Returns On Large Stock Price Declines And Increases In The South African Stock Market: A Note On Market Efficiency

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ABSTRACT

This study tests for underreaction and overreaction in the South African stock market by examining abnormal returns on the stocks included in the FTSE Group Johannesburg Stock Exchange Top 40 index following large price rises and drops. The results of our empirical investigation suggest that large price increases and declines are likely to be followed by positive market returns. In addition, for the post-2008 time period the risk of these stocks increases significantly for up to two years following the original event. Therefore, the results lend further support to the Uncertain Information Hypothesis.

Keywords: Stock Price Performance; Market Efficiency; Overreaction; Uncertain Information Hypothesis

1. INTRODUCTION

The Efficient Market Hypothesis is an integral part of modern financial economics and one of the pillars of neoclassical finance theory. De Bondt and Thaler (1985) challenged this pillar when they, motivated by findings in the field of experimental psychology, detected predictable return reversals in stock prices. They attributed these patterns to overreaction to new information by investors. The ability to use past data to predict future returns is a violation of the Efficient Market Hypothesis. Not surprisingly, the detection of overreaction prompted a large body of further research, which focused on the predictability of stock returns. While there is considerable evidence in favor of stock return predictability, the underlying reasons remain largely unclear. One possible explanation for this pattern is suggested by Zarowin (1990) and Atkins and Dyl (1990). Their results indicate that overreaction is a manifestation of the size-effect. However, other researchers argue that it is caused by the bid-ask-spread and infrequent trading (Conrad & Kaul, 1993). In addition, some studies report momentum after large stock price drops (Ising, Schiereck, Simpson, & Thomas, 2006), which they attribute to investor underreaction. Brown, Harlow, and Tinic (1988) develop a competing hypothesis to the Overreaction Hypothesis, which reconciles the empirical findings with the Efficient Market Hypothesis. Their Uncertain Information Hypothesis assumes that rational, risk-averse investors overreact to bad news and underreact to good news, since the actual impact of the new information is not immediately clear.

More recent research on markets outside the US find supportive evidence for the Efficient Market Hypothesis (e.g., Lobe & Rieks, 2011; Himmelmann, Schiereck, Simpson, & Zschoche, 2012). Consequently, the question arises whether international stock markets are efficient in general or if efficiency only holds for more mature markets. As the development of financial markets is often closely related to the overall development of a country one would expect to find more market inefficiencies in not yet fully developed countries rather than in developed ones. The question of market efficiency is particularly interesting with regard to emerging markets, such as the BRICS-countries (Brazil, Russia, India, China, and South Africa) as they become major players in the global economy and increasingly draw the interest of international investors.

This study contributes to the current literature on market efficiency by examining the market reaction to large price movements in the South African stock market. In contrast to prior research, the present study does not focus on a well-established developed market, but rather on one of the most prominent emerging markets and aims at establishing whether emerging stock markets display the same efficiency as developed ones. South Africa, often considered the gateway to Africa, is a particularly interesting market to investigate as it holds a unique position among African nations as the by far most developed economy on the continent. According to the World Banks' World Development Indicators, South Africa accounted for 71.87% (US$ 311.778 billion) of the African stock market capitalization and 90.53% (US$ 612.308 billion) of the value of shares traded in 2012. It is also the most liquid African market, even though it still lags considerably behind the most liquid markets in the world.

The rest of this study is organized as follows. Section 2 briefly summarizes the existing empirical literature on the efficiency of stock markets with a special focus on South Africa. Section 3 describes the data sample and the methodology. Section 4 presents the main empirical results. The final section concludes the paper.

2. LITERATURE REVIEW

A considerable body of literature already exists on the predictability of stock prices after large price increases and declines (for a comprehensive review see Amini, Gebka, Hudson, and Keasey (2013)). In order to exploit price reversals contrarian strategies are applied, which entail buying securities of previously losing firms and selling those of previous winners. Price continuation, on the other hand, can be exploited by applying a momentum strategy. In this case the investor buys securities of previous winners and sells those of losers. In the relevant literature, winners and losers are predominately identified either by their performance over a particular time period or by exceeding a certain predetermined threshold (e.g., 10% price change in one day).

A considerable amount of the relevant literature follows De Bondt and Thaler (1985) in constructing portfolios of stocks that displayed either a comparatively weak or strong performance over a certain time period; the loser and winner portfolios, respectively. Based on the results of their empirical analysis, De Bondt and Thaler (1985) derive the Overreaction Hypothesis. Investors seem to emphasize recent information more strongly compared to prior data. This leads to an overreaction and subsequent price adjustments, which can be exploited. This in turn is a violation of the weak-form market efficiency, because future returns are predictable from past data. Lehmann (1990) confirms these results on a very short investment horizon, as his findings also suggest price reversals and hence overreaction.

The results of Atkins and Dyl (1990) also point towards an overreaction by investors. However, in contrast to prior studies, they also compare the magnitude of the price reversals to the bid-ask spreads. According to their findings, arbitrageurs would not be able to profit from these price reversals, since the abnormal returns are small when compared to the bid-ask spreads. Therefore, Atkins and Dyl (1990) conclude that although there is an overreaction, it does not contradict market efficiency once transaction costs are accounted for. Employing a contrarian strategy, Chan (1988) only observes small abnormal returns and concludes that the results of De Bondt and Thaler (1985) are most likely due to a size effect, caused by the Sharpe (1964)-Lintner (1965) Capital Asset Pricing Model (CAPM). Zarowin (1990) complements the findings of Chan (1988). His results indicate significant size effects. Loser portfolio firms are on average smaller and even smaller winners outperform larger losers. Chopra, Lakonishok, and Ritter (1992) also find significant overreaction effects. Their results in particular indicate that the overreaction effect is more distinct for small companies. This can potentially be explained on the grounds that a relatively large percentage of the shares of small firms are frequently held by individual investors, while the shares of large firms are often predominantly held by institutional investors.

Overreaction of winner and loser portfolios has also been documented for various international stock markets, such as Japan (Iihara, Kato, & Tokunaga, 2004), Brazil (da Costa, 1994), and the UK (Dissanaike, 1997). However, Dissanaike (1997) also finds short- and medium-turn momentum patterns in the UK market, a result later confirmed by Hon and Tonks (2003). The results of Gaunt (2000) also indicate price reversals on the Australian stock market, but this finding disappears once a buy and hold strategy is used.

In contrast to the Overreaction Hypothesis, the Uncertain Information Hypothesis by Brown et al. (1988) reconciles the observed anomalies with the Efficient Market Hypothesis. The underlying assumption of the Uncertain Information Hypothesis is that new information introduces uncertainty, so that the impact of the new information is not immediately apparent. Rational, risk-averse investors account for this uncertainty through additional risk-premiums and will overreact to bad news and underreact to good news. The empirical results of Brown et al. (1988) prove that this pattern exists in the US Market. Later studies corroborate these initial results for the US and other international markets (Ajayi & Mehdian, 1994; Schnusenberg & Madura, 2001; Yu, Rentzler, & Tandon, 2010).

Besides constructing winner and loser portfolios based on past stock performance, another line of research identifies events based on securities exceeding a certain threshold with regards to their price change within a day, a week, or a month. Bremer and Sweeney (1991) report a significant rebound of stock prices during the two days following a price drop in excess of -10% on a given trading day. They conclude that this is largely inconsistent with the Efficient Market Hypothesis, as markets are supposed to correctly reflect news in the price of a security almost instantaneously. Benou and Richie (2003) examine monthly returns of the S&P 100 constituents and use a month-on-month price change of at least -20% for a given security to determine an event month. They find significant positive abnormal returns following the initial price declines, lending further support to the Overreaction Hypothesis. Choi and Jayaraman (2009) also find overreaction patterns up to two days after a large price decline, albeit only for nonoptional stocks. However, this pattern can largely be explained by an abnormal rise in the bid-ask spread prior to the price decline event.

Bremer, Hiraki, and Sweeney (1997) examine daily returns of stocks included in the NIKKEI 300 index. They find price reversals after large one day stock price drops, but remain doubtful of the possibility of being able to exploit this anomaly. Bowman and Iverson (1998) examine the behavior of stock prices in New Zealand after large weekly price changes. Their results suggest an asymmetric overreaction effect that persists even after testing for seasonality, size, and bid-ask spread effects. Ising et al. (2006) examine the performance of the largest 100 German firms. Their study shows that large price increases are followed by reversal patterns, but large price declines are followed by further declines, which they interpret as a sign of overoptimism by investors. Mazouz, Alrabadi, & Yin (2012) find evidence for continuation patterns after large price drops and increases. However, only stocks with high liquidity risk underreact, while stocks with low systematic risk show efficient reactions. Hence the authors reason that trading on the observed anomalies may not be profitable, as substantial liquidity risks are taken. Maher and Parikh (2011) also observe underreaction to large price drops by medium and small capitalization indices in India. In contrast, large price increases are not followed by a discernable pattern. The recent findings of Himmelmann et al. (2012) for Europe lend further support the Efficient Market Hypothesis, since neither reversal nor momentum patterns can be detected.

Only few studies exist that investigate the South African stock market or African stock markets in general. In an early study Okeahalam and Jeffries (1999) investigate how quickly earning announcements are incorporated into the stock price of companies on the Johannesburg stock exchange. Using weekly data, their results suggests that the market displays semi-strong efficiency. Appiah-Kusi and Menyah (2003) use weekly index returns and show that the South African stock market is not weak-form market efficient. However, Jefferis and Smith (2005) find that the returns on the Johannesburg stock exchange follow a random walk and therefore to be weak-form efficient. The results of Smith (2008) further corroborate this finding. However, overall the evidence on the efficiency of the South African stock market remains contradictory.

3. DATA AND METHODOLOGY

3.1 Data Sample and Selection

The present study examines the largest South African stocks, as listed in the FTSE/JSE Top 40 index from January 2003 to December 2011. This index consists of the 40 largest South African companies, ranked by full market value and listed on the Johannesburg stock exchange. Utilizing only the largest firms mitigates any biases that might arise due to size differentials. During the investigation period 68 different companies have been constituents of the FTSE/JSE Top 40, with an average listing time of 5.25 years. The index was originally launched in 2002 and is subject to quarterly revisions. Events are determined based on price data, while subsequent calculations are carried out with total return data. Data is provided by Thomson Reuters Financial Datastream. Following, among others, Benou and Richie (2003), Ising et al. (2006), and Himmelmann et al. (2012), a month is identified as an event month for a particular firm, if there is an absolute price change of more than 20% in that month, using closing prices of the last trading day of the previous and actual month, respectively. Additionally, the investigated firm had to be a constituent of the index at the time of the event.

Table 1: Distribution of Events Across Time

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Panel A: Distribution of Price Increases over Time													
2003					9			2		2	1	1	15
2004							1	3	1		3		8
2005	1	2			4		1		5		1		14
2006	2					2		1		2	1		8
2007	1				1				1	2			5
2008		6			1		3	2	1	1	3		17
2009	1		8		7		3	3		1		1	24
2010									1				1
2011			1							1			2
Total	5	8	9	0	22	2	8	11	9	9	9	2	94
Panel B: Distribution of Price Decreases over Time													
2003		2	1	1									4
2004				2									2
2005				3									3
2006		1											1
2007								1			1		2
2008	2					1	5		9	12	7		36
2009	1	4		2									7
2010			1										1
2011													0
Total	3	7	2	8	0	1	5	1	9	12	8	0	56

Using this methodology, 150 events are identified between 2003 and 2011; 94 price increases and 56 price declines. Only 43 out of the 68 firms exhibit an event, resulting in an average of 3.49 events per firm.

Table 1 shows that almost all events occur prior to 2010. Furthermore, 56% of all events occur in 2008 and 2009. In addition, Panel B of Table 1 shows that 50% of all price declines are clustered between September and November 2008. This period can be viewed as the onset of the recent financial crisis on the South African Stock market. Besides these two anomalies, the event distribution does not provide any further insights.

3.2 Methodology

Event study results depend to a certain degree on the chosen asset pricing model. Fama (1998) points out that this effect multiplies when cumulating abnormal returns (ARs) to cumulative abnormal returns (CARs). Nevertheless, CARs seem to be more robust than long-term buy and hold abnormal returns, making them preferable.

To define ARs, both the market-adjusted-model and the market-model are used. The usage of the market-model is motivated by the work of Brocket, Chen, and Garven (1999). Their results suggest that the classical event study approach appears to be detecting more events than actually exist. In order to avoid this, Brocket et al. (1999) propose a model that incorporates autoregressive conditional heteroskedastic effects (ARCH). This is also supported by the findings of Schwert and Seguin (1990), who show that stock returns often exhibit a considerable degree of heteroskedasticity. They also suggest that taking time-varying volatility into account, evidence for abnormal returns ought to be weakened. Consequently, the error term in this model is not considered to be white noise. Instead, it is assumed to follow a generalized autoregressive conditional heteroskedastic process (GARCH) with a lag of one in the conditional variance and the squared error, respectively (GARCH(1,1)).

The market-adjusted-model is specified as:

$$R_{jt} = R_{mt} + e_{jt}, \tag{1}$$

where R_{jt} denotes the return of stock j at time t, R_{mt} is the return of the market portfolio at time t and e_{jt} is the error term. Monthly ARs are calculated according to:

$$AR_{jt} = R_{jt} - R_{mt} \tag{2}$$

As suggested by Brocket et al. (1999), and later used by Benou and Richie (2003) and more recently Himmelmann et al. (2012), the GARCH (1,1) market-model is specified as:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt}, \tag{3}$$

where α_j is the intercept for stock j, R_{mt} is the return of the market portfolio at time t, and β_j the sensitivity of stock j to the market portfolio. The error term ε_{jt} is conditioned on the prior information set Ω_{t-1}:

$$\varepsilon_{jt}|\Omega_{t-1} \sim N(0, h_t), \tag{4}$$

where $N(0,h_t)$ denotes the conditional distribution of the error term, given all available information at time t_{-1}. The conditional distribution has a mean of zero and a variance of h_t. The conditional variance h_t in this GARCH(1,1) process is specified as:

$$h_t = \phi_0 + \phi_1 h_{t-1} + \phi_2 \varepsilon_{t-1}^2 \tag{5}$$

The parameters in (3) and (5) are estimated using the maximum likelihood method with daily returns during the 1 year period prior to the event month. Using the market-model, the monthly ARs are calculated as:

$$AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt}) \tag{6}$$

where $\hat{\alpha}_j$ and $\hat{\beta}_j$ are the regression estimates obtained from equation (3). The following calculations are the same for both models. For a sample of N events, monthly average ARs (AARs) are calculated as:

$$AAR_t = \frac{1}{N} \sum_{j=1}^{N} AR_{jt} \tag{7}$$

where t denotes the month relative to the event month and $t = 0$ denotes the event month itself. The CAR during the time window $[\tau_1,\tau_2]$ is then calculated as:

$$CAR_{j,[\tau_1,\tau_2]} = \sum_{t=\tau_1}^{\tau_2} AR_{jt} \tag{8}$$

where τ_1 and τ_2 denote the months relative to the event month. Finally, for a sample of N events, average CARs (ACARs) are calculated as:

$$ACAR_{[\tau_1,\tau_2]} = \frac{1}{N} \sum_{j=1}^{N} CAR_{j,[\tau_1,\tau_2]} \tag{9}$$

In order to make the results comparable to previous studies (e.g., Benou & Richie, 2003; Himmelmann et al., 2012), the AARs are calculated for the interval τ_1 $\tau_2 \epsilon [-6;6]$ and CARs up to 36 months after the original event. If there is missing data in the calculation month or the subsequently investigated time period (e.g., due to insolvencies or acquisitions), the event is left out.

In order to test for normality of the return distribution, the Jarque-Bera test on normality (Jarque & Bera, 1987) is applied and in order to test whether AARs and ACARs differ statistically significantly from zero the standard t-Test and the Mikkelson and Partch (1986) test are applied. Furthermore, for the determination of time-varying risk, the Wilcoxon rank-sum test is used as a nonparametric difference test.

4. EMPIRICAL RESULTS

4.1 Descriptive Statistics

During the examination period from January 2003 to December 2011, the FTSE/JSE Top 40 comprised 68 different firms with an average listing period of 5.25 years. Only 25 firms were constituents of the index during the entire examination period.

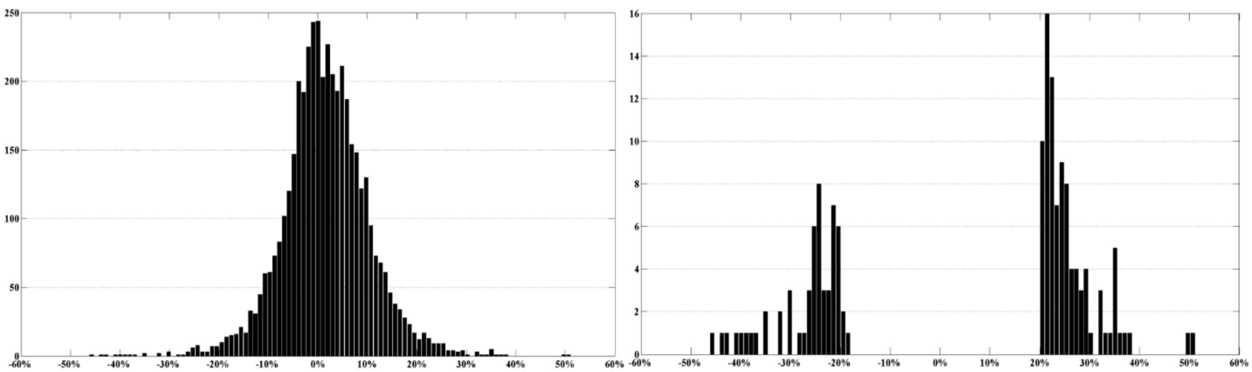

Figure 1: Panel A: Return Distribution of Sample **Panel B: Return Distribution of Events**

The sample contains 4,369 monthly returns of the respective current constituents. Panel A of Figure 1 shows the distribution of the sample returns. The mean and the median of the sample returns are 1.59% and 1.37%, respectively. Further, the standard deviation of the monthly returns is 8.75% (annualized standard deviation of 30.32%) with a maximum and minimum return of 51.16% and -46.24%, respectively. Applying the Jarque-Bera test for normality, the null hypothesis that the sample comes from a normal distribution has to be rejected at the 0.1% significance level.[1]

Panel B of Figure 1 shows the return distribution of the events. The average return for a month representing an increase event is 25.78% (median = 24.18%) with a standard deviation of 5.86% (annualized standard deviation of 20.30%). The average return for a month representing a decline event is -26.77% (median = -24.51%) with a standard deviation of 7.05% (annualized standard deviation of 24.42%). The magnitudes of event returns are always above or below the relevant index returns, thereby preventing a bias through the event determination process.

4.2 Analysis of Stock Returns Following Price Increases

The market-model AARs,[2] surrounding large price increases are shown in Table 2. In the 13-month period starting 6 months before the event month, which is denoted as month 0, and ending 6 months after the event month, no particular patterns can be observed with regard to AARs. In addition, the t-Test does not show any statistical significance, except for the AAR in the fourth month after the event. As expected, the AAR in the event month is large and significant. The Mikkelson-Partch test statistic indicates statistical significance for almost all months. The test statistic normalizes ARs by the weighted residual variance from the parameter estimation. However, since the residual variance is rather small in nearly all models, which may be caused by a bias in the residual variance estimation, the Mikkelson-Partch test indicates significance more frequently. Therefore, relying on the t-Test as the reference test seems to be a more conservative approach and hence only the results with regards to the t-Test will be discussed in more detail in this and the following sections.

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[1] In addition to the Jarque-Bera test for normality, the Anderson-Darling test and the Shapiro-Wilk test were also applied. Both tests reject the assumption of a normal distribution at the 0.1% significance level, confirming the results of the Jarque-Bera test.

[2] Due to the similarity of results, the results of the market-adjusted-model are not provided. However, significant deviations between the two models are indicated.

Table 3 shows market-model ACARs prior to and following large price increases. All ACARs following the event month are positive. Hence, price increases show momentum. All ACARs over time periods that end 36 months after the initial event are statistically significant. In addition, the windows [3;6] and [3;24] are significant as well. ACARs in the time windows prior to the event are not statistically significant. This, in combination with the AARs during the pre-event period, indicates that large price increases are not predictable. It should be noted, that market-adjusted ACARs are generally smaller in magnitude but still significant. It should also be noted that most of the statistically significant ACARs exhibit a smaller sample size, indicating a possible survivor bias.

Table 2: AARs Surrounding Large Price Increases (Market-Model)

Month	Sample Size	AAR	Median AR	t-Test	Mikkelson/Partch
-6	90	-1.45%	-1.40%	-1.30	-5.42[a]
-5	90	0.64%	0.85%	0.52	1.53
-4	90	1.56%	0.51%	1.20	4.30[a]
-3	90	0.58%	0.00%	0.67	1.13
-2	90	-1.53%	-2.21%	-1.43	-4.30[a]
-1	90	-1.82%	-0.79%	-1.57	-4.02[a]
0	90	19.26%	19.02%	22.34[a]	73.97[a]
1	90	-0.29%	0.44%	-0.37	-0.65
2	90	-0.72%	-1.31%	-0.71	-0.83
3	90	1.46%	2.07%	1.55	4.62[a]
4	90	1.87%	0.19%	1.79[c]	5.72[a]
5	89	-0.67%	-0.90%	-0.78	-1.43
6	89	1.36%	0.29%	1.39	6.10[a]

[a], [b], [c] denote statistical significance at the 1%, 5%, and 10% level, respectively.

Summarizing the above findings, stock returns after large price increases exhibit a momentum pattern. The following periods exhibit positive ACARs, although they are mostly only statistically significant with regards to the event window ending 36 months after the original event. The findings point, at least superficially, towards an underreaction to good news by investors in the South African stock market. However, it can also be seen as supporting the Efficient Market Hypothesis as many result lack statistical significance.

Table 3: ACARs Surrounding Large Price Increases (Market-Model)

Time Window	Sample Size	ACAR	Median CAR	t-Test	Mikkelson/Partch
[-12;-1]	90	3.14%	-2.83%	0.82	3.62[a]
[-6;-1]	90	-2.02%	-1.30%	-0.75	-2.77[a]
[1;6]	89	3.09%	4.81%	1.45	5.68[a]
[1;12]	88	3.84%	0.52%	1.21	4.97[a]
[1;24]	87	7.22%	2.14%	1.49	9.05[a]
[1;36]	64	27.42%	25.94%	3.91[a]	16.67[a]
[3;6]	89	4.00%	2.59%	2.47[b]	7.36[a]
[3;12]	88	4.70%	2.10%	1.65	5.61[a]
[3;24]	87	8.01%	3.70%	1.80[c]	9.47[a]
[3;36]	64	26.95%	25.62%	4.12[a]	16.69[a]
[6;12]	88	2.03%	1.38%	0.74	3.44[a]
[12;24]	87	4.36%	3.64%	1.26	7.75[a]
[12;36]	64	24.05%	22.14%	4.26[a]	16.59[a]
[24;36]	64	21.11%	17.24%	4.95[a]	16.97[a]

[a], [b], [c] denote statistical significance at the 1%, 5%, and 10% level, respectively.

4.3 Analysis of Stock Returns Following Price Declines

Table 4 shows the market-model AARs starting 6 months before the event month, which is denoted as month 0, and ending 6 months after the event month. Again most of the AARs are not statistically significant with regard to the t-Test. There is also no discernable pattern in regard to the sign and magnitude of the returns. As expected, the event month exhibits a large, statistically significant, and negative AAR. There is some evidence for price reversals in the fifth post-event month based on the t-Test, which might point to initial overreaction by investors. Nevertheless, the findings in general do not necessarily contradict the Efficient Market Hypothesis.

The ACARs are shown in Table 5. As in the case of large price increases, the months prior to the decline do not exhibit statistically significant ACARs. The ACARs following the event month are positive except for the last two time windows ([12;36] and [24;36]). However, only three time windows, [3;6], [3;12], [3;24], show statistical significance in regard to the t-Test. It seems that the statistically significant reversal disappears if the third year after the event is also considered.

Table 4: AARs Surrounding Large Price Declines (Market-Model)

Month	Sample Size	AAR	Median AR	t-Test	Mikkelson/Partch
-6	55	0.70%	0.63%	0.58	1.87[c]
-5	55	-1.16%	-1.89%	-0.72	-3.33[a]
-4	55	1.60%	1.07%	1.10	3.09[a]
-3	55	0.58%	-2.36%	0.36	0.70
-2	55	-1.38%	-0.87%	-0.96	-5.22[a]
-1	55	-2.36%	-0.81%	-1.53	-4.33[a]
0	55	-19.45%	-19.33%	-16.57[a]	-54.02[a]
1	55	-1.22%	-0.97%	-0.52	-3.52[a]
2	55	0.01%	0.26%	0.01	-2.35[b]
3	55	-0.38%	-0.79%	-0.19	-3.77[a]
4	55	-0.36%	-0.90%	-0.23	-3.10[a]
5	55	4.18%	2.50%	2,80[a]	9.43[a]
6	55	1.36%	-0.95%	0.91	1.89[c]

[a], [b], [c] denote statistical significance at the 1%, 5%, and 10% level, respectively.

Summing up the findings on returns following large price declines, there are statistically significant reversal patterns up to 2 years after the original event. However, these patterns disappear, if the third year after the event is also included. The results lend some support to the Overreaction Hypothesis.

Table 5: ACARs Surrounding Large Price Declines (Market-Model)

Time Window	Sample Size	ACAR	Median CAR	t-Test	Mikkelson/Partch
[-12;-1]	55	3.71%	2.22%	0.71	0.90
[-6;-1]	55	-2.02%	-2.89%	-0.64	-2.94[a]
[1;6]	55	3.59%	1.62%	1.01	-0.58
[1;12]	55	6.61%	7.51%	1.59	2.26[b]
[1;24]	54	9.29%	15.68%	1.52	4.41[a]
[1;36]	52	8.30%	1.71%	1.09	2.06[b]
[3;6]	55	4.80%	4.61%	1.72[c]	2.22[b]
[3;12]	55	7.82%	5.99%	2.19[b]	4.33[a]
[3;24]	54	10.38%	14.31%	1.86[c]	5.78[a]
[3;36]	52	9.79%	0.18%	1.40	3.18[a]
[6;12]	55	4.38%	6.15%	1.43	4.21[a]
[12;24]	54	-0.85%	-2.61%	-0.19	0.97
[12;36]	52	-2.90%	-12.55%	-0.45	-1.46
[24;36]	52	-2.02%	-8.38%	-0.42	-3.16[a]

[a], [b], [c] denote statistical significance at the 1%, 5%, and 10% level, respectively.

In light of the observed return continuation after large price increases and the return reversal after large price declines, the findings seem to support the Uncertain Information Hypothesis. However, the ACARs are of larger magnitude after price increases than after price declines. This asymmetry is opposite to the expectations of the Uncertain Information Hypothesis and hence contradicts it to a certain degree.

4.4 Robustness Checks

Multiple robustness checks are applied in order to check the validity of the prior results. Since the FTSE/JSE Top 40 index only comprises the largest and therefore most liquid South African firms, the results ought to be relatively stable against size and illiquidity effects. Nevertheless, as additional robustness checks, different trigger values and subsamples are analyzed and time variation in risk is investigated. By using a trigger value of

30% instead of 20%, only 15 events remain to be analyzed. The findings largely confirm the previous results.[3] ACARs generally increase in magnitude but at the same time their significance is reduced. Furthermore, not all observed ACARs have the positive sign anymore, questioning the previously observed continuation pattern. Using a trigger value of -30% instead of -20%, only 12 events remain. The results still largely corroborate earlier findings. The previously significant windows ([3;6], [3;12], [3;24]) increase in significance and, in addition, the windows [1;6], [1;12] also become significant. These ACARs increase in magnitude and are positive. Hence, these price reversals after large declines lend further support to overreaction by investors.

Splitting up the sample of large price increases into pre- and post-2008 subsamples (i.e., the period prior to the onset of the recent financial crisis on the South African market (January 2003 to December 2007) and the period largely including it (January 2008 to December 2011)) does not lead to particularly new insights and hence the results are not reported here.[4] However, splitting the price declines into these two subsamples leads to some interesting insights (see Table 6 and Table 7).

Table 6: ACARs Surrounding Large Price Declines Prior to 2008 (Market-Model)

Time Window	Sample Size	ACAR	Median CAR	t-Test	Mikkelson/Partch
[-12;-1]	12	-4.27%	-11.89%	-0.26	-4.44[a]
[-6;-1]	12	-9.80%	-13.98%	-1.15	-6.15[a]
[1;6]	12	4.49%	-3.07%	0.60	-0.92
[1;12]	12	4.62%	5.94%	0.43	-0.17
[1;24]	12	-0.18%	19.02%	-0.01	1.29
[1;36]	12	19.93%	23.36%	1.19	3.38[a]
[3;6]	12	4.81%	2.07%	0.74	-0.46
[3;12]	12	4.95%	8.12%	0.45	0.24
[3;24]	12	0.14%	16.81%	0.01	1.63
[3;36]	12	20.26%	13.31%	1.12	3.71[a]
[6;12]	12	-1.01%	8.89%	-0.10	-1.09
[12;24]	12	-10.32%	-2.78%	-0.62	-0.35
[12;36]	12	9.79%	18.31%	0.54	2.54[b]
[24;36]	12	19.95%	-7.42%	1.33	4.19[a]

[a], [b], [c] denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: ACARs Surrounding Large Price Declines 2008 and Later (Market-Model)

Time Window	Sample Size	ACAR	Median CAR	t-Test	Mikkelson/Partch
[-12;-1]	43	5.94%	2.39%	1.18	3.36[a]
[-6;-1]	43	0.15%	-2.15%	0.05	-0.08
[1;6]	43	3.33%	2.86%	0.82	-0.17
[1;12]	43	7.17%	7.67%	1.60	2.64[a]
[1;24]	42	12.00%	12.70%	1.99[c]	4.31[a]
[1;36]	40	4.81%	-5.43%	0.56	0.50
[3;6]	43	4.79%	4.75%	1.54	2.76[a]
[3;12]	43	8.62%	5.33%	2.51[b]	4.77[a]
[3;24]	42	13.31%	14.31%	2.83[a]	5.68[a]
[3;36]	40	6.65%	-2.08%	0.90	1.59
[6;12]	43	5.89%	4.34%	2.11[b]	5.33[a]
[12;24]	42	1.86%	-2.61%	0.56	1.29
[12;36]	40	-6.71%	-14.99%	-1.04	-3.05[a]
[24;36]	40	-8.61%	-8.38%	-2.14[b]	-5.90[a]

[a], [b], [c] denote statistical significance at the 1%, 5%, and 10% level, respectively.

As Table 6 shows, large price declines do not lead to any statistically significant returns with regards to the t-Test during the pre-2008 period. This might be due to the rather small sample size, but it is still a noteworthy result. The results for the time period between 2008 and 2011 are presented in Table 7. The previously significant reversals for the windows [3;12] and [3;24] increase in significance and the windows [1;24] and [6;12] become

[3] For brevity only the main results are discussed here. Tables with the exact results are available from the authors upon request.
[4] The tables with the results of the price increases for the period prior to 2008 and for 2008 and later are available from the authors upon request.

significant. Since these price reversals are positive in magnitude, these results seem to further support the Overreaction Hypothesis. In addition, the overall results for large price declines seem to be largely driven by the 2008-2011 time period. This result is not surprising, since this time period includes approximately 78% of all investigated price declines.

The abnormal returns observed so far may be induced by a variation of risk and could therefore potentially change over time. In order to check for time-varying risk, we estimate the parameters of the market-model during the one year period prior to the event and additionally estimate the parameters during a one year period, beginning two years after the initial event. Table 8 shows the medians of both betas; the one estimated during the period prior to the event β_1, and during the period after the event β_2.

The difference in betas of decline events is significant. This difference is even more pronounced for events that occurred in 2008 and subsequent years. This effect may explain the reversal patterns found after large price declines and can be construed as evidence for the Uncertain Information Hypothesis, which states that the arrival of new information leads to uncertainty and hence an increase in risk. In addition, the risk in the third year (not reported) after the event, is not significantly different from β_1. This, in combination with the price reversals after large price declines and price continuation after large price increases, can be seen as a confirmation of the Uncertain Information Hypothesis, as once the event induced uncertainty is resolved, the risk reverts to its previous level. Furthermore, the betas for both large price increases and large price declines increase significantly in the post-2008 time period. This suggests that the recent financial crisis raised the systematic market risk in the South African equity market.

Table 8: Differences in Beta between a Pre- and a Post-Event Period

Sample	Sample Size	β_1	β_2	$\Delta\beta$
All Events				
Increases	87	0.89	0.97	0.08
Declines	55	0.82	1.02	0.20[c]
Pre-2008 Events				
Increases	46	0.90	0.88	-0.01
Declines	12	0.91	0.78	-0.14
Post-2008 Events				
Increases	41	0.85	1.11	0.26[c]
Declines	43	0.81	1.13	0.32[b]

[a], [b], [c] denote statistical significance at the 1%, 5%, and 10% level, respectively.

5. CONCLUSION

This study analyses cumulative abnormal returns following large price increases and declines for stocks included in the South African FTSE/JSE Top 40 index in the period from January 2003 to December 2011. Events are identified by using a trigger value of ±20%. Various robustness checks are implemented in order to check the overall results.

The analysis finds that large price increases are followed by positive ACARs. These ACARs are statistically significant with regard to the period ending 36 months after the initial event and beginning in the first, third, 12^{th}, or 24^{th} month following the initial event. In addition, the ACARs are always positive. Large price declines are also followed by positive but smaller ACARs. These ACARs are statistically significant in time windows beginning in the third month after the initial event and ending up to 24 months later. Further robustness checks reveal that the magnitude of these positive returns even increases when using a trigger value of -30%. In addition, an analysis of the betas shows that the systematic risk in the post-2008 years has increased for the investigated stocks in the South African market, but returns to normal levels two years after the original event. These findings weakly support the Uncertain Information Hypothesis. However, the almost complete lack of significance of the ACARs after price increases of more than 30% somewhat weaken this conclusion.

The patterns observed for the South African stock market in this paper stand in contrast to some of the more recent research findings for developed markets (e.g., Himmelmann et al., 2012). In particular the more pronounced overreaction observed after the recent financial crisis make it apparent that the South African stock market is not fully efficient yet. Nevertheless, the anomalies observed in this paper can also be observed for well-developed and well-established markets, such as the US (e.g., Benou & Richie, 2003). However, it remains doubtful whether the observed anomalies can really be exploited by arbitrageurs, as liquidity concerns might play a major role, since the South African market still shows significantly lower levels of liquidity than more developed economies.

Future research in this area should investigate whether the results obtained in the present study also hold for other emerging economies, such as Brazil and China. Especially due to their increased importance to the global economy additional research on the market efficiency of these economies is certainly justified. In addition, it would be interesting to see whether any particular factors can explain the observed inefficiencies.

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REFERENCES

1. Ajayi, R. A., & Mehdian, S. (1994). Rational investors' reaction to uncertainty: Evidence from the world's major markets. *Journal of Business Finance & Accounting, 21*(4), 533-545.
2. Amini, S., Gebka, B., Hudson, R., & Keasey, K. (2013). A review of the international literature on the short term predictability of stock prices conditional on large prior price changes: Microstructure, behavioral and risk related explanations. *International Review of Financial Analysis, 26*, 1-17.
3. Appiah-Kusi, J., & Menyah, K. (2003). Return predictability in African stock markets. *Review of Financial Economics, 12*(3), 247-270.
4. Atkins, A. B., & Dyl, E. A. (1990). Price reversals, bid-ask spreads, and market efficiency. *Journal of Financial and Quantitative Analysis, 25*(4), 535-547.
5. Benou, G., & Richie, N. (2003). The reversal of large stock price declines: The case of large firms. *Journal of Economics and Finance, 27*(1), 19-38.
6. Bowman, R. G., & Iverson, D. (1998). Short-run overreaction in the New Zealand stock market. *Pacific-Basin Finance Journal, 6*(5), 475-491.
7. Bremer, M., & Sweeney, R. J. (1991). The reversal of large stock-price decreases. *The Journal of Finance, 46*(2), 747-754.
8. Bremer, M., Hiraki, T., & Sweeney, R. J. (1997). Predictable patterns after large stock price changes on the Tokyo Stock Exchange. *Journal of Financial and Quantitative Analysis, 32*(3), 345-365.
9. Brocket, P. L., Chen, H.-M., & Garven, J. R. (1999). A new stochastically flexible event methodology with application to Proposition 103. *Insurance: Mathematics and Economics, 25*(2), 197-217.
10. Brown, K. C., Harlow, W. V., & Tinic, S. M. (1988). Risk aversion, uncertain information, and market efficiency. *Journal of Financial Economics, 22*(2), 355-385.
11. Chan, K. C. (1988). On the contrarian investment strategy. *Journal of Business, 61*(2), 147-163.
12. Choi, H.-S., & Jayaraman, N. (2009). Is reversal of large stock-price declines caused by overreaction or information asymmetry: Evidence from stock and option markets. *Journal of Futures Markets, 29*(4), 348-376.

13. Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics, 31*(2), 235-268.
14. Conrad, J., & Kaul, G. (1993). Long-term market overreaction or biases in computed returns? *The Journal of Finance, 48*(1), 39-63.
15. da Costa, Jr., N. C. (1994). Overreaction in the Brazilian stock market. *Journal of Banking and Finance, 18*(4), 633-642.
16. De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance, 40*(3), 793-805.
17. Dissanaike, G. (1997). Do stock market investors overreact? *Journal of Business Finance & Accounting, 24*(1), 27-49.
18. Fama, E. F. (1998). Market effciency, long-term returns, and behavioral finance. *Journal of Financial Economics, 49*(3), 283-306.
19. Gaunt, C. (2000). Overreaction in the Australian equity market: 1974-1997. *Pacific-Basin Finance Journal, 8*(3/4), 375-398.
20. Himmelmann, A., Schiereck, D., Simpson, M. W., & Zschoche, M. (2012). Long-term reactions to large stock price declines and increases in the European stock market: a note on market efficiency. *Journal of Economics and Finance, 36*(2), 400-423.
21. Hon, M. T., & Tonks, I. (2003). Momentum in the UK stock market. *Journal of Multinational Financial Management, 13*(1), 43-70.
22. Iihara, Y., Kato, H. K., & Tokunaga, T. (2004). The winner-loser effect in Japanese stock returns. *Japan and the World Economy, 16*(4), 471-485.
23. Ising, J., Schiereck, D., Simpson, M. W., & Thomas, T. W. (2006). Stock returns following large 1-month declines and jumps: Evidence of overoptimism in the German market. *The Quarterly Review of Economics and Finance, 46*(4), 598-619.
24. Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review, 55*(2), 163-172.
25. Jefferis, K., & Smith, G. (2005). The changing efficiency of African stock markets. *South African Journal of Economics, 73*(1), 54-67.
26. Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics, 105*(1), 1-28.
27. Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance, 20*(4), 587-615.
28. Lobe, S., & Rieks, J. (2011). Short-term market overreaction on the Frankfurt stock exchange. *The Quarterly Review of Economics and Finance, 51*(2), 113-123.
29. Maher, D., & Parikh, A. (2011). Short-term under/overreaction, anticipation or uncertainty avoidance? Evidence from India. *Journal of International Financial Markets, Institutions and Money, 21*(4), 560-584.
30. Mazouz, K., Alrabadi, D. W. H., & Yin, S. (2012). Systematic liquidity risk and stock price reaction to shocks. *Accounting & Finance, 52*(2), 467-493.
31. Mikkelson, W. H., & Partch, M. M. (1986). Valuation effects of security offerings and the issuance process. *Journal of Financial Economics, 15*(1/2), 31-60.
32. Okeahalam, C. C., & Jefferis, K. R. (1999). An event study of the Botswana, Zimbabwe and Johannesburg Stock Exchange. *South African Journal of Business Management, 30*(4), 131-140.
33. Schnusenberg, O., & Madura, J. (2001). Do U.S. stock market indexes over- or underreact? *The Journal of Financial Research, 24*(2), 179-204.
34. Schwert, G. W., & Seguin, P. J. (1990). Heteroskedasticity in stock returns. *The Journal of Finance, 45*(4), 1129-1155.
35. Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*(3), 425-442.
36. Smith, G. (2008). Liquidity and the informational efficiency of African stock markets. *South African Journal of Economics, 76*(2), 161-175.
37. Yu, S., Rentzler, J., & Tandon, K. (2010). Reexamining the uncertain information hypothesis on the S&P 500 Index and SPDRs. *Review of Quantitative Finance and Accounting, 34*(1), 1-21.
38. Zarowin, P. (1990). Size, seasonality, and stock market overreaction. *Journal of Finance and Quantitative Analysis, 25*(1), 113-125.

