“Do daily price extremes influence short-term investment decisions? Evidence from the Indian equity market”

AUTHORS	Sarveshwar Kumar Inani Harsh Pradhan R. Prasanth Kumar Ajay Kumar Singal

ARTICLE INFO	Sarveshwar Kumar Inani, Harsh Pradhan, R. Prasanth Kumar and Ajay Kumar Singal (2022). Do daily price extremes influence short-term investment decisions? Evidence from the Indian equity market. *Investment Management and Financial Innovations*, *19*(4), 122-131. doi:10.21511/imfi.19(4).2022.10
DOI	http://dx.doi.org/10.21511/imfi.19(4).2022.10
RELEASED ON	Monday, 07 November 2022
RECEIVED ON	Monday, 08 August 2022
ACCEPTED ON	Wednesday, 26 October 2022
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
50	0	4

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

Sarveshwar Kumar Inani (India), **Harsh Pradhan** (India), **R. Prasanth Kumar** (India), **Ajay Kumar Singal** (India)

DO DAILY PRICE EXTREMES INFLUENCE SHORT-TERM INVESTMENT DECISIONS? EVIDENCE FROM THE INDIAN EQUITY MARKET

Abstract

For short-term investments in equity markets, investors use price points, candlestick patterns, moving averages, support and resistance levels, trendlines, price patterns, relative strength index, and moving average convergence-divergence as reference(s) for making decisions. This study investigates whether investors use daily price extremes (highest and lowest prices for the day) for making short-term investments or trading decisions in the context of the Indian equity market. Using 6,902 observations of daily data of the NIFTY 50 index since its launch, it is observed that daily price extremes (high or low) have no impact on opening returns of the next trading day. Based on the dummy regression analysis, next-day opening returns were found to be statistically significant, which implies the presence of momentum behavior. However, insignificant coefficients for high or low-price extremes of the day mean that investors do not use them as an anchor or reference point for decisions. Results are consistent over time and robust to the rising or falling markets. Further, opening returns were seen to be more volatile than closing returns in the first half of the sample, and they are less volatile in the second half, implying that markets have become more efficient in the last few years.

Received on: 8th of August, 2022
Accepted on: 26th of October, 2022
Published on: 7th of November, 2022

Sarveshwar Kumar Inani, Assistant Professor, Faculty of Finance and Accounting, Jindal Global Business School, OP Jindal Global University, India. (Corresponding author)

Harsh Pradhan, Assistant Professor, Faculty of Management Studies, Banaras Hindu University, India.

R. Prasanth Kumar, Associate Professor, School of Management Studies, University of Hyderabad, India.

Ajay Kumar Singal, Associate Professor of Strategy, Indian Institute of Management Sirmaur, India.

Keywords anchoring bias, equity market, momentum, price extremes, short-term investments

JEL Classification G10, G11, G14, G41

INTRODUCTION

Stock markets are ideal avenues for wealth creation (Bessembinder, 2021) and attract many retail and institutional investors who want to make a fortune. Investors use numerous fundamentals-based or technical analysis tools to make investment decisions (Arévalo et al., 2017; Shah et al., 2019). They make decisions based on time horizon (short-term versus long-term) and expectations (bulls versus bears) of the market direction (Bahadar et al., 2019). Long-term investors base their investment decisions on the intrinsic value (Lee et al., 1999) and expected returns (Lyle & Yohn, 2021) derived by analyzing the fundamentals of a firm, i.e., financial ratios, macroeconomic environment, geopolitical situation, and risk. In contrast, short-term investors use patterns in asset prices (Friesen et al., 2009) supported by various technical analyses such as price-volume action, candlestick patterns, moving averages, support and resistance levels, trendlines, relative strength index (RSI), moving average convergence-divergence (MACD) indicators. Short-term investors look for potential inefficiency in the market due to imperfect information and make decisions (entry, exit, stop loss) that are anchored to the price points suggested by different technical indicators (Metghalchi et al., 2019). Their decisions also reflect the influence of psychological biases (Daniel et al.,

Conflict of interest statement:
Author(s) reported no conflict of interest

http://dx.doi.org/10.21511/imfi.19(4).2022.10

1998) and market sentiments (Hao et al., 2018). Price extremes (i.e., 52-weeks, monthly, weekly, or daily high/low prices) are typical candidates for reference and pricing points that influence investment decisions (George & Hwang, 2004; Li & Yu, 2012; Parkinson, 1980). Price extremes are comparatively more publicized and readily available in mainstream and social media (George & Hwang, 2004). Compared to long-term investors, short-term traders react to new information quickly due to the limited time window available for trades (Sturm, 2013), and they are more prone to price extremes.

In a recent study, Sturm (2021) examined whether extreme prices can serve as reference points for short-term investment decisions. The use of daily price extremes (highest and lowest prices) as reference points provides evidence of anchoring bias (Tversky & Kahneman, 1974) in the short-term decision-making of traders and investors. Sturm (2021) used S&P 500 index data to investigate the impact of daily price extremes on the opening price returns and concluded that excess momentum returns in opening prices are found for days in which prices open outside the previous day's price extremes. The current research paper extends the modeling approach of Sturm (2021) and examines the impact of daily price extremes, as an anchor or reference point, on short-term investments in the context of the Indian equity market. Understanding extreme price behavior in the Indian equity market would be interesting as it is one of the fastest among emerging economies, and the participation of retail investors is increasing with the rise in disposable incomes. Recent studies (Baker et al., 2018; Raut et al., 2020) indicate the presence of anchoring bias among Indian investors. Hence, examining the anchoring bias, especially daily price extremes in the context of Indian investors, would be quite fascinating due to its unique market setting and ensuing volatility.

1. LITERATURE REVIEW

The topic of stock price prediction is debatable in the scholarly literature (Sturm, 2013), and the impact of daily price extremes on the next day's index returns in an emerging market context is a little studied phenomenon. Using historical monthly or daily data, researchers forecast indices that capture broader market movement than individual stocks. For example, researchers have investigated daily data of the NASDAQ Stock Exchange Index (Guresen et al., 2011), Dow Jones Industrial Average Index (O'Connell et al., 2011), Istanbul Stock Exchange, S&P 500 Index (Cao & Tay, 2001; Sturm, 2021), S&P 500 Index ETF (Zhong & Enke, 2017), MSCI World Index (Eugster & Uhl, 2022). However, because of the unique setting of different markets and ensuing volatility, and despite the availability of machine learning algorithms and advanced statistical techniques, stock price prediction continues to remain challenging (Shah et al., 2019).

Believers in the efficient market hypothesis (Fama, 1970) emphasize that stock prices fully reflect the publicly available information, and advocate that using any analysis, whether technical or fundamental, for predicting stock prices is a futile exercise. The efficient market hypothesis is also consistent with the random walk hypothesis (Fama, 1995; Malkiel, 2003), which posits that stock prices are random and historical prices cannot be used to predict the future price movements of a stock. However, Shiller (2015) argues that prices across all asset categories are psychologically driven as reflected in the bubbles in stock markets when stock prices become inflated and burst over time. As regulatory environments and tax laws change, market participants' risk and reward preferences also change (Lo, 2004). As stock prices fully discount all available information, the historical path taken by the stock prices also influences the aggregate risk preferences (Lo, 2004). Because of behavioral patterns and some short-term phenomena (Shiller, 2015), markets may show information asymmetry. Short-term investors look for potential inefficiency in the market due to imperfect information and link their decisions to the price points suggested by different technical indicators (Metghalchi et al., 2019). Because equity prices are less predictable in the short run than in the long run, price points act as reference points to make the decisions for investing in the equity markets. In a significant way, the technical analysis contains valuable information for decision-making (Sturm, 2013) and a plethora of studies (Abu-Mostafa & Atiya, 1996; Lu et al., 2012; Metghalchi et al., 2019;

Park & Irwin, 2007) highlight that technical analysis is a valuable technique in predicting prices. Technical analysts argue that stock prices move in specific patterns, which makes them predictable in the short term (Murphy, 1999; Pring, 2002). In a novel dataset of news sentiments, Eugster and Uhl (2022) found no significant relationship between technical analysis indicators and future asset returns. Nevertheless, it is worthwhile to note that historical prices (or returns) and past technical analysis have explanatory power to forecast future price behavior in the short run (Chong et al., 2017; Eugster & Uhl, 2022; Zhong & Enke, 2017).

Overreaction and momentum are popular hypotheses from a behavioral finance perspective explaining the predictive power of historical prices. The overreaction hypothesis suggests that when historical price changes (returns) are extreme, the subsequent price reversals will be more pronounced (De Bondt & Thaler, 1985, p. 80). It implies that investors tend to reverse the price directions in the following days. On the other hand, the momentum hypothesis suggests that buying past winners and selling past losers will generate abnormal returns as prices react in a delayed manner to firm-specific information (Jegadeesh & Titman, 1993). The momentum profits are generated mainly from time-series predictability in stock market indices (Chan et al., 2000). Scholars have found evidence for both hypotheses, momentum, and overreaction, in the context of the Indian stock market (Ansari & Khan, 2012; Choudhary & Sethi, 2014).

Short-term investors use past stock prices and signals from technical analysts to predict the direction of daily stock market returns. As per the behavioral models discussed above, this might be caused by the serial correlation of daily returns (Jegadeesh & Titman, 2011). However, there is little evidence to show whether the serial correlation is under-reaction or over-reaction. Another view outlined by Park and Sabourian (2011) suggest that investors herd if they see extreme outcomes as more likely, else they act as contrarian if any technical analyses such as RSI, technical support, or resistance levels lead them to middle values.

Also, markets can turn inefficient and offer a potential to earn returns because of psychological reasons of participants (Shiller, 2015) and asset mispricing (Hirshleifer, 2001) resulting from decision biases such as overconfidence bias, anchoring bias, representativeness bias, loss aversion, optimism. It makes financial decision-making complex. Investors tend to suffer from anchoring bias, a concept popularized by Tversky and Kahneman (1974), who argued that investors rely on some popular price levels such as a 52-week high/low (George & Hwang, 2004; Li & Yu, 2012), 200-day moving average, or technical support or resistance levels for making investment decisions (Murphy, 1999; Pring, 2002). Anchoring bias influences investors when they evaluate, a priori, future stock prices. However, this estimation is a complex task involving a higher degree of uncertainty (Cen et al., 2013). These price levels are well covered by print media (TV channels, business newspapers) and social media (YouTube, Telegram, and Twitter, among others). Hence, the role of these salient price levels, however irrelevant as an anchor, becomes pivotal in influencing investment decisions (Cen et al., 2013). Sturm (2008, 2021) argues that investors consider price extremes as new reference levels and anchor their decisions based on them. Sturm (2021) used the previous day's highest or lowest trading prices to calculate excess momentum returns on the days in which prices open outside of the previous day's highest or lowest trading price and found it to be robust to the market direction (up/down) and consistent over time. Price extremes become crucial reference points and influence short-term investment decisions as investors adjust their previous anchors based on recent significant real price (Zielonka, 2004). Previous studies (George & Hwang, 2004; Li & Yu, 2012) showed evidence of the explanatory power of price extremes in future returns. Investors can forecast aggregate market returns when prices are near to 52-week high or historical high (Li & Yu, 2012). Similarly, daily price extremes are expected to act as an anchor when traders analyze the available information for forecasting next-day prices (Sturm, 2021). However, the impact of daily price extremes on the daily index returns might not be the same across countries because of volatility and other macro variables such as regulations and corporate governance. The current research paper aims to look for empirical evidence of the impact of daily price extremes, as a psychological anchor, on the daily index returns in the context of the India stock index.

http://dx.doi.org/10.21511/imfi.19(4).2022.10

2. DATA AND METHODOLOGY

To proxy investor behavior, adjusted daily prices of the NIFTY50 index were extracted from Bloomberg in open, high, low, and close (OHLC) format. NIFTY50 index is India's benchmark index, the underlying index for the world's most liquid derivatives contracts (futures and options), index mutual funds, and exchange-traded funds (ETFs). The data spans from November 3, 1995 to April 30, 2022. The data have been taken since the origin of the National Stock Exchange (where NIFTY 50 is traded) to date to do a comprehensive analysis. This study examines the impact of price extremes (highest and lowest prices on a day) on the next day's opening prices. Stock market studies generally are based on close prices (or close-to-close returns). However, the current study will use open prices (or open-to-open returns) to examine the impact of price extremes (the high and low prices) on the opening returns. In the literature, many renowned scholars have also used open-to-open returns for different scholarly purposes. For example, Parkinson (1980) used extreme values (the high and low prices) for the volatility modeling of stock returns. Whereas Garman and Klass (1980) used open and close prices as well, in addition to the extreme values (the high and low prices), to estimate stock return volatility. However, the properties of opening and closing returns might differ as they are recorded at different times, and they might discount different sets of information for price discovery. Hence, a comparison of opening and closing prices are shown in Table 1.

These descriptive statistics align with the findings of Sturm (2021). Both price series, opening and closing, have the same average return of 0.04% (Column 2 of Table 1). However, there is a slight variation in the standard deviation of both series. Column 3 indicates that opening returns are more volatile than closing returns, which is consistent with the findings of Hong and Wang (2000). Such behavior can also be attributed to the findings of Moshirian et al. (2012), who report that opening prices immediately discount the overnight news, but the discounting process is slower when information arrives during the day. Statistically, both price series are identical, as shown by the highly insignificant p-value of 0.991 for the difference in returns in column 5 of Table 1. Column 6 shows that the correlation between the two series is significant but low, suggesting that both series discount different sets of information.

Finally, consistent with Sturm (2021), both price series exhibit a positive and highly significant first-order autocorrelation of 0.029 and 0.042, respectively (column 7 of Table 1). Though the first-order correlation coefficient's magnitude is much less in both series, opening return autocorrelation (0.029) is much less than closing return autocorrelation (0.042). It suggests that opening price discovery is more efficient than closing price discovery. The study also compares the nuances of opening and closing returns to understand the nature of the two-price series.

Before investigating the impact of price extremes on opening price returns, opening price returns were investigated to find evidence of momentum or overreaction behavior. As suggested in the literature (Bremer & Sweeney, 1991; Sturm, 2021), the entire data set was sorted in the order of opening returns of day t and divided into deciles. Later, returns of the following five days were averaged and examined for abnormal returns. These results are reported in Table 3. Next, the impact of price extremes on opening returns was examined using dummy variable regression analysis, which was the primary motivation of this study. The purpose was to isolate the impact of price extremes and the

Table 1. Descriptive statistics

Source: Authors' calculation.

Series	Mean	Standard Deviation	Observations	Difference in returns	Correlation	First order Autocorrelation
Opening Returns	0.04%	1.48%	6902	0.000 (0.991)	0.185*** (0.000)	0.029** (0.013)
Closing Returns	0.04%	1.45%	6902			0.042*** (0.000)

Note: This table exhibits descriptive statistics for opening (open-to-open returns) and closing returns (close-to-close returns) of the NIFTY 50 index from November 3, 1995 to April 30, 2022. Returns are computed as log differences in respective prices. Column 5 presents the difference in opening and closing returns; Column 6 shows the correlation between opening and closing returns; Column 7 exhibits the first-order autocorrelation of opening and closing returns. The p-value of test statistics is reported in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 2. The setup of extreme price event and returns on day t+1

Source: Authors.

Day t-1	Extreme price event on Day t	Day t+1
For example, the prices on day t-1 are as follows: Open price is 50 Close price is 52 Highest price is 55 Lowest price is 49	An extreme price event occurs only if the price opens below 49 (lowest of the previous day) or above 55 (highest of the previous day). If the opening price is above 55, D_H will be assigned 1, or 0 otherwise. If the opening price is below 49, D_L will be assigned 1 or 0 otherwise.	Opening price returns calculated on the day following the extreme price event.

previous day's opening prices on today's opening price returns. For the estimation of impact, the following regression model was used:

$$R_{t+1} = \alpha + \gamma_1 R_t + \gamma_2 D_H + \gamma_3 D_L + \varepsilon, \quad (1)$$

where R_{t+1} and R_t are opening price returns on day t+1 and day t of the event; D_H and D_L are dichotomous variables taking the value of 1 if the opening price on day t is higher (lower) than that of the previous day's high (low) and 0 otherwise; α is the intercept term, γ_s are the coefficients for the variables, and ε is the error term.

In the regression equation, γ_1 estimates the momentum in opening price returns (i.e., impact of the previous day's opening returns), γ_2 and γ_3 capture the influence of daily price extremes (high and lows). γ_2 captures the impact of the event when the price on day t is opening higher than the previous day's highest price, whereas γ_3 captures the impact of the event when the price on day t is opening lower than the previous day's lowest price. The setup of extreme price events and returns on day t+1 is explained in Table 2.

If daily price extreme events (on Day t) work anchors and influence short-term investment behavior and decisions, γ_2 and γ_3 will be statistically significant. The regression results are reported in Table 4.

3. RESULTS

To understand the impact of the previous day's opening prices on today's opening price returns, it is essential to isolate the effect of price extremes from the impact of the previous day's opening prices on today's opening price returns. The first column of Table 3 shows the deciles (from 1 to 10), where decile 1 is for the largest returns and decile 10 is for the smallest returns. Column 2 shows the average opening returns on day t, and columns 3-7 present the average opening returns for five days following day t.

Table 3. Momentum in opening price returns

Source: Authors' calculation.

Decile	t	t+1	t+2	t+3	t+4	t+5
1	2.61	0.1	–0.04	0.05	0.15	0.03
	–	0.95	–1.32	0.13	1.72*	–0.19
2	1.25	0.24	0.12	0.11	0.04	0.09
		3.39***	1.29	1.11	0(1)	0.81
3	0.79	0.09	0.08	0	0.06	0.12
	–	0.84	0.73	–0.71	0.37	1.34
4	0.45	0.03	0.04	0.08	0	–0.01
	–	–0.26	–0.02	0.63	–0.67	–0.95
5	0.15	0.04	–0.01	0.04	0.16	0.07
	–	–0.09	–0.94	–0.01	2.06**	0.52
6	–0.03	0.07	0.04	0.04	0.13	–0.02
	–	0.53	0.02	–0.05	1.48	–1.07
7	–0.28	–0.04	0.08	0.07	0	0.03
	–	–1.39	0.6	0.48	–0.77	–0.16
8	–0.64	0	0.03	–0.01	0.04	0.05
	–	–0.66	–0.17	–0.92	0.04	0.11
9	–1.17	–0.08	0.01	0	–0.04	0.11
	–	–2.05**	–0.47	–0.64	–1.46	1.15
10	–2.73	–0.03	0.06	0.04	–0.12	–0.05
	–	–1.18	0.29	–0.01	–2.64***	–1.47

Note: This table exhibits the average daily returns calculated from opening prices for the NIFTY 50 over the period from November 3, 1995 to April 30, 2022. Returns are in % (no decimals). Returns (on Day t) are sorted first and then divided into deciles. Column 2 shows the returns of each decile, and Columns 3 to Column 7 exhibit average daily returns along with their test statistic for the consecutive 5 days (1, 2, 3, 4, and 5 days) following Day t. The test statistic tests the difference of means between the entire return series and the period under examination (each decile). ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Though Table 3 does not show any strong evidence of short-term momentum in opening returns, some deciles on two days (t+1 and t+4) following the day t show abnormal average opening returns, which reflects the possibility of the existence of momentum. Abnormal returns are visible for the day t+1 in deciles 2 and 9 only (in the bold font in Table 3). Similarly, for the day t+4, deciles 1, 5, and

http://dx.doi.org/10.21511/imfi.19(4).2022.10

10 show statistical significance. Previously, Table 1 showed that first-order autocorrelation in opening price returns is 0.029. Hence, the likelihood of impact of price extremes on opening price returns cannot be ruled out. Next, the impact of price extremes on opening returns is examined using dummy variable regression analysis. The regression results are reported in Table 4.

Table 4. Regression results for the full sample and sub-samples

R_t	N	γ_1	γ_2	γ_3
Panel A: Full Sample (November 3, 1995 to April 30, 2022)				
All Observations	6901	0.04	–0.04	0.05
	–	2.68***	–0.81	0.66
$R_t > 0$	3475	0.03	–0.08	NA
	–	1.13	–1.64	–
$R_t < 0$	3063	–0.01	NA	0.06
	–	–0.48	–	0.79
Panel B: First Half of the sample (November 3, 1995 to January 23, 2009)				
All Observations	3450	0.06	0.04	–0.03
	–	3.19***	0.32	–0.22
$R_t > 0$	1720	–0.01	0.04	NA
		–0.21	0.31	–
$R_t < 0$	1543	0.02	NA	0.01
	–	0.58	–	0.03
Panel C: Second Half of the sample (January 26, 2009 to April 30, 2022)				
All Observations	3451	–0.03	–0.02	–0.02
	–	–1.62	–0.31	–0.21
$R_t > 0$	1755	0.04	–0.07	NA
	–	1.31	–1.20	–
$R_t < 0$	1520	–0.17	NA	–0.09
	–	–4.37***	–	–1.11

Note: Regression results are obtained from estimating equation (1). ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A of Table 4 shows the regression results for the full sample period, while Panels B and C represent results for the first and second half of the sample period, respectively. Within each panel, three rows present the results for all observations, positive, and negative Day *t* returns, respectively. Columns 3, 4, and 5 of each panel present the coefficients and their test statistics.

The first row in Panel A of Table 4 exhibits regression results for the entire dataset spanning November 3, 1995 to April 30, 2022 (6,901 observations). It shows that γ_1 is 0.04 and statistically significant at the 1% level of significance, which implies that, despite the presence of the prior day's price extremes, momentum behavior is evident in opening returns. However, γ_2 and γ_3 are not statistically significant, which implies that daily price extremes (highs or lows) do not work as an anchor or reference point for investors while making a short-term investment or trading decision in the Indian equity market.

For robustness check, data is divided into two halves (first half and second half), and regression is run on two subsamples. The regression results for the first half (November 3, 1995 to January 23, 2009) are reported in row 1 of Panel B. Results for the second half (January 26, 2009 to April 30, 2022) are reported in row 1 of Panel C. Results for the first half are similar and indicate that momentum persists (statistically significant γ_1) and there is no impact of daily price extremes (statistically insignificant γ_2 and γ_3). However, regression results for the second half are different and suggest that all coefficients (γ_1, γ_2 and γ_3) are statistically insignificant. It implies that there is no effect of momentum and daily price extremes on opening price returns in the second half of the sample.

Next, the impact of falling or rising prices is tested. Row 2 in all three panels reports the regression results for days having positive returns only for Day t ($R_t > 0$). And, row 3 in all three panels reports the regression results for days having negative returns only on Day t ($R_t < 0$). One clear finding is that there is no impact of daily price extremes in rising or falling markets as γ_2 and γ_3 are statistically insignificant in row 2 and row 3 of all panels. However, the momentum behavior of the investors is not the same in the rising and falling markets. Row 1 of Panel A shows that investors are displaying momentum behavior for the full sample, evident from statistically significant γ_1 (0.04). However, row 2 and row 3 indicate that investors are not showing any momentum behavior as γ_1 (0.03 and –0.01, respectively) becomes statistically insignificant. Panel B for the first half also reports similar results. However, the results for the second half (Panel C) are different. Row 3 of Panel C shows that investors are showing momentum behavior in the declining markets, which is evident from statistically significant γ_1 (–0.17), which was insignificant for the entire dataset of the second half (–0.03).

4. DISCUSSION

Analysis shows the presence of momentum on fewer days. Except for these statistically significant values, there is no other reliable presence of momentum or overreaction. In fact, there is no consistent pattern (from decile 1 to decile 10) to show the presence of momentum. Hence, these results might be just artifacts of the sample. It is also evident from Table 3 that there is no momentum or overreaction found in the opening price returns (decile-wise), as most of the average returns on all five days following day t are statistically insignificant. This finding is consistent with Hong and Wang (2000) but contradictory to that of Sturm (2021), who finds strong momentum in the results. The plausible reason for such different findings can be the different nature of time series data or periods studied.

The regression findings (refer to Table 4) also contradict the findings of Sturm (2021), who indicated that price extremes of the day might serve as reference points for short-term decisions in the equity markets. The divergence in the results can be attributed to the different regulatory environments, different time series, different time periods, or the nature of volatility. The findings do not provide conclusive evidence that behavioral biases can affect aggregate market returns in the Indian context.

The findings are robust over the years, which indicates that over the years, the Indian equity markets have become more efficient, in the weak form, due to enhanced regulations and a better focus on corporate governance practices. Moreover, such an evolution of the Indian equity market points to the adaptive market hypothesis (Lo, 2004), which combines the efficient market hypothesis with behavioral economics. So, with the shift in the regulatory environment and tax laws over time, the risk/ reward relationship also changes (Lo, 2004). Through findings, row 1 in all three panels in Table 4 (Panel A, B, and C), implies that daily price extremes have no impact on short-term investment and trading decisions, they might become profitable when environmental conditions for risk/reward relationships become favorable.

It would be interesting to investigate whether investor behavior remains the same or changes during the regime of rising versus falling stock prices. The well-established disposition effect (Odean, 1998) suggests that investors behave differently during periods of rising versus falling prices. Generally, short-term investors keep loser stocks and sell the winner stocks.

In a nutshell, the regression results, as reported in Table 4, show that daily price extremes do not work as an anchor or reference point for investors while making short-term investments or trading decisions in the Indian equity market. This investor behavior is consistent irrespective of rising and falling markets. However, momentum behavior is seen in opening returns for the entire sample, which can be attributed to the first half of the sample. The findings mean that asset pricing and returns are dynamic and psychology-based because of the high degree of uncertainty associated with estimating the future (Cen et al., 2013; Hirshleifer, 2001).

CONCLUSION

The decision-making for investing (entry, exit, and stop-loss) in the equity markets is very complex, and investors resort to price extremes or some other price points (moving averages, support and resistance levels, trendlines, price patterns, RSI, or convergence-divergence indicator, among others) as reference for making the investing decisions in equity markets. Price extremes are helpful in forecasting returns and volatility of financial assets. Reference price points act as anchors, thereby creating an anchoring bias in decision making. Current research examines the momentum behavior due to the previous day's opening returns and daily price extremes (highest and lowest prices) in the Indian equity markets. Based on 6,902 observations of daily price data (open, high, low, and close) of NIFTY 50 over the period

http://dx.doi.org/10.21511/imfi.19(4).2022.10

from November 3, 1995 to April 30, 2022, this study finds that opening returns were found to be more volatile than closing returns. Opening prices are more volatile because at the opening hour, markets discount the overnight news quickly, whereas the discounting process is comparatively slower during the rest of the day.

After isolating the impact of the previous day's price extremes on today's opening price returns, the study finds that daily price extremes have no influence on the opening price returns. It implies that extreme daily price events do not work as an anchor or reference point for investors when making a short-term investment or trading decisions in the Indian equity market. This investor behavior is consistent over time, irrespective of rising or falling markets. However, momentum behavior is seen in opening returns for the entire sample, which can be attributed to the first half of the sample. However, Indian equity markets have become more efficient (weak form) over time as there was no momentum effect in the second half of the sample. Such evolution of the Indian equity market can be attributed to the adaptive market hypothesis, which combines the well-known efficient market hypothesis with behavioral finance.

Overall, this study provides evidence that daily price extremes do not work as the reference point for short-term investment decisions in the Indian equity market, which contradicts the anchoring bias theory but is consistent with the efficient market hypothesis. This finding is useful to investors, traders, and portfolio managers who make short-term trading/investment decisions in confirming that certain trading strategies work well in specific environments and perform poorly in others. Future research can examine the impact of daily price extremes on price returns in other equity markets. Moreover, it would also be fruitful to extend such analysis to other asset classes such as commodities or bullion.

AUTHOR CONTRIBUTIONS

Conceptualization: Sarveshwar Kumar Inani, Harsh Pradhan.
Data curation: Harsh Pradhan, Ajay Kumar Singal.
Formal analysis: Sarveshwar Kumar Inani, Harsh Pradhan, R. Prasanth Kumar, Ajay Kumar Singal.
Investigation: Sarveshwar Kumar Inani, Harsh Pradhan, R. Prasanth Kumar, Ajay Kumar Singal.
Methodology: Sarveshwar Kumar Inani, Harsh Pradhan.
Project administration: Sarveshwar Kumar Inani, Harsh Pradhan.
Software: Sarveshwar Kumar Inani, Harsh Pradhan.
Supervision: Sarveshwar Kumar Inani.
Validation: R. Prasanth Kumar, Ajay Kumar Singal.
Writing – original draft: Sarveshwar Kumar Inani, Harsh Pradhan.
Writing – review & editing: Sarveshwar Kumar Inani, Harsh Pradhan, R. Prasanth Kumar, Ajay Kumar Singal.

REFERENCES

1. Abu-Mostafa, Y. S., & Atiya, A. F. (1996). Introduction to financial forecasting. *Applied Intelligence, 6*(3), 205-213. https://doi.org/10.1007/BF00126626
2. Ansari, V. A., & Khan, S. (2012). Momentum anomaly: Evidence from India. *Managerial Finance, 38*(2), 206-223. https://doi.org/10.1108/03074351211193730
3. Arévalo, R., García, J., Guijarro, F., & Peris, A. (2017). A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting. *Expert Systems with Applications, 81,* 177-192. https://doi.org/10.1016/j.eswa.2017.03.028
4. Bahadar, S., Mahmood, H., & Zaman, R. (2019). The Herds of Bulls and Bears in Leveraged ETF Market. *Journal of Behavioral Finance, 20*(4), 408-423. https://doi.org/10.1080/15427560.2019.1553177
5. Baker, H. K., Kumar, S., Goyal, N., & Gaur, V. (2018). How financial literacy and demographic variables relate to behavioral biases. *Managerial Finance, 45*(1),

124-146. https://doi.org/10.1108/MF-01-2018-0003

6. Bessembinder, H. (2021). Wealth Creation in the US Public Stock Markets 1926–2019. *The Journal of Investing, 30*(3), 47-61. https://doi.org/10.3905/joi.2021.1.168

7. Bremer, M., & Sweeney, R. J. (1991). The Reversal of Large Stock-Price Decreases. *The Journal of Finance, 46*(2), 747-754. https://doi.org/10.1111/j.1540-6261.1991.tb02684.x

8. Cao, L., & Tay, F. E. H. (2001). Financial Forecasting Using Support Vector Machines. *Neural Computing & Applications, 10*(2), 184-192. https://doi.org/10.1007/s005210170010

9. Cen, L., Hilary, G., & Wei, K. C. J. (2013). The Role of Anchoring Bias in the Equity Market: Evidence from Analysts' Earnings Forecasts and Stock Returns. *Journal of Financial and Quantitative Analysis, 48*(1), 47-76. https://doi.org/10.1017/S0022109012000609

10. Chan, K., Hameed, A., & Tong, W. (2000). Profitability of Momentum Strategies in the International Equity Markets. *The Journal of Financial and Quantitative Analysis, 35*(2), 153-172. https://doi.org/10.2307/2676188

11. Chong, E., Han, C., & Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications, 83*, 187-205. https://doi.org/10.1016/j.eswa.2017.04.030

12. Choudhary, K., & Sethi, N. (2014). A Study of Overreaction Hypothesis in the Indian Equity Market. *Asia-Pacific Journal of Management Research and Innovation, 10*(4), 355-366. https://doi.org/10.1177/2319510X14553720

13. Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance, 53*(6), 1839-1885. https://doi.org/10.1111/0022-1082.00077

14. De Bondt, W. F. M., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793-805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

15. Eugster, P., & Uhl, M. W. (2022). Technical analysis: Novel insights on contrarian trading. *European Financial Management, n/a*(n/a). https://doi.org/10.1111/eufm.12389

16. Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work*. *The Journal of Finance, 25*(2), 383-417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

17. Fama, E. F. (1995). Random Walks in Stock Market Prices. *Financial Analysts Journal, 51*(1), 75-80. https://doi.org/10.2469/faj.v51.n1.1861

18. Friesen, G. C., Weller, P. A., & Dunham, L. M. (2009). Price trends and patterns in technical analysis: A theoretical and empirical examination. *Journal of Banking & Finance, 33*(6), 1089-1100. https://doi.org/10.1016/j.jbankfin.2008.12.010

19. Garman, M. B., & Klass, M. J. (1980). On the Estimation of Security Price Volatilities from Historical Data. *The Journal of Business, 53*(1), 67-78.

20. George, T. J., & Hwang, C.-Y. (2004). The 52-Week High and Momentum Investing. *The Journal of Finance, 59*(5), 2145-2176. https://doi.org/10.1111/j.1540-6261.2004.00695.x

21. Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications, 38*(8), 10389-10397. https://doi.org/10.1016/j.eswa.2011.02.068

22. Hao, Y., Chou, R. K., Ko, K.-C., & Yang, N.-T. (2018). The 52-week high, momentum, and investor sentiment. *International Review of Financial Analysis, 57*, 167-183. https://doi.org/10.1016/j.irfa.2018.01.014

23. Hirshleifer, D. (2001). Investor Psychology and Asset Pricing. *The Journal of Finance, 56*(4), 1533-1597. https://doi.org/10.1111/0022-1082.00379

24. Hong, H., & Wang, J. (2000). Trading and Returns under Periodic Market Closures. *The Journal of Finance, 55*(1), 297-354. https://doi.org/10.1111/0022-1082.00207

25. Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65-91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

26. Jegadeesh, N., & Titman, S. (2011). Momentum. *Annual Review of Financial Economics, 3*(1), 493-509. https://doi.org/10.1146/annurev-financial-102710-144850

27. Lee, C. M. C., Myers, J., & Swaminathan, B. (1999). What is the Intrinsic Value of the Dow? *The Journal of Finance, 54*(5), 1693-1741. https://doi.org/10.1111/0022-1082.00164

28. Li, J., & Yu, J. (2012). Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics, 104*(2), 401-419. https://doi.org/10.1016/j.jfineco.2011.04.003

29. Lo, A. W. (2004). The Adaptive Markets Hypothesis. *The Journal of Portfolio Management, 30*(5), 15-29. https://doi.org/10.3905/jpm.2004.442611

30. Lu, T.-H., Shiu, Y.-M., & Liu, T.-C. (2012). Profitable candlestick trading strategies – The evidence from a new perspective. *Review of Financial Economics, 21*(2), 63-68. https://doi.org/10.1016/j.rfe.2012.02.001

31. Lyle, M. R., & Yohn, T. L. (2021). Fundamental Analysis and Mean-Variance Optimal Portfolios. *The Accounting Review, 96*(6), 303-327. https://doi.org/10.2308/TAR-2019-0622

32. Malkiel, B. G. (2003). *A random walk down Wall Street: The time-tested strategy for successful investing* (Completely rev. and updated). W. W. Norton.

http://dx.doi.org/10.21511/imfi.19(4).2022.10

33. Metghalchi, M., Hayes, L. A., & Niroomand, F. (2019). A technical approach to equity investing in emerging markets. *Review of Financial Economics, 37*(3), 389-403. https://doi.org/10.1002/rfe.1041

34. Moshirian, F., Nguyen, H. G. (Lily), & Pham, P. K. (2012). Overnight public information, order placement, and price discovery during the pre-opening period. *Journal of Banking & Finance, 36*(10), 2837-2851. https://doi.org/10.1016/j.jbankfin.2012.06.012

35. Murphy, J. J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. Penguin.

36. O'Connell, D., Hickerson, K., & Pillutla, A. (2011). Organizational Visioning: An Integrative Review. *Group & Organization Management, 36*(1), 103-125. https://doi.org/10.1177/1059601110390999

37. Odean, T. (1998). Are Investors Reluctant to Realize Their Losses? *The Journal of Finance, 53*(5), 1775-1798. https://doi.org/10.1111/0022-1082.00072

38. Park, A., & Sabourian, H. (2011). Herding and Contrarian Behavior in Financial Markets. *Econometrica, 79*(4), 973-1026. https://doi.org/10.3982/ECTA8602

39. Park, C.-H., & Irwin, S. H. (2007). What Do We Know About the Profitability of Technical Analysis? *Journal of Economic Surveys, 21*(4), 786-826. https://doi.org/10.1111/j.1467-6419.2007.00519.x

40. Parkinson, M. (1980). The Extreme Value Method for Estimating the Variance of the Rate of Return. *The Journal of Business, 53*(1), 61-65.

41. Pring, M. J. (2002). *Technical analysis explained: The successful investor's guide to spotting investment trends and turning points*. McGraw-Hill Professional.

42. Raut, R. K., Das, N., & Mishra, R. (2020). Behaviour of Individual Investors in Stock Market Trading: Evidence from India. *Global Business Review, 21*(3), 818-833. https://doi.org/10.1177/0972150918778915

43. Shah, D., Isah, H., & Zulkernine, F. (2019). Stock Market Analysis: A Review and Taxonomy of Prediction Techniques. *International Journal of Financial Studies, 7*(2), 26. https://doi.org/10.3390/ijfs7020026

44. Shiller, R. J. (2015). Irrational Exuberance: Revised and Expanded Third Edition. In *Irrational Exuberance*. Princeton University Press. https://doi.org/10.1515/9781400865536

45. Sturm, R. R. (2008). The 52-Week High Strategy: Momentum and Overreaction in Large Firm Stocks. *The Journal of Investing, 17*(2), 55-67. https://doi.org/10.3905/joi.2008.707218

46. Sturm, R. R. (2013). Market Efficiency and Technical Analysis Can they Coexist? *Research in Applied Economics, 5*(3), 1-16. https://doi.org/10.5296/rae.v5i3.4049

47. Sturm, R. R. (2021). The Influence of Daily Price Extremes on Short-Term Stock Returns. *Journal of Behavioral Finance, 22*(3), 254-264. https://doi.org/10.1080/15427560.2020.1772262

48. Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science, 185*(4157), 1124-1131. https://doi.org/10.1126/science.185.4157.1124

49. Zhong, X., & Enke, D. (2017). Forecasting daily stock market return using dimensionality reduction. *Expert Systems with Applications, 67*, 126-139. https://doi.org/10.1016/j.eswa.2016.09.027

50. Zielonka, P. (2004). Technical analysis as the representation of typical cognitive biases. *International Review of Financial Analysis, 13*(2), 217-225. https://doi.org/10.1016/j.irfa.2004.02.007