ON STOCK RETURN PATTERNS FOLLOWING LARGE MONTHLY PRICE MOVEMENTS: EMPIRICAL EVIDENCE FROM INDIA

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Abstract: The purpose of this study is to examine the short-horizon stock behaviour following large monthly price changes of the large, liquid stocks in the Indian stock market. The event study methodology is used with two different methodologies and three abnormal return computational methods to improve the robustness and reliability of the results. This study evidences significant reversals following both large price declines and increases up to six months. Further, stronger initial shocks were followed by stronger reversals. The results are consistent with the 'overreaction hypothesis' in the Indian stock market. The results are robust to microstructure effects, extreme events, industry, period, methodology and market effects. The abnormal returns following large price declines might be economically significant with potential economic profits for traders.

Keywords: India; overreaction; large price changes; contrarian strategy

JEL codes: D53; E44; G12; G14

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Introduction

A considerable body of literature has investigated the short-term reaction of stocks following large price changes. The research in this area has generally suggested that the stock returns are predictable and found evidence of systematic patterns in stock returns. According to the 'Efficient market hypothesis' (EMH), security prices should incorporate quickly and correctly all relevant information and the presence of systematic reversal patterns and return predictability in stock returns directly contradicts the EMH. The implications of EMH are that the stock returns are not predictable and as such abnormal returns cannot be earned by investors by trading on past prices. The EMH is important to both theoretical and empirical finance and has dominated economics in the last five decades. It has implications on the government policy, institutional structure and portfolio management.

Sims (1984) contended that the accuracy of the efficient market hypothesis is a short-run phenomenon. He asserted that at longer intervals, like over a year, asset prices may be predictable, but the EMH can be tested effectively only in the short horizon. Also, in the short run, systematic changes in the valuation of individual securities should be minimal in an efficient market (Lehman, 1990). The debate on the systematic patterns has revolved around three major explanations, namely, behavioural, risk-related and microstructure-based explanations.

In their influential paper, Debrondt and Thaler (1985) attempted to explain the reversals and contended that the people tend to overweight current data and to underweight past data. People tend to 'overreact' to unexpected and dramatic news events causing stock prices to overshoot. In their 'overreaction hypothesis', they suggest two hypotheses: Extreme price movements will be followed by subsequent reversals (Directional effect); more extreme initial price change will be followed by stronger reversals (Magnitude effect).

Overreaction implies that the market does not have sufficient liquidity to arbitrage the short-term price deviation (Grossman and Miller, 1988 and Jegadeesh and Titman, 1992). Further, Jegadeesh and Titman (1992) highlighted the policy implications of behavioural issues. The underlying assumptions of the EMH are rationality and arbitrage. Conrad and Kaul (1998) and Chan (1988) suggested that the abnormal returns may be a compensation for the additional risk and can be explained by the cross-sectional variance in the mean, which is an explanation consistent with the EMH. Pesaran (2005) asserted that the less liquid stocks were likely to be more predictable, as the return predictability and liquidity are correlated. This study intends to contribute to this debate by studying the short-horizon stock behaviour following large shocks, using monthly data of large liquid stocks in the Indian stock market, in order to discriminate between the behavioural explanations and the explanations consistent with EMH.

The prior literature has documented the behaviour of stock returns subsequent to large price changes in the developed markets. De Bondt and Thaler (1987), Chan (1988), and Zarowin (1989) have focused on the longer horizon returns. While Lo and Macinlay (1990), Jegadeesh (1990) and Benou and Ritchie (2003) focused on the medium-horizon returns, Bremer and Sweeney (1991), Pritamani and Singhal (2001) and others have focused on the short-run price reversals. These studies are few and limited in the Indian stock market.

The focus of this study is the short-horizon stock price behaviour following large 'one-month' price changes using the large, liquid stocks in the Indian stock market in the 2000-2019 period. The stock behaviour following large 'one-month' changes is examined to empirically test the directional and magnitude effect of the 'overreaction hypotheses' and to discover potential profitable short-horizon trading strategies following both positive and negative shocks in the Indian stock market. In contrast to prior literature, this study uses multiple methodologies, abnormal returns and robustness checks in order to ensure that the findings are not due to chance.

In this study, only the large and liquid stocks in the Indian stock market are examined to mitigate the microstructure effects like non-synchronous trading, transaction costs and illiquidity. Further, this study uses monthly data, which mitigates the microstructure effect like bid-ask spread. Any predictable pattern should be limited in such large stocks for two reasons; investors should generally possess superior quality information about such large stocks and these stocks enjoy significant shareholdings by the institutional investors.

The Indian economy is one of the fastest-growing economies in the world and the Indian equity market is the 5th largest in the world in 2019 in terms of both traded value and market capitalisation. The increasing participation by foreign institutional investors provides a perfect platform for analysing the institutional structure, efficiency and integration mechanism with the developed markets. These studies are very relevant to traders as they may unearth simple trading strategies with potential for economic trading profits. The fact that these studies provide a perfect stage to discriminate between the traditional ideas and the behavioural explanations will be of interest to the researchers. Hacibedel's (2008) contention that the emerging markets like India differ from developed markets in many ways is still valid. Consequently, evidence of predictable patterns in the Indian stock market would be very interesting as this would imply that the patterns may be due to less than rational behaviour of the investors rather than systemic reasons.

The next section reviews past literature and the third section explains the data and details the methodology used. The fourth sections reports and analyses the findings and the fifth section concludes.

Review of literature

Barberis et al. (1998) defined overreaction as when the average return following favourable news is less than the average return after unfavourable news. Investors, due to inherent cognitive biases, use heuristics resulting in error-prone predictions (De Bondt and Thaler, 1990, Jegadeesh and Titman, 2001). Daniel et al. (1998) contended that overconfidence about private information caused overreaction and reversals, whereas public information caused momentum and attributed overreactions to overconfidence and self-attribution due to the bounded rational behaviour of the market agents. Barberis et al. (1998) explained that the market agents would overreact or under-react depending on the flow of the past news.

They asserted that the overreaction and the consequent reversal are caused by extrapolation; the under-reaction and the consequent momentum are caused by conservatism. Hong and Stein (1999) contend that the interaction between the news watchers and price watchers cause momentum and later overreaction. The gradual diffusion of news causes momentum and the price watchers who act on this momentum create subsequent overreaction. However, explanations consistent with EMH suggest that these reversals and momentum are compensation for additional risk (Conrad and Kaul, 1998 and Chan, 1988).

The overreaction was confirmed using different methodologies with stock portfolio returns and index returns (De Bondt and Thaler, 1985 and Lakonishok et al. 1994). Bremer and Sweeney (1991) used a novel approach, where stock returns exceeding a trigger value were included in the sample, unlike the earlier approach of ranking stocks based on their past returns. This approach was followed by Pritamani and Singhal (2001), Benou and Richie (2003), Himmelmann et al. (2012) and Parthasarathy (2019).

The existing important empirical literature on short-term stock behaviour following large price changes are Jegadeesh (1990), Lo and Macinlay (1990). While Jegadeesh (1990) found evidence in favour of behavioural explanations, Lo and Macinlay (1990) asserted that the 'lead-lag structure' may be one of the reasons for the evidenced reversals and not overreaction. However, Jegadeesh and Titman (1995) concluded that overreaction may be the major reason for the evidenced reversals and short-term contrarian profits and showed that lead-lag structure accounts for a very small part of the short-term contrarian profits.

Brown, Harlow and Tinic (1988), studying S&P 500 companies, evidenced asymmetric reversals following large one-day price changes and advanced the EMH consistent 'Uncertain information hypothesis' (UIH). The UIH postulates that when rational investors are faced with new information, they are expected to underreact to good news and overreact to bad news. However, Corrado and Jordan (1993) reexamined the tests and found that the sample selection of that study did not distinguish between event and non-event periods. Once this lacuna was addressed, they evidenced significant short-term reversals for both increases and declines.

Atkins and Dyl (1990) and Park (1995) studied reversals following large price changes in the US stock market and concluded that, after controlling for bid-ask spreads, the reversals still persisted but were not big enough for significant contrarian profits. However, Bremer et al. (1991) contended that the bid-ask spread will have minimal impact on transaction cost for large stocks. Platt (2006), studying reversal following large price shocks in the US stock market, concluded that the contrarian profits persisted despite accounting for the bid-ask spreads. Choi and Jayaraman (2008) examined the stock behaviour following large price changes for the optionable stocks in the US stock market and evidenced significant reversals. They concluded that the bid-ask spread does not explain the reversal for such stocks. Further, Jegadeesh (1990) argued that the bias due to bid-ask spread is greatly reduced as one moves from daily intervals to longer intervals like weekly or monthly intervals. We examine the reversals following large 'one-month' changes and consequently, the bid-ask spread may not be a major factor.

Bremer and Sweeney (1991) examined the reversal pattern following large one-day raw price declines of -10% in the US market using large stocks for the period from 1962 to 1986. They evidenced significant, systematic price reversals inconsistent with EMH. The existing literature on reversals following large price changes, using raw monthly returns as the trigger, is further discussed in this section. Brown and Harlow (1988) used residuals of stock returns and examined reversal patterns of stocks that experienced ±20% changes in a month. They found support for the overreaction hypothesis and concluded that the tendency to overreact in a systematic manner was much stronger and systematic for negative price changes. Benou and Richie (2003) examined the long-run reversal pattern for US stocks which experienced a 20% price decline in a month and found support for the overreaction hypothesis. Ising, Schiereck, Simpson and Thomas (2006) analysed the short-run and long-run performance of the largest 100 German firms that experienced monthly stock price changes of more than ±20% between 1990 and 2003. They evidenced continuation following large declines and reversals following large increases. Himmelmann, Schiereck, Simpson and Zschoche (2012) examined the European large-cap stocks in the EuroStoxx 50 index following large one-month increases & declines and evidenced normal returns in support of EMH. Also, Kolaric, Kiesel and Schiereck (2016) examined stock returns of the constituents of the KOSPI 50 from 2000 to 2014 following large one-month price changes and evidenced asymmetric responses to positive and negative shocks. The study found support for the EMH consistent, 'Uncertain information hypothesis'.

The studies based on contrarian strategies in the Asian stock markets are detailed below. Most of the studies have generally used monthly returns to rank stocks based on their past returns to form winner and loser portfolios, similar to De Bondt and Thaler (1985). Kang et al. (2002) and Yang et al. (2006) studied the contrarian and momentum strategies in the Chinese and Taiwanese stock markets, respectively and concluded that the 'overreaction hypotheses explained the phenomenon. McInish et al. (2006) examined the short horizon contrarian and momentum strategies in the Southeast Asian stock markets during the 1990-2000 period and evidenced reversal for the 'winner' portfolio and momentum for loser portfolio for all the markets except Korean and Japanese markets. Ramiah et al. (2011) studied the Hong Kong stock market using monthly returns and evidenced that the contrarian portfolios earn monthly profits of 8.1%. Vo and Troung (2017) studied winner and loser portfolios in the Vietnamese market and evidenced significant momentum. Reddy et al. (2019) examined the reversal phenomenon in the Shanghai A stock market and evidenced short-term continuations and long-term reversals.

Almost all Indian studies have used monthly returns to rank stocks based on their past returns to form winner and loser portfolios. Sehgal and Balakrishnan (2004) studied the Indian stock market during 1989-1999 using the monthly returns of the broad-based index stocks and evidenced statistically significant difference between long term winners and losers, supporting a contrarian investment strategy, but evidenced momentum for both winners and losers in the short run. Chowdhury and Mitchello (2008) studied the monthly returns in the 1991-2006 period in the Indian stock market and evidenced short term reversals for both the winner and loser portfolios for up to three months and found that the evidenced contrarian profits were primarily due to medium and small stocks. Joshipura (2009) studied the NSE based on monthly return data for the 1995-2008 period and evidenced momentum for both winners and losers in the short run but significant reversals later. They also showed that the risk-based explanations could not explain the evidenced reversals. Parthasarathy (2019) examined the reversal patterns following large price shocks using raw daily returns as the trigger and found support for the behavioural explanations. The study found that large price changes accompanied by low volume exhibited significant reversals over the following 20-day period and suggested significant economic profits. The large price changes accompanied by high volume's exhibited continuations.

Though the existing literature generally suggests predictable patterns following large price changes, the results appear to be sensitive to the sample and the methodology used. Most studies have used returns to rank stocks based on their past returns to form winners' and losers' portfolios. Some studies evidence continuation following large increases, while other studies evidence reversals. There is also a lack of consensus about the explanation for the observed predictable patterns. This study enters the debate by examining the short-horizon stock behaviour subsequent to one-month large raw price changes of the large liquid stocks in the Indian stock market using two different methodologies and three different abnormal return models. This study, unlike most previous studies, focuses on the short-horizon stock behaviour following one-month raw price changes as a trigger, similar to Brown and Harlow (1988), Ising et al. (2006) and Himmelmann et al. (2012) and provides a practical framework for profitable trading strategies with potential for significant economic profits. This analysis of short-horizon stock behaviour following large one-month price shocks has not been attempted so far in the Indian stock market. This study also makes an important contribution by extending the literature to the hitherto unexplored recent period.

Research methodology

The time period under investigation in this study starts from January 2000 and ends in December 2019. The NIFTY index is the premier benchmark index representing the 50 large and liquid stocks of the National stock exchange (NSE). The National stock exchange (NSE) is the leading stock exchange with the highest turnover in India. The NIFTY represented about 66% of the Free Float Market Capitalization and about 53% of the traded value of all stocks on the NSE as of March 2018. NIFTY stocks have the highest institutional holding and the lowest transaction cost. They are optionable with no short-selling restrictions. All the stocks which were part of the NSE 50 index during the test period were considered from the time of their inclusion into the index and till their exclusion from the index. A monthly stock return that represents a large abnormal price change is an 'event'. This study uses a raw percentage return[1] as a trigger, similar to Bremer and Sweeney (1991). A specific trigger of $\pm$20% is considered as a 'large monthly price change', similar to Brown and Harlow (1988), Ising et al. (2006) and Himmelmann et al. (2012). This enables this study to compare the results with the existing literature. If, on any single calendar month, the monthly stock return is more than +20% or less than -20%, then that is defined as an event and month '0'.

Only the large and liquid stocks are considered in this study to avoid methodological issues, as in Bremer and Sweeney (1991). The sample includes all the large one-month price changes of the NIFTY stocks in the 2000-2019[2] period. The complete sample includes 474 events for declines and 412 events for increases in the tested period based on the mentioned criteria, which is about 4 events per month. A second criterion requires that the selected stocks do not have abnormal price changes in the past six months, similar to Pritamani and Singhal (2001). This screen is used to ensure that no multiple events would be included in the same period for the same stock. Further, it was also ensured that the corporate actions like stock dividends and stock splits do not vitiate the sample. The additional criteria reduced the sample to 247 for negative events and 210 for positive events.

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[1] The large return that exceeds some multiple of past standard deviation of returns was not considered, as that would require at least 120 data points to detect an event. As this study is examining monthly returns, stocks that have at least 10 years of trading history can only be considered which would greatly reduce the sample size.

[2] The stock index futures and options were introduced in the Indian stock market in the year 2000.

The Monthly returns are log-returns using closing prices adjusted for capitalization changes like stock dividends and stock splits. This study analyses the post-event stock returns for six months[3], similar to Benou and Richie (2003) and Himmelmann et al. (2012). The abnormal or excess return for a stock is calculated by subtracting the corresponding monthly return by the average monthly return of the control stocks, similar to Pritamani and Singhal (2001). The average of five control stocks, similar in size to the event stock and which did not experience a large price change in the event month, is calculated and subtracted from the corresponding monthly return. The control stocks[4] are chosen by sorting the NIFTY Index stocks by size and choosing the five stocks that are immediately below the event stock in order to avoid bias. The second abnormal return calculation is based on a single-factor market model employing the GARCH (1,1) process, similar to Benou and Richie (2003). The traditional OLS regression model used to estimate expected return assumes that the beta and error term are constant over time. However, Chen and Keown (1981) show that the market model beta is non-stationary and also, the variance of the error term may not be independent but dependent on prior information (Schwert and Senguin, 1990). *Therefore, if the traditional OLS regression is used, this will lead to incorrect conclusions due to the violation of the assumptions.* So, Brockert, Chen and Garven (1999) suggest a market model, estimated using a GARCH (1,1) process, to account for the time-varying nature of Beta.

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt}, \text{ where} \quad (1)$$

βj is normally calculated using the above static market model regression and, R_{jt} and R_{mt} are the stock return and market return, respectively. α_j is the intercept term for stock 'J' and 'ε_{jt}' represents the error term. The GARCH (1,1) process does not assume stationarity of beta coefficient and also the independence of the variance of the error term, unlike the normal OLS regression. So the error term is conditioned on the prior information set, as the independence assumption has been dispensed with

$$\varepsilon_{jt} \mid \Omega_{\tau-1} \sim N(0, h_t) \quad (2)$$

The information set $\Omega_{\tau-1}$ includes all information at t-1 and the error term is normally distributed with mean 0 and variance h_t. The conditional variance h_t is conditioned on squared past errors and past conditional variance and calculated as

$$h_t = \phi_0 + \phi_1 \varepsilon^2_{\tau-1} + \phi_2 h_t \quad (3)$$

As the GARCH (1,1) modelling does not assume the independence of the variance of the error term, the variance of the error term is modelled to be dependent upon squared past errors represented by $\varepsilon^2_{\tau-1}$ and past conditional variance as in eq (3).

Another, abnormal or excess return for a stock is calculated by subtracting the corresponding monthly stock return by the NIFTY index monthly return. According to De Bondt and Thaler (1985), the use of market-adjusted abnormal return has the advantage of biasing the research design against the overreaction hypothesis. Hence,

[3] Unlike this study, those studies also examine medium -and long-term horizons

[4] This study repeated the examination by considering the five stocks that are immediately above the event stock and evidenced similar results.

the results using market-adjusted returns are likely to be a conservative estimation.

This study uses a nonparametric test to ascertain whether the proportion of firms in the sample which have positive (negative) cumulative abnormal returns, in months following the event month, is significantly different from 50% (Bremer and Sweeney, 1991 and Pritamani and Singhal, 2001). Assuming there is an equal chance of success and failure, with success defined as cumulative abnormal return (CAR) greater than zero (less than zero) for large declines (increases). The resulting binomial z-statistic suggests whether the predictable patterns are present.

Z = (Proportion of CAR greater than zero – 0.5) / SQRT ($(0.05)^2$ / N) (4)

This study also employs a cross-sectional analysis to investigate the role of risk, period, industry and size on the degree of overreaction. The CARs of the different horizons are regressed on the Beta, standard deviation, period, industry classification and size. The cross-sectional model is specified as

$$CAR_i = b_0 + b_1 Beta_i + b_2 SD_i + b_3\, Industry_i + b_4\, Size_i + b_5\, Period_i + e_i \quad (5)$$

Whereas:

CAR_i = Cumulative abnormal return for different horizons

$Beta_i$ = OLS beta of the stocks in the sample for the sample period

SD_i = Standard deviation for the sample period

$Industry_i$ = The stocks were grouped in industry classifications and numbered 1 to 10

$Size_i$ = This is based on market capitalisation in March 2019.

$Period_i$ = The full period is divided into four equal sub periods and numbered 1 to 4

The cross-sectional OLS regression is estimated using 'White' heteroskedasticity of consistent standard errors.

The limitations of the methodology are that the control stocks are chosen based on a certain methodology; the linear regression model though statistically worthwhile, in reality, the independent and dependent variables might have non-linear relationships. There are also limitations to the CAPM model.

Analysis and findings

Descriptive Statistics

Table 1 reports the descriptive statistics of the raw returns following large one-month changes. The average return for month '0' price declines is -27.74%, with a standard deviation of 9.04% and + 27.36% and 7.89% for a month '0' price increases. The skewness and kurtosis for month '0' raw returns are on expected lines. The month 1 to month 6 average raw returns following large price declines are consistently greater than of the raw returns following large price increases, except for the month 5, providing prima facie support for the overreaction hypothesis (Barberis et al. 1998) in the Indian stock market. The distribution of the monthly raw returns is skewed and exhibits kurtosis suggesting the presence of heteroskedasticity. The Jarque Bera statistics show that for all the monthly returns, except for month 2 raw returns following large declines, the null of the normal distribution is rejected at the 10% level.

Table 1. Descriptive statistics of raw returns

Decreases	Obs	Mean	Median	Std. Dev	Skew	Kurt	Jarque-Bera	Prob
Month 0	247	-27.74%	-24.68%	9.04%	-2.412	10.167	768.125	0.000
Month 1	247	2.20%	3.24%	14.46%	-0.585	3.772	20.228	0.000
Month 2	247	4.86%	4.21%	12.90%	0.033	2.983	0.047	0.977
Month 3	247	2.08%	1.98%	12.94%	-0.082	4.152	13.923	0.001
Month 4	247	2.53%	2.44%	14.57%	-0.697	8.061	283.577	0.000
Month 5	247	1.37%	0.28%	13.05%	0.240	3.951	11.680	0.003
Month 6	247	1.20%	0.68%	14.18%	0.017	4.349	18.737	0.000
Increases	Obs	Mean	Median	Std. Dev	Skewness	Kurtosis	Jarque-Bera	Prob
Month 0	210	27.36%	24.75%	7.89%	1.895	7.115	273.895	0.000
Month 1	210	0.91%	0.25%	15.82%	0.556	4.825	39.958	0.000
Month 2	210	2.03%	2.12%	16.13%	-1.009	7.569	218.286	0.000
Month 3	210	0.73%	1.68%	16.26%	-0.846	7.673	216.123	0.000
Month 4	210	0.67%	1.03%	14.38%	-0.543	4.677	34.764	0.000
Month 5	210	2.94%	2.45%	14.34%	0.515	5.046	45.706	0.000
Month 6	210	-0.74%	0.00%	12.46%	-0.944	5.859	102.265	0.000

Note: The sample includes the one-month large price changes of all NIFTY stocks for the period 2000-2019 period based on the event trigger of +/ -20%, with 247 events for declines and 210 events for increases in the tested period based on the Pritamani and Singhal (2001) criteria. The descriptive statistics of the monthly raw returns of individual months following Month ‘0’ is presented.

Source: Own calculations

Reversal Pattern – Directional effect

This section examines the stock returns following large one-month price changes of large liquid stocks in order to ascertain whether a reversal pattern exists. Table 2 reports the cumulative abnormal returns (CAR) following a ± 20% monthly price changes for the NIFTY stocks over the period from January 2000 to December 2019. The horizontal row marked ‘CAR’ represents the cumulative abnormal return up to the mentioned month. Table 2 Panel A reports the CARs estimated using the control return sample (CCAR). The month 1 CCAR of 3.07% following large price declines is not only statistically significant, but also the proportion of positive returns shows the presence of a significant systematic pattern. The month 2 CAR of 6.52% reaches 11.61% by the sixth month.

The month 1 CAR and all the CARs up to six months are at a significant 1% level. The proportion of positive returns is statistically significant at a 5% level of significance for CARs from Month 1 to Month 6 suggesting systematic reversal following large price declines. This result of significant short-horizon reversals following large price one-month declines is similar to Brown and Harlow (1988) and Benou and Richie (2003). This result is similar to Chowdhury and Mitchello (2008) but unlike Sehgal and Balakrishnan (2004) & Joshipura (2009) in the Indian stock market.

Table 2. Predictable patterns following large one month price changes – Directional Effect

Panel A: Abnormal return estimated using control sample return

Events	Negative			Positive		
Sample size	247			210		
Trading Month	CCAR	t-stat	Proportion of positive abnormal returns	CCAR	t-stat	Proportion of negative abnormal returns
Month '0'	-27.74%	-21.261**	1.00***	27.32%	45.961**	1.00**
+1	3.07%	3.461**	0.60**	-1.61%	-1.502*	0.58**
[+1 +2]	6.52%	5.957**	0.66**	-2.70%	-1.777**	0.59**
[+1 +3]	6.97%	5.274**	0.63**	-2.64%	-1.398*	0.56*
[+1 +6]	11.61%	5.537**	0.64**	-4.58%	-2.008**	0.58**

Panel B: Abnormal return estimated using GARCH (1,1)

Events	Negative			Positive		
Sample size	247			210		
Trading Month	GCAR	t-stat	Proportion of positive abnormal returns	GCAR	t-stat	Proportion of negative abnormal returns
Month '0'	-27.74%	-21.261**	1.00**	27.32%	45.961**	1.00**
+1	1.63%	1.964**	0.57**	-1.59%	-1.777**	0.58**
[+1 +2]	5.18%	5.030**	0.63**	-1.64%	-1.324*	0.56*
[+1 +3]	6.85%	5.606**	0.64**	-0.81%	-0.521	0.54
[+1 +6]	11.25%	6.022**	0.64**	-0.78%	-0.384	0.52

Panel C: Abnormal return estimated using Market returns

Events	Negative			Positive		
Sample size	247			210		
Trading Month	MCAR	t-stat	Proportion of positive abnormal returns	MCAR	t-stat	Proportion of negative abnormal returns
Month '0'	-27.74%	-21.261**	1.00**	27.32%	45.961**	1.00**
+1	1.97%	2.357**	0.60**	-1.47%	-2.616*	0.59**
[+1 +2]	5.75%	5.564**	0.66**	-1.61%	-1.268	0.56*
[+1 +3]	6.84%	5.736**	0.64**	-0.75%	-0.479	0.53
[+1 +6]	10.48%	5.740**	0.64**	-1.08%	-0.538	0.51

Note: The sample includes the one-month large price changes of all NIFTY stocks for the period 2000-2019 period based on the event trigger of +/ -20%, with 247 events for declines and 210 events for increases in the tested period based on the Pritamani and Singhal (2001) criteria. The Month '0' returns are the raw returns. The abnormal or excess return for a stock (CCAR) is calculated by subtracting the corresponding monthly return from the average monthly return of the control stocks for month 1 to month 6. The second abnormal return (GCAR) calculation is based on single-factor market model employing the GARCH (1,1) process. Further, an alternate method of abnormal return (MCAR) using the market returns is used to calculate market-adjusted CAR. [+1 +2] implies that the abnormal return of month 2 is added to that of month 1 to get the CAR of month 2 and so on. The month 1 CAR is the simple average of the abnormal returns of the complete sample in the first month following the one-month price changes. The proportion of stocks greater (lesser) than zero is the percentage of stocks with positive (negative) returns up to a particular month.

**, * implies significance at 5% and 10% levels, respectively.

Source: Own calculations.

The month 1 CAR and month 2 CARs, following large price increases are statistically significant -1.61% and -2.7%, respectively and reach -4.58% by the sixth month. The proportion of negative abnormal return is also statistically significant at the 5% level of significance for month 1, month 2 and month 6 CARs. The proportion of negative abnormal return is statistically significant at 10 % levels for the month 3 and month 4 CARs. These results show the presence of significant systematic reversals up to six months following large price increases. This short-horizon reversal following large positive shocks is similar to that of Ising, Schiereck, Simpson and Thomas (2006).

In order to avoid the possibility that the reversal phenomenon is due to choice of abnormal returns, GARCH (1,1) and the market adjusted abnormal returns are also examined. Table 2 Panel B and Panel C report the CARs estimated using the GARCH (1,1) model (GCAR) and market returns (MCAR), respectively. Both the short horizon GCAR and MCAR results following large one-month declines are similar to that of the CCAR results up to six months. The proportion of positive returns is also very similar to that of CCAR results. However, the short horizon GCAR and MCAR results following large price increases are different from month 3 onwards. The GCAR month 1 & month 2 CARs and MCAR month 1 and month 2 CARs are statistically significant at 5% and 10% level, respectively. Even though, the reversals stay at around -1% till the sixth month, neither the CARs nor the proportion of negative returns are statistically significant from Month 3 onwards. The statistically significant CARs and the proportion of positive/negative returns suggest systematic and predictable patterns following large one-month price changes.

Overall, the results indicate the presence of significant overreaction in the Indian stock market as extreme price movements are followed by significant reversals up to six months – a directional effect. The reversals do not appear temporary, with the month 6 CARs of nearly 10% and -1% for large price declines and increases, respectively. Even though, statistically significant reversals are evidenced following both the large price declines and increases, the striking aspect is that the reversals following large declines are much stronger than the reversals following large increases across all the tested horizons. This result is similar to that of Brown and Harlow (1988). These results suggest that the Indian stock market overreacts more to negative information compared to positive information. The results suggest that the predictable returns following large price declines can potentially give an economically significant annual return of 40%. Further, the proportion of positive returns is nearly 66% across all horizons for declines, suggesting that the reversal phenomenon is due to a huge majority of the stocks and not a few volatile stocks. However, the reversals following large increases may not be economically significant.

Reversal Pattern – magnitude effect

Table 3 reports the results of short-horizon CCAR results with the month '0' trigger[5] of -22% and -24% in the case of large declines and +22% and +24% in the case of large increases. The reversals increase in intensity as we move from the initial trigger of ±20% to ±22% and ±24%. For an initial trigger of -20%, the month 0 and month 6 CARs are 3.07% and 11.61%, respectively. But for an initial trigger of -24%, the month 0 and month 6 CARs

[5] The experiment was repeated with the initial trigger of -23%/+23% and -25%/+25% respectively and evidenced similar results.

become 3.97% and 14.95%, respectively. The result of stronger reversals following larger price declines is similar to Brown and Harlow (1988) and Benou and Richie (2003). Similarly, in the case of large increases for an initial trigger of 20%, the month 0 and month 6 CARs are -1.61% and -4.58%, respectively. But for an initial trigger of 24%, the month 0 and month 6 CARs increase to -2.44% and -5.83%, respectively. The proportion of positive/negative returns also increases as we move from the initial trigger of ±20% to ±22% and ±24%. The results clearly show that the stronger initial trigger is followed by stronger reversals after both large price declines and increases (magnitude effect). The symmetric reversals and stronger initial trigger followed by stronger reversal seem to support the overreaction hypothesis in the Indian stock market.

Table 3. Predictable pattern following large price changes – Magnitude effect

Events	**Negative**					
Trigger	**-20%**		**-22%**		**-24%**	
Sample size	**248**		**185**		**139**	
Trading Month	CCAR	Proportion of positive abnormal returns	CCAR	Proportion of positive abnormal returns	CCAR	Proportion of positive abnormal returns
Month '0'	-27.74%	0.00	-30.04%	0.00	-32.46%	0.00
+1	3.07%	0.60**	2.55%	0.58**	3.97%	0.63**
[+1 +2]	6.52%	0.66**	7.03%	0.67**	9.14%	0.72**
[+1 +3]	6.97%	0.63**	7.91%	0.64**	8.98%	0.65**
[+1 +4]	8.88%	0.64**	10.38%	0.67**	11.09%	0.67**
[+1 +5]	11.67%	0.68**	13.06%	0.70**	13.67%	0.71**
[+1 +6]	11.61%	0.64**	13.86%	0.68**	14.95%	0.71**
Events	**Positive**					
Trigger	**20%**		**22%**		**24%**	
Sample size	**210**		**160**		**125**	
Trading Month	CCAR	Proportion of negative abnormal returns	CCAR	Proportion of negative abnormal returns	CCAR	Proportion of negative abnormal returns
Month '0'	27.32%	0.00	29.62%	0.00	31.55%	0.00
+1	-1.61%	0.57**	-1.61%	0.58**	-2.44%	0.60**
[+1 +2]	-2.70%	0.59**	-2.75%	0.60**	-4.35%	0.65**
[+1 +3]	-2.64%	0.56*	-2.25%	0.56*	-3.77%	0.60**
[+1 +4]	-4.50%	0.56*	-4.64%	0.59**	-6.55%	0.62**
[+1 +5]	-2.74%	0.52	-2.97%	0.54	-5.02%	0.56*
[+1 +6]	-4.58%	0.58**	-4.14%	0.59**	-5.83%	0.63**

Note: The sample includes the one-month large price changes of all NIFTY stocks for the period 2000-2019 period. The abnormal or excess return for a stock (CCAR) is calculated by subtracting the corresponding monthly return from the average monthly return of the control stocks. Apart from the original +/-20%, events with +/-22% and +/-24% are also considered. [+1 +2] implies that the abnormal return of month 2 is added to that of month 1 to get the CAR of month 2 and so on. The month 1 CAR is the simple average of the abnormal returns of the complete sample in the first month following the one-month price changes. The proportion of stocks greater (lesser) than zero is the percentage of stocks with positive (negative) returns up to a particular month.

**, * implies significance at 5% and 10% levels, respectively.

Source: Own calculations

Multivariate regression results

Table 4 reports the results of the multivariate regression conducted to examine whether Beta, standard deviation, industry classification, size and period can explain the reversals following large one-month price changes. Even though, only large liquid stocks are considered for the study and as such size cannot have an impact, it is also included in the study. The slope coefficients for both large declines and increases are not significant even at a 10% level of significance except for standard deviation. However, the slope coefficient for standard deviation, though statistically significant at 5% level, is negative, suggesting that stocks with lower standard deviation experience stronger reversals compared to stocks with higher standard deviation. This is exactly the opposite to the predictions of the risk-based explanations, which suggest stronger reversals for risky stocks compared to less risky stocks. The results suggest that the independent variables cannot meaningfully explain the evidenced significant reversals following both large declines and increases. The regression was repeated for other significant CARs and the study evidenced similar results.

Table 4. Multivariate regression results

Events	**Negative**					
Dependent variable	**Month 1 CAR**		**Month 2 CAR**		**Month 3 CAR**	
Independent variables	Std. coefficient	t-stat	Std. coefficient	t-stat	Std. coefficient	t-stat
C	0.098	2.450	0.086	1.992	0.133	2.588
BETA	-0.004	-0.145	0.038	1.192	0.026	0.557
SD	-0.369	-1.193	-0.641	-2.036**	-0.796	-1.978**
Industry	-0.001	-0.442	0.001	0.309	-0.001	-0.231
Size	0.000	0.311	0.000	-0.849	0.000	-0.725
Period	-0.005	-0.564	0.013	1.270	0.016	1.313
Events	**Positive**					
Dependent variable	**Month 1 CAR**		**Month 2 CAR**		**Month 3 CAR**	
Independent variables	Std. coefficients	t-stat	Std. coefficients	t-stat	Std. coefficients	t-stat
C	0.077	1.968	0.098	1.650	0.229	3.049
BETA	0.042	1.369	-0.007	-0.151	-0.007	-0.147
SD	-0.634	-2.750	-0.668	-1.659*	-1.254	-2.571**
Industry	-0.005	-1.409	0.000	0.038	0.003	0.394
Size	0.000	-0.449	-0.001	-1.192	-0.001	-1.555
Period	-0.008	-0.974	0.004	0.307	-0.016	-1.122

Note: The table reports the regression coefficients using the model:

$CAR_i = b_0 + b_1Beta_i + b_2SD_i + b_3\,Period_i + b_4\,Industry_i + b_5Size_i + e_i$

The variables are described in section 3. Section 5.2 describes the results reported in this table.

**, * implies significance at 10% and 5% levels, respectively.

Source: Own calculations

Robustness Checks

The robustness of the evidenced results is checked in this section. In order to verify the sensitivity of the evidenced reversals to extreme observations, the reversals following large one-month changes were reexamined by excluding the top and bottom 2% in the total sample. The cumulative abnormal returns for month 1 to month 6 continued to remain statistically significant at a 5% level for both inclines and decreases. The microstructure effects might not have much impact on the evidenced reversals because of the choice of large liquid optionable stocks and the monthly time period used to calculate large returns. It is reasonable to conclude that the abnormal returns following a large one month price decline are not sensitive to either microstructure effects or extreme observations.

Approximately 20% of the large price decline events occur during the financial crisis between January 2008 and February 2009. The stock markets in India turned the corner by March 2009 and were followed by surprisingly stable results in the general elections in India in May 2009, resulting in a nearly 30% increase for most NIFTY stocks during that period. In order to avoid the possibility that the reversal phenomenon may be influenced by these rare events, the large price declines in the year 2008 and between October 2008 and February 2009 were removed from the sample separately. The reversal phenomenon was still significant at a 5% level of significance in both situations, implying that market conditions cannot explain the significant reversals.

It may be possible that the large price changes may be due to industry classifications. However, the results suggest that the proportion of each major industry in the NIFTY index is not too different from the proportion of event occurrences in major industries. It was also ascertained that no particular month had dominated the evidenced contrarian profits in the Indian stock market. The robustness tests and the multivariate regression results indicate that the contrarian strategy following large one-month price changes is not conditional on common measures of risk, industry, period, size, extreme events, microstructure effects or market effects and directly challenges the weak form of market efficiency in the Indian stock market.

Further robustness checks for the economically significant reversals following large declines

In order to avoid sample bias, this study uses Bremer and Sweeney's (1991) methodology of one event per month. On multi-event months, the stocks are ordered as per alphabetical order and only the first stock is considered for any event month. The initial sample of 417 events was reduced to 91. This means that out of the total 204 months in the 2000-2019 period, 91 months experienced at least one large decline. This section discusses the results of the short-horizon reversals following large price declines using Bremer and Sweeney's (1991) methodology.

Table 5 reports the results of the cumulative abnormal returns (CAR) following ± 20% monthly price changes for the NIFTY stocks over the period from January 2000 to December 2019 based on Bremer and Sweeney's (1991) methodology of one event per month. The month 1 CCAR of 3.91% following large price declines is not only statistically significant, but also the proportion of positive returns shows the presence of a significant systematic pattern. The month 2 CAR of 6.24% and month 3 CAR of 7.85% reach 8.75% by the sixth month. The CARs for all the tested horizons, up to six months, are significant at a 5% level. The proportion of positive returns is statistically significant at a 5% level of significance for CARs for all the horizons, except month 4, suggesting systematic reversal following large price declines. The GCAR and MCAR results corroborate the CCAR results. The results confirm the earlier evidence of a predictable pattern in the short-horizon stock returns up to six months following large one-month declines in the Indian stock market. In order to verify that the evidenced predictable patterns were not conditional on the ordering based on alphabetical order, ordering based on size was also considered, which also suggested significant predictable patterns following large one-month price declines.

Table 5. Predictable pattern following large price declines – one event per month

Events	**Negative**					
Sample size	**91**		**91**		**91**	
Trading Month	CCAR	Proportion of positive abnormal returns	GCAR	Proportion of positive abnormal returns	MCAR	Proportion of negative abnormal returns
Month '0'	-26.82%	0.00	-26.82%	0.00	-26.82%	0.00
+1	3.91%	0.60**	3.92%	0.58*	3.70%	0.60*
[+1 + 2]	6.24%	0.63**	7.82%	0.66**	6.75%	0.67**
[+1 + 3]	7.85%	0.65**	9.62%	0.66**	8.37%	0.65**
[+1 + 4]	6.22%	0.57*	8.63%	0.66**	7.50%	0.61**
[+1 + 5]	8.35%	0.65**	10.80%	0.69**	9.06%	0.67**
[+1 + 6]	8.75%	0.63**	11.29%	0.63**	9.82%	0.60**

Note: The sample includes the one-month large price changes of all NIFTY stocks for the period 2000-2019 period based on the event trigger of +/ -20% with 91 events for declines in the tested period based on the Bremer and Sweeney (1991) criteria of one event per month. On multi-event months, the stocks are ordered as per alphabetical order and only the first stock is considered for any event month. The Month '0' returns are the raw returns. The abnormal or excess return for a stock (CCAR) is calculated by subtracting the corresponding monthly return from the average monthly return of the control stocks for month 1 to month 6. The second abnormal return (GCAR) calculation is based on a single-factor market model employing the GARCH (1,1) process. Further, an alternate method of abnormal return (MCAR) using the market returns is applied to calculate market-adjusted CAR. [+1 + 2] implies that the abnormal return of month 2 is added to that of month 1 to get the CAR of month 2 and so on. The month 1 CAR is the simple average of the abnormal returns of the complete sample in the first month following the one-month price changes. The proportion of stocks greater (lesser) than zero is the percentage of stocks with positive (negative) returns up to a particular month.

**, * implies significance at 5% and 10% levels, respectively.

Source: Own calculations.

Contrarian profits and risk

The 'Uncertain information hypotheses' attempted to explain the response of the rational and risk-averse investor to unanticipated information (Brown et al. 1988) and predicts asymmetric response following both large price declines and increases. This study evidences significant symmetric reversals across all the tested short-horizons contradicting the 'uncertain information hypothesis' and consequently, the abnormal contrarian profits following large declines may not be due to the risk in holding stocks which had experienced a large change in a very short period like one month. Also, the multivariate regression results reported in Table 4 show that common risk factors like stock beta and standard deviation might not explain the evidenced reversals, which suggests that the evidenced contrarian profits cannot be explained by the cross-sectional variance in the mean (Conrad and Kaul, 1998). In this section, we re-examine whether the stock beta can explain the observed significant contrarian profits using a different methodology. The sample of the short-horizon CARs following large one-month declines numbering 247 for the complete period was ranked in ascending order on the basis of their stock betas. The complete sample was divided into four almost equal portfolios (P1 to P4) based on the stock betas, where P1 (P4) is the equal-weighted portfolio representing stocks with the highest (lowest) betas representing the top (lowest) quintile when ranked in the descending order based on stock betas. If the risk-based explanations can explain the evidenced reversals, portfolio P4 should have the least CARs and portfolio P1 should have the maximum CARs following large one-month declines (Conrad and Kaul, 1998). The results of the study show that portfolio P1 representing stocks with the highest betas did not have the highest cumulative abnormal returns in any of the tested holding periods. In fact, portfolio P3 has the maximum CARs in four out of the six tested horizons. The examination was repeated with the portfolios formed based on standard deviation and this study evidenced similar results. In order to avoid bias due to the choice of the portfolios, the examination was repeated by dividing the sample into five approximately equal portfolios and this study evidenced similar results. The evidenced results corroborate the multivariate regression results those common measures of risk like stock betas and standard deviations do not explain the economically significant contrarian profits following large one-month declines in the Indian stock market.

Overall, this study has evidenced significant short-horizon reversals, following both large positive and negative one-month changes, up to six months. This result is similar to studies in the developed and other emerging markets and supports the behavioural 'overreaction hypotheses. The results support De Bondt and Thaler's (1985) assertion that investors tend to overweight recent information and to underweight past information. The stronger reversals following large declines compared to reversals following large increases seem to support Kahneman and Travesky's (1979) assertion that losses affect investment decisions more than equivalent gains. The choice of only the large liquid stocks minimises microstructure effects and the results show that the risk-based explanations could not explain the evidenced reversals. This study finds that the behavioural explanations might explain the time series predictability in the Indian stock market. The EMH contends that the market quickly reflects all relevant information which is not consistent with the predictable pattern and slow multiple month adjustment evidenced in this study. This study is different from most other similar studies in both the developed and emerging markets as we used a different and easily implementable strategy of buying (selling) stocks which have fallen (risen) more than 20% in a calendar month. This study has unearthed a simple profitable trading strategy, based on reversals following large one-month price declines, with potential for significant economic profits and it also appears that ordinary investors can take advantage of the irrationality of the aggregate market.

Conclusion

This paper examines the short-horizon stock behaviour following large one-month changes in the Indian stock market during the 2000-2019 period. It also sets out to examine the validity of the 'overreaction hypothesis' in the Indian stock market. This paper documents evidence of significant predictable patterns in stock behaviour in the Indian stock market. This study evidences statistically significant short-horizon reversals up to six months following both large positive and negative price shocks. The reversals and the slow multiple month adjustments to initial price shocks are not consistent with the EMH, which posits that the market incorporates relevant information correctly and quickly. The findings in this study support the 'overreaction hypothesis' in the Indian stock market due to the symmetric response to both large positive and negative price changes and stronger reversals following stronger initial price shocks. However, the reversals following large declines are stronger than the reversals following large increases. The magnitude of reversals to the tune of nearly 40% (annualised), following large price declines, suggests significant economic profits. However, the reversals following large price increases may not be economically significant. Hence, it is reasonable to conclude that the contrarian strategy of buying stocks with large 'one-month' declines produced significant short-horizon economic profits in the Indian stock market.

This reversal phenomenon is devoid of microstructure issues and most biases due to the choice of large stocks along with the monthly time period to calculate return. The magnitude of the reversals is interesting, as these stocks enjoy informational superiority. The evidenced results are robust to market conditions, market effects, industry, period, extreme observations, and different from other anomalies. The results are also robust to alternate methods of abnormal returns and methodologies. Also, the risk-based explanations could not satisfactorily explain the significant reversals. The reversals, similar to the developed market and other emerging markets, seem to suggest that the behavioural theories can explain the reversals better than institutional issues.

This study examines only the large stocks in the Indian stock market and future research can focus on other stocks and industry classifications. The variables, used in the cross-sectional regression, were based on past research. There might be other variables that were overlooked which can be avenues for future research. Future research may include other variables like volume to discriminate between the different behavioural explanations.

Conflict of interest

The authors declare no conflict of interest.

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