robustness test. We find significant evidence of price reversals for increases in all the three proxies, which is consistent with Kliger & Kudryavtsev (2010) and Kudryavtsev (2018). However, the support for the availability heuristic is residual as in many cases we have reversals augmented by the opposite sign of the market and all the tests performed lack statistical significance. For decreases, the results are aligned with the general test performed, with no significant differences to point out. Therefore, we can conclude that the exclusion of the 10€ price has a slight impact on the results.

5.3. Brexit impact

On June 23, 2016, British citizens, through a referendum, decided by majority that the UK should cease to be a member of the EU. On January 17, 2017, the government stated its claims in the Lancaster announcement: there is no intention to belong to the European Economic Area, as this would require the free movement of people, nor to the Customs Union, which would remove the desired autonomy in the negotiation of agreement business. These facts led to financial turmoil during that year on European financial markets and mainly in the United Kingdom.

Some studies were performed to understand how stock prices and the economy reacted to this announcement. Starting with Oehler et al. (2017), the authors analyzed intraday prices and found that on the day of the announcement stocks of firms with higher proportions of domestic sales realized more negative abnormal returns than stocks of firms with more sales abroad. In addition, Raddant (2016) concluded that stock prices declined sharply and returned close to their previous levels within 3 weeks, and that the UK volatility peaked the day after the vote. To conclude, Ramiah et al. (2017) found negative cumulative abnormal returns for days 2, 5, and 10 after the referendum decision announcement for most of the sectors of the British economy.

To understand if Brexit had a significant impact on the results provided in this paper, we will perform another robustness test where we will exclude all the events referring to 2016. In Table 13 we can see the abnormal number of events in this year for all the proxies in the United Kingdom.

Table 13. Observations excluded during Brexit impact.

Total Observations Excluded Days Relative to the Event	$\lvert SR0i\rvert > 8\%$	$\lvert SR0i\rvert > 10\%$	$\lvert SR0i\rvert > 3\sigma i$	$\lvert SR0i\rvert > 4\sigma i$	$\lvert AR0i\rvert > 8\%$	$\lvert AR0i\rvert > 10\%$
Total Initial Observations	761	343	2629	854	468	232
Increases Excluded	132	52	169	43	63	33
Decreases Excluded	153	83	220	100	72	43
Total Observations Excluded	285	135	389	143	135	76
Total Observations Final	476	208	2240	711	333	156

Analyzing the average post-event ARs, we do not detect significant differences from the general test performed earlier in this paper for all the windows, for both stock price increases and stock price decreases. This shows that the year of the announcement of the Brexit has not significantly influenced the results for the United Kingdom.

6. Conclusions

This paper examined if the effect of the availability heuristic is present in the United Kingdom, taking the FTSE 100 as the basis for the sample from 2010 until 2018.

We hypothesize that if we observe stock price reversals following large daily price changes, and these reversals are more pronounced when the direction of the initial price change corresponds to the sign of the stock market index return on the day when the price change takes place, then this is indicative of the availability effect on investors. Consequently, in this situation we expect investors to be more influenced by the returns of the market in general on the day of the event, which may lead them to overreact.

Regarding price increases, we found no evidence for the impact of the availability heuristic in absolute thresholds, but for the relative threshold (proxy II) we found evidence of reversals in the following 2 trading days and over −5 and −20 intervals following the event when the sign of the market was also positive. This last result is consistent with the availability heuristic, although the results lack statistical significance for −2 and −5 periods. In addition, our robustness tests show greater evidence of reversals for all the proxies, either absolute or relative, although the availability heuristic is observable mainly when considering the 10% threshold for absolute returns and 4σi for relative returns with low statistical significance in the majority of the cases. Concerning decreases, the results are very similar to those observed in increases. Absolute proxies (I and III) indicate randomness in price behavior, as we can identify price continuation and price reversals considering the different post-event windows and the tests present high p-values. For proxy II, we found price reversals for ARs 1, 5, and 1–20 days when considering MR > 0. When the sign of the market is negative, there is evidence of reversals on AR day 2 and 1–20 after the event, being more pronounced on day 2. Therefore, we found evidence for the availability heuristic for the 2-day window.

In addition, we also conducted a robustness test to isolate the effect of Brexit on the results of the United Kingdom since a large portion of our sample refers to 2016, but the results from the general test remained unchallenged.

It is important to mention that when considering longer time intervals (−5 and −20) after the event, the average ARs present a trend very close to 0. This fact considered together with the higher p-values observed in the tests employed in this paper are indicative of market efficiency as they denote price randomness.

The methodology employed is based on Kudryavtsev (2018). This author found significant evidence of this effect in the United States from 1993 to 2014. However, for the United Kingdom the results shown in the current paper are considerably dissimilar. One reason for this discrepancy could be the period on which the sample of this paper is focused. We focused on a more recent period, where the technology development, mainly information and communication technologies, can contribute to the efficiency of the financial markets, which is consistent with the findings that the spread of the Internet, mobile phones and fixed phones all helped to improve stock market efficiency (Lee et al., 2019).

Another reason for these differences could be attributed to the fact that the United Kingdom presents a stock market with very different characteristics from that of the United States, as the number of investors is considerably lower. Furthermore, companies are very dependent on the banking institutions and they do not resort very often to the financial markets to raise funds for investment, which makes the number of firms publicly quoted much more restricted. These factors make a direct comparison of studies more difficult.

For investors, our results imply that there is a lack of abnormal arbitrage opportunities on the effect studied, as prices do not follow defined patterns. Therefore, an active investment strategy could not be designed to successfully exploit the price overreaction in the UK stock market.

For the academic community, this paper contributes with empirical evidence about the United Kingdom, as the previous work regarding the country is limited and with very little reference to this heuristic. Moreover, most of the previous research employed older datasets. Our sample is based on a much more recent period, capturing the post-2008 financial crisis effects on financial markets as well as the effects of the Brexit referendum. Furthermore, in recent years we have observed an intense technological development that has impacted the way the markets work and perform as well as their main constituents, which translates into the considerable weight of technological companies nowadays in comparison with previous periods.

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Conflict of interest

The authors declare no conflict of interest.

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