Unmasking the Grey Swan : Investor Biases in Times of Turbulence

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Abstract

Objective : This study examined the disposition effect in the Indian stock market during the steady "white swan" and uncertain "grey swan" phases induced by COVID-19 to analyze the variations in investor biases influenced by market conditions. This study also tested the capacity of two techniques to elucidate the disposition effect during these periods.

Methodology : The disposition effect among the constituent stocks of the Nifty50 index was examined during the white swan (Jan 2019–Dec 2019) and grey swan (Jan 2020–Dec 2021) phases using the security vector autoregression (SVAR) model and a regression model.

Findings : The study emphasized the impact of uncertainty on the prejudices of investors in the Indian stock market. The uncertainty and dread of the market during the grey swan phase affected equities more than it did during the white swan period. The regression model proved ineffectual in identifying the disposition effect, but SVAR indicated the existence of bias.

Practical Implications : Market participants and regulators could create robust investment strategies and manage uncertainty by having a thorough understanding of the disposition impact and its variations. It also provided academics with important insights into the efficacy of various methods for tracking the disposition effects.

Originality : The disposition effect was compared in the white and grey swan phases in this study. Using different methodologies yielded unique insights into the effectiveness of different ways of tracking the disposition impact.

Keywords : loss aversion bias, disposition effect, grey swan, white swan, COVID-19, winning stocks, declining stocks

JEL Classification Codes : G11, G14, G41

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The COVID-19 pandemic completely upended the investment environment. Risk was viewed differently by the public due to an ambiguous financial market move. These intricate actions set up the disposition effect, a behavioral bias that draws interest from both academics and industry professionals. In this bias, investors sell their winning stocks quickly to turn a profit while holding onto loser stocks in the hopes of a price bounce. The study investigates whether the pandemic's disruption influenced investors' loss aversion in the dynamically developing stock market.

Behavioral biases are more important in investment decision-making (Dangi & Kohli, 2018). While several studies have examined the disposition effect on global markets, its presence on the Indian stock market during

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different periods remains relatively unexplored. This research compares the "white swan" (pre-pandemic) and "grey swan" (pandemic) periods to bridge this gap. The disposition effect may be studied in reasonably normal market circumstances during the "white swan" era of market stability and optimism. The "grey swan" phase (Taleb, 2007) began with the COVID-19 pandemic, causing unprecedented uncertainty, volatility, and economic disruptions. The spread and casualties of COVID-19 influenced the stock market return adversely (Veeravel et al., 2022). It has affected the health as well as the economic well-being of people (Dey & Brown, 2021). This stage allows a unique look at how the global health crisis has affected investors' risk perception and decision-making. This study is relevant as it aims to shed light on investor behavior amid extreme market instability, volatility, and economic disruption. The disposition effect makes the market unstable, resulting in bubble formation and crashes in the stock market (Cafferata et al., 2024).

The approaches of Bharandev and Rao (2020) for disposition effect and vector autoregression (VAR) are also compared. The findings will support market participants, regulators, and legislators in developing sound investment strategies during both steady and erratic market phases. This will help to shape long-term investment strategies. A comparison of two models used to identify the disposition effect will be helpful to future researchers in deciding which model should be used for their study. The subsequent parts delineate the prior research and methodologies utilized in this investigation, succeeded by the conclusions and remarks. Finally, we examine our results and the directions of future study.

Theoretical Background

We investigate a subset of studies that have paved the way for our research in this context. The initial phases of the pandemic had a strong negative impact on various indices (Dey & Sharma, 2022). The COVID-19 spread significantly impacted global economies, affecting developed and emergent markets (Aslam et al., 2020; Liu et al., 2020; Syed et al., 2021). The development of COVID-19 resulted in poor results for stock markets globally (Singh et al., 2024). The unfavorable news during that period had a substantial impact, making the Indian stock market volatile both in the short and long term (Sahoo & Kumar, 2023). This extreme volatility resulted in lower returns than in the pre-COVID-19 period (Bora & Basistha, 2021; Lalwani & Meshram, 2020).

An analysis of the disposition effect among Indonesian stock market investors during the pandemic period found that important information about changes in stock price and internal performance affected investors' actions (Basana & Tarigan, 2022). In contrast to normal periods, COVID-19 dread had a major and enduring effect on stock market sentiments (Subramaniam & Chakraborty, 2021; Vasileiou, 2021). The Indian bourse exhibited greater volatility over the pandemic than it did during the global financial crisis (Rakshit & Neog, 2022) while it was reported that the ramifications of the pandemic on returns were severe, surpassing that of currency reform and the implementation of the GST (Mishra et al., 2020). Throughout the pandemic period, the Pakistan Stock Exchange had a prevalence of the disposal effect due to uncertainty and market volatility (Parveen et al., 2023). However, when the Indian stock market during the lockdown phase exhibited high volatility, above-average return on stocks was reported (Alam et al., 2020). Studies conducted by Bharandev and Rao (2020), Ganesh et al. (2020), and Sushmita et al. (2018) revealed that the Indian stock exchange is susceptible to the disposition effect.

Aspara and Hoffmann (2015), Bergsma et al. (2020), Ganesh et al. (2020), Hur et al. (2010), Jiao (2017), Prosad et al. (2013), Rau (2014), and Statman et al. (2003) examined the disposition effect using primary data obtained from investors, secondary data from brokerage houses, and trading data of stock exchanges using a variety of techniques like ANOVA, regression, PGR to PLR, capital gain overhang, OLS regression, and VAR. A shortage of research comparing prejudice levels during the white swan and grey swan periods has been documented in the literature. Previous studies have employed a single model to investigate the disposition impact. However, this study brought something new to the field by comparing the market psychology in the Indian stock exchange between the white and grey swan phases utilizing the VAR model in addition to Bharandev and Rao's (2020) model.

Objectives

The purpose of this article is to compare the effects of the disposition effect on the Indian equity market in the phases of the white and grey swans. It also aims to determine the best method for identifying the disposition effect.

Hypotheses

- **H_{01} :** The incidence of the disposition effect does not differ significantly between the grey swan and white swan phases on the Indian stock market.

- **H_{a1} :** The incidence of disposition effect differs significantly between the grey swan and white swan phases on the Indian stock market.

- **H_{02} :** The S-VAR and Bharandev and Rao (2020) methodologies do not significantly differ in identifying the presence of the disposition effect.

- **H_{a2} :** The S-VAR and Bharandev and Rao (2020) methodologies significantly differ in identifying the presence of the disposition effect.

Data and Methodology

The NSE website provided trading data for 50 equities of the Nifty 50, India's benchmark stock index, from January 2019 to December 2021, which was used in this analytical study. This index is constituted by the 50 largest and the most liquid stocks of NSE, which is capable of providing insights into the performance of the Indian bourse. The study period was categorized into pre-pandemic and pandemic phases. The onset of the COVID-19 pandemic in India occurred in January 2020; hence, the period before that, 2019, is referred to as the pre-COVID-19 period, while the subsequent period of 2020–2021 is considered the pandemic period. The low price, closing price, turnover, high price, and market return of the Nifty 50 during the 743 trading days are the main factors.

Two models from the literature were extracted to test the disposition effect, i.e., security vector autoregression (SVAR) and the regression model of Bharandev and Rao (2020). Analysis was done with the help of EViews 10 and SPSS 26 software.

Security-Wide Vector Autoregression (S-VAR)

The SVAR model captures the interrelation among trading volume, lagged volume values, market return, stock return, and idiosyncratic volatility (Statman et al., 2003). We examined the relation between security return and volume with their lagged values to test the disposition effect. To proceed with S-VAR, it is essential to confirm the stationarity of variables; the PP and ADF unit root tests were applied to check the presence of the unit root.

$$\text{Log}T_t = \propto + \Sigma^k_{j=1}\beta_j \,\text{Log}T_{t-1} + \Sigma^k_{j=1}\gamma_j \,\text{Log}Ri_{t-1} + \Sigma^k_{j=1}\lambda_j \text{Log}Rm_{t-1} + v\text{Log}Ivol_t + \varepsilon_{1t} \quad (1)$$

$$\text{Log}Ri_t = \propto' + \Sigma^k_{j=1}\beta'_j \,\text{Log}T_{t-1} + \Sigma^k_{j=1}\gamma'_j \,\text{Log}Rt_{t-1} + \Sigma^k_{j=1}\lambda'_j \text{Log}Rm_{t-1} + v'\text{Log}Ivol_t + \varepsilon_{2t} \quad (2)$$

$$\text{Log}Rm_t = \alpha'' + \Sigma^k_{j=1}\beta''_j \,\text{Log}T_{t-1} + \Sigma^k_{j=1}\gamma''_j \,\text{Log}Rt_{t-1} + \Sigma^k_{j=1}\lambda''_j \text{Log}Rm_{t-1} + v''\text{Log}Ivol_t + \varepsilon_{3t} \quad (3)$$

Each security's volume traded is Log T, Log Rm is the daily market return, Log Ri is the stock i's daily return, Log $Ivol_t$ is the firm i's day-t idiosyncratic volatility, and k is the number of lags, and ε is the error term.

$$Return = \ln(current\ closing\ price/previous\ closing\ price) \quad (4)$$

Parkinson's model (1980) is applied to calculate the idiosyncratic volatility.

$$Volatility = \sqrt{250} * \sqrt{\frac{1}{4*\ln(2)} * \ln\left(\frac{h}{l}\right)^2} \quad (5)$$

Variable h and l represent the day's high and low prices, respectively. The disposition effect is evident when the security return lags (Ri) exhibit significant positive values. IRF demonstrates the relationship between the variables over time. It is employed to ascertain the duration of the bias in the market.

Methodology of Bharandev and Rao (2020)

The disposition effect may be assessed by examining anomalous trading volumes of shares that have been gained or lost. If the disposition effect is real, winners should have higher anomalous trade volumes than losers. Barber and Odean (2006) defined anomalous trading volume as a stock's daily turnover divided by the average of the previous year. This method manages stock-specific characteristics.

$$ABVOL_{i,t} = \frac{V_{i,t}}{\overline{V_{i,t}}} \quad (6)$$

$ABVOLi$ is the stock i's anomalous turnover on trading day t. $V_{i,t}$ is the stock i's trading day volume. $\overline{V_{i,t}}$ is the average turnover of the stock i's trading day t.

$$\overline{V_{i,t}} = \sum\nolimits^{t-1}_{day=t-252} \frac{V_{i,day}}{252} \quad (7)$$

The research considered 252 trading days annually (Chiang et al., 2016; Odean, 1999). Once aberrant trade volume was computed, trading days for each stock were divided into gaining and declining days. By comparing the closing price to the reference point, profitability is found. Since 52-week high and low prices have psychological significance (De Bondt & Thaler, 1985), are useful in evaluating relative price performance (Barber & Odean, 2006), are related to momentum effects (Bhootra & Hur, 2013; Ma et al., 2017), and are pertinent in identifying support and resistance levels (Chan et al., 1996), they are regarded as valuable references. A trading day wins if the closing price surpasses the prior 52-week peak (Equation 10) and loses if it goes below the previous 52-week low price (Equation 11) (Bharandev & Rao, 2020; Huddart et al., 2009). Similar Equations (8) and (9) compute 52-week peak and low prices.

$$52\text{-}week\ high_{i,t} = Maximum\ of\ closing\ price\ of\ previous\ 52\ weeks \quad (8)$$

$$52\text{-}week\ low_{i,t} = Minimum\ of\ closing\ price\ of\ previous\ 52\ weeks \quad (9)$$

$$Winning\ day_{i,t} = \begin{cases} 1, if\ closing\ price\ i,t > 52\ week\ high\ i,t \\ 0, else \end{cases} \quad (10)$$

$$Losing\ day_{i,t} = \begin{cases} 1, if\ closing\ price\ i,t < 52\ week\ high\ i,t \\ 0, else \end{cases} \quad (11)$$

The disposition impact is felt by investors who sell stocks when they are doing well and hold onto them when they are not. Therefore, it is anticipated that equities with a higher frequency of positive trading days would have more irregular trading volumes, while stocks with a higher frequency of negative trading days will likely have less or negligible abnormal trading volumes. Thus, the stock market's unusual trade volumes and the fraction of days with gains (losses) should be correlated. According to prior research (Barberis & Xiong, 2012; Gallant et al., 1992; Siddiqui & Roy, 2019), volatility and liquidity impact trade volume. The study adopted Parkinson's (1980) approach of daily high and low stock prices to calculate stock volatility. Stock liquidity was calculated by using the Amivest ratio (AR). Equation 12 represents the AR model.

$$ARj = \frac{\sum_t V_{jt}}{\sum_t \left| R \right|_{jt}} \qquad (12)$$

V_{jt}: volume of stock j on day t, whereas R_{jt}: return. Zero yields are undefined in the AR. Hence, zero return days were removed for computation purposes. The average volume and liquidity of stocks for the white swan and grey swan phases were compared to calculate the ABVOL of each stock. We used a regression model to examine the link between a stock's ABVOL and market volatility, liquidity, and the fraction of days with positive or negative returns.

$$ABVOLi = \propto_i X_i + \sum B_{ij} X_{ij} + e_i \qquad (13)$$

αi reflects the fraction of gaining or declining days, whereas $\beta_{i,j}$ represents the stock i's volatility and liquidity. Three regression models examined the relationship between ABVOL and other parameters. Stocks with no gaining or declining days are excluded from the study. In Model I regression analysis, ABVOL is the dependent variable, and the percentage of gaining/declining days is the independent variable. Volatility and gaining/declining days are independent variables in Model II. Model III adds liquidity to Model II's variables. Two panels analyze regression. Panel 1 analyzes the percentage of gaining days, whereas Panel 2 analyzes declining days.

It is crucial to show that shares with high irregular trading volume have more gaining days. Equities' daily anomalous trading volume increases from Decile-1 to Decile-10. For stock i in decile d, the percentage of gaining (declining) days is calculated as follows:

$$Decile\,\%\,of\,WD_{d,i} = \frac{\Sigma\, Winning\ days_{d,i}}{\Sigma\, Trading\ days_i} \qquad (14)$$

$$Decile\,\%\,of\,LD_{d,i} = \frac{\Sigma\, Losing\ days_{d,i}}{\Sigma\, Trading\ days_i} \qquad (15)$$

This theoretical framework predicts that higher deciles will have more gaining days. It predicts no correlation between deciles and declining days. ANOVA was used to identify the significant variations in gaining day percentages between the upper and lower deciles. The experiment was run twice to determine whether there were any statistical differences in the disposition effects.

Analysis and Results

The data spans 499 days during the pandemic phase and 244 days during the pre-pandemic period. For the two periods, there was no average return for the 50 securities. Furthermore, the average standard deviation of the 50 securities is 0.0252 during the pandemic period compared to 0.0196 during the pre-pandemic period, suggesting higher market volatility during the grey swan phase.

ADF and PP tests show stationarity, with *P*-values for all equities in both periods below 0.01. Thus, the non-stationarity null hypothesis is rejected at 1%. Schwarz Information Criterion (SIC) lag length criterion recommended 5 for VAR analysis. The study found that out of 50 stocks, only eight were influenced by the disposition effect during 2019, as they showed positive and significant security returns. The outputs are highlighted in Table 1.

Table 1. ***Results of SVAR for the Year 2019***

Stock Symbol	Lag One		Lag Two		Lag Three		Lag Four		Lag Five	
	Coef.	*t*-val.	Coef.	*t*-val.	Coef.	*t*-val.	Coef.	*t*-val.	Coef.	*t*-val.
ADANIPORTS	–2.05	–1.26	0.87	0.52	**3.89**	**2.29****	–2.83	–1.65	–2.58	–1.52
APOLLOHOSP	1.34	0.95	0.86	0.61	0.43	0.30	1.38	0.98	–0.38	–0.29
ASIANPAINT	–0.41	–0.19	–1.54	–0.70	2.46	1.14	0.98	0.45	–1.62	–0.94
AXISBANK	–0.34	–0.18	–0.41	–0.22	0.15	0.08	–0.67	–0.37	1.43	1.03
BAJFINANCE	0.40	0.34	0.64	0.54	–0.28	–0.24	–2.17	–1.86	0.31	0.37
BAJAJFINSV	0.57	0.37	–0.64	–0.42	–0.50	–0.33	–0.40	–0.27	1.24	1.08
BAJAJ-AUTO	3.21	1.60	–1.39	–0.71	–0.55	–0.28	1.76	0.92	1.83	1.07
BPCL	–2.85	–2.30	0.46	0.37	–1.69	–1.36	0.76	0.60	–2.66	–2.43
BHARTIARTL	1.39	1.02	–1.67	–1.23	3.01	2.22	–2.09	–1.56	–1.70	–1.35
BRITANNIA	–5.95	–3.10	–2.70	–1.42	–0.49	–0.26	0.79	0.42	–3.70	–2.17
CIPLA	0.09	0.05	–1.25	–0.59	1.05	0.50	–1.55	–0.74	2.67	1.35
COALINDIA	–0.26	–0.13	0.21	0.11	3.36	1.76	0.38	0.20	–1.84	–1.02
DIVISLAB	0.39	0.24	0.98	0.61	0.71	0.44	–0.29	–0.18	–0.09	–0.06
DRREDDY	1.56	0.90	–1.15	–0.67	0.72	0.42	–0.01	0.00	0.98	0.58
EICHERMOT	–3.22	–3.26	–0.88	–0.90	–0.68	–0.68	–0.17	–0.17	–0.31	–0.39
GRASIM	–0.35	–0.25	1.45	1.05	–1.38	–1.00	–1.80	–1.30	1.14	1.04
HCLTECH	–0.01	–0.01	–0.35	–0.63	0.23	0.42	–0.37	–0.67	–0.39	–0.70
HDFCBANK	–0.47	2.58	–0.72	–0.77	–0.21	–1.17	–0.11	–0.35	–0.47	–0.18
HDFCLIFE	–1.94	–0.99	–3.33	–1.69	–0.78	–0.40	3.81	1.89	2.72	1.42
HDFC	**3.72**	**1.78***	–3.87	–1.85	–1.45	–0.69	–1.14	–0.55	1.03	0.66
HEROMOTOCO	–5.28	–3.42	–0.63	–0.40	–2.15	–1.36	–0.18	–0.11	–0.43	–0.32
HINDALCO	1.82	1.13	0.46	0.29	2.37	1.50	1.07	0.69	–0.41	–0.31
HINDUNILVR	–2.40	–0.99	–6.68	–2.71	–0.48	–0.19	–3.42	–1.36	–1.12	–0.52
ICICIBANK	0.82	0.46	1.38	0.77	0.77	0.43	0.54	0.30	0.14	0.11
INDUSINDBK	0.48	0.84	–0.38	–0.66	–0.16	–0.28	0.52	0.95	0.10	0.22
INFY	–0.40	–0.29	–0.43	–0.32	0.11	0.08	1.35	1.02	–2.76	–2.11
ITC	3.35	–1.54	1.15	0.53	0.11	0.05	0.14	0.07	0.78	0.43
JSWSTEEL	**3.04**	**2.66*****	–0.06	–0.05	–1.60	–1.37	0.77	0.66	1.44	1.53
KOTAKBANK	0.68	0.26	0.29	0.11	–0.29	–0.11	–3.63	–1.41	1.54	0.75
LT	–2.70	–1.39	–2.07	–1.06	**3.27**	**1.67***	–3.08	–1.57	–1.00	–0.72

M&M	–0.49	–0.28	0.72	0.42	0.18	0.11	–1.16	–0.68	–0.73	–0.59
MARUTI	–3.66	–2.92	–1.19	–0.94	–1.11	–0.88	–0.46	–0.37	–0.65	–0.68
NESTLEIND	–0.73	–0.32	–2.98	–1.32	0.27	0.12	–1.03	–0.47	–1.21	–0.60
NTPC	–0.70	–0.40	–3.33	–1.89	–0.48	–0.27	0.02	0.01	–2.69	–1.56
ONGC	–0.51	–0.25	2.47	1.22	0.42	0.21	1.46	0.73	0.75	0.43
POWERGRID	0.69	0.26	–3.03	–1.17	0.26	0.10	–2.89	–1.12	–0.60	–0.24
RELIANCE	–1.16	–0.81	0.92	0.63	–0.04	–0.03	–1.01	–0.71	–0.79	–0.65
SBILIFE	0.99	0.33	–4.20	–1.40	–3.13	–1.02	–7.32	–2.43	–8.31	–2.80
SHREECEM	1.95	0.80	–4.72	–1.96	–2.85	–1.17	–0.12	–0.05	1.88	0.96
SBIN	–1.94	–1.73	1.35	1.20	–0.86	–0.78	3.25	2.93	0.83	1.05
SUNPHARMA	–1.36	–1.10	0.10	0.08	–0.17	–0.14	1.02	0.82	2.82	2.34
TCS	0.53	0.34	–0.61	–0.38	–2.34	–1.48	1.43	0.92	–0.42	–0.27
TATACONSUM	**3.30**	**2.08******	0.63	0.39	–0.42	–0.27	–1.64	–1.08	–2.13	–1.51
TATAMOTORS	**1.18**	**2.04******	0.62	1.07	0.65	1.12	–0.40	–0.68	–0.26	–0.50
TATASTEEL	1.23	1.13	–0.34	–0.32	**1.85**	**1.73***	1.01	0.94	1.21	1.36
TECHM	2.28	1.09	1.51	0.73	2.45	1.18	–3.70	–1.80	–1.23	–0.61
TITAN	–0.14	–0.10	–3.00	–2.07	–1.42	–0.97	–1.69	–1.15	–1.36	–1.03
ULTRACEMCO	2.63	1.38	–4.37	–2.29	**5.04**	**2.57******	–4.82	–2.45	1.54	1.02
UPL	–0.38	–0.45	–1.68	–1.95	–0.80	–0.90	–0.59	–0.68	–1.78	–2.07
WIPRO	1.43	1.09	–1.71	–1.31	0.67	0.51	–0.19	–0.14	1.74	1.33

Note. The significant and positive values of security return lags are highlighted in bold. *Denotes significance at 10%, ** denotes 5% level of significance, and *** shows significance at 1% level.

Table 2. *Results of IRF for the Year 2019*

Sl. No.	Symbol	No. of Days	Peak Day
1	ADANIPORTS	5	4
2	HDFC	3	23
3	JSWSTEEL	4	1
4	LT	2	1
5	TATACONSUM	6	1
6	TATAMOTORS	30	1
7	TATASTEEL	30	1
8	ULTRACEMCO	3	2

The market bias, according to IRF, peaks at 1.62 days after 10.37 days. The IRF results for eight Nifty 50 equities impacted by the disposal effect in 2019 are displayed in Table 2. The number of days that the market bias persists is shown in the third column, and the day that the bias is most noticeable is shown in the last column.

Table 3 displays the security-wide VAR results. The findings indicate that, in comparison to the year prior to the pandemic (i.e., 2019), a higher number of stocks—18 out of the Nifty 50 index—exhibited the disposition effect during the pandemic phase.

This analysis shows that the pandemic affected the stock market in the same way as all previous crises. The average volatility before the pandemic was 1.36; however, during the epidemic, it increased to 1.65, showing that the crisis period brought with it more volatility, which resulted in loss aversion (Bora & Basistha, 2021; Rakshit &

Table 3. ***Results of Security-Wide VAR for the Period 2020–2021***

NSE Stock Symbol	Lag One		Lag Two		Lag Three		Lag Four		Lag Five	
	Coeff.	*t*-val.	Coeff.	*t*-val.	Coeff.	*t*-val.	Coeff.	*t*-val.	Coeff.	*t*-val.
ADANIPORTS	**1.60**	**1.75***	–1.12	–1.22	–0.58	–0.63	0.48	0.53	0.54	0.61
APOLLOHOSP	**1.59**	**1.93***	1.13	1.39	–0.02	–0.02	–0.02	–0.03	0.80	1.13
ASIANPAINT	–0.86	–0.79	–1.17	–1.07	–1.04	–0.94	–1.69	–1.54	0.49	0.56
AXISBANK	1.02	1.34	1.00	1.32	–1.09	–1.43	0.25	0.33	0.44	0.89
BAJFINANCE	**1.19**	**1.74***	0.80	1.19	0.29	0.44	–0.26	–0.38	**0.83**	**1.78***
BAJAJFINSV	1.18	1.54	1.23	1.62	0.76	0.99	0.07	0.09	0.83	1.62
BAJAJ-AUTO	–0.89	–0.71	–0.77	–0.61	0.99	0.78	–0.82	–0.65	0.66	0.67
BPCL	0.42	0.46	0.48	0.53	–0.03	–0.04	–0.54	–0.60	0.62	0.87
BHARTIARTL	1.40	1.30	–1.26	–1.16	–1.71	–1.57	–0.55	–0.51	1.35	1.51
BRITANNIA	–1.17	–0.89	–2.12	–1.60	–1.35	–1.01	–0.29	–0.22	–0.57	–0.52
CIPLA	–0.79	–0.78	–1.61	–1.59	–0.70	–0.69	0.38	0.38	0.41	0.44
COALINDIA	1.00	1.17	1.19	1.39	–1.18	–1.38	0.00	0.00	**2.10**	**2.86*****
DIVISLAB	1.31	1.20	0.39	0.36	–1.54	–1.42	–1.29	–1.19	–1.12	–1.16
DRREDDY	–0.45	–0.44	0.55	0.53	–1.78	–1.73	–1.86	–1.81	–0.15	–0.15
EICHERMOT	–0.58	–3.13	–0.28	–1.49	–0.09	–0.47	0.01	0.03	0.10	0.54
GRASIM	1.50	1.29	–1.12	–0.97	–0.50	–0.44	–1.07	–0.93	0.59	0.73
HCLTECH	0.32	0.31	–1.46	–1.42	0.25	0.24	**2.82**	**2.71*****	**2.58**	**3.01*****
HDFCBANK	1.89	1.55	–0.12	–0.10	–0.18	–0.15	–0.18	–0.15	**1.96**	**2.72*****
HDFCLIFE	1.70	1.33	–2.10	–1.65	0.52	0.41	–1.57	–1.25	0.97	1.08
HDFC	0.95	0.84	–0.27	–0.24	0.12	0.10	–1.10	–0.99	**1.19**	**1.74***
HEROMOTOCO	–1.03	–1.03	–3.57	–3.61	–0.26	–0.26	–2.28	–2.31	0.64	0.81
HINDALCO	0.42	0.52	–0.68	–0.84	0.26	0.32	0.57	0.72	0.90	1.64
HINDUNILVR	–1.72	–1.48	–4.84	–4.21	–2.10	–1.78	–2.62	–2.25	–1.88	–1.85
ICICIBANK	–0.16	–0.17	1.14	1.26	–0.11	–0.12	–0.59	–0.65	**1.09**	**2.12***
INDUSINDBK	0.48	0.84	–0.38	–0.66	–0.16	–0.28	0.52	0.95	0.10	0.22
INFY	0.25	0.23	0.42	0.40	0.09	0.08	**1.81**	**1.71***	1.27	1.58
ITC	0.38	0.40	**1.86**	**1.94***	–0.05	–0.05	–1.59	–1.70	1.35	1.65
JSWSTEEL	0.94	1.10	0.24	0.28	0.32	0.38	**1.90**	**2.26****	0.89	1.51
KOTAKBANK	–0.41	–0.37	–0.48	–0.43	0.08	0.07	0.07	0.06	**1.80**	**2.34***
LT	0.94	0.80	–0.47	–0.40	0.44	0.37	–1.28	–1.11	0.03	0.04
M&M	–0.59	–0.69	0.34	0.39	–0.71	–0.82	0.08	0.09	0.90	1.35
MARUTI	–0.20	–0.21	–0.50	–0.55	–0.91	–1.00	–0.79	–0.87	–0.01	–0.02
NESTLEIND	–3.05	–2.47	–2.43	–1.96	–2.31	–1.85	–1.14	–0.91	0.63	0.58
NTPC	–0.42	–0.38	0.44	0.40	0.33	0.31	–0.50	–0.46	1.43	1.57
ONGC	–0.90	–1.18	0.60	0.78	1.28	1.65	0.56	0.73	0.98	1.53
POWERGRID	–1.22	–1.32	1.07	1.16	0.34	0.37	–0.49	–0.54	1.84	2.19
RELIANCE	–0.06	–0.06	–1.03	–1.13	–0.88	–0.97	–1.37	–1.51	0.66	1.04
SBILIFE	–0.85	–0.61	–2.73	–1.92	0.93	0.64	–1.70	–1.17	1.42	1.27

SHREECEM	0.87	0.72	–0.13	–0.11	–0.38	–0.33	–0.69	–0.59	–0.15	–0.17
SBIN	1.05	1.36	0.84	1.09	0.21	0.27	–1.69	–2.21	0.73	1.42
SUNPHARMA	**3.02**	**3.03*****	–0.04	–0.04	–0.88	–0.87	–0.61	–0.61	0.45	0.54
TCS	0.41	0.40	1.13	1.09	–0.85	–0.82	**1.95**	**1.89***	1.30	1.55
TATACONSUM	0.93	0.82	–0.36	–0.32	–0.45	–0.40	**2.20**	**1.93***	2.14	2.41
TATAMOTORS	0.28	0.50	–0.40	–0.71	–0.36	–0.65	–0.04	–0.07	–0.08	–0.19
TATASTEEL	–0.17	–0.25	–0.16	–0.24	0.68	1.02	0.98	1.47	**0.97**	**1.87***
TECHM	–0.18	–0.17	0.18	0.17	–0.02	–0.02	2.33	2.26	**1.78**	**2.16****
TITAN	0.76	0.69	–2.60	–2.36	0.53	0.48	1.44	1.31	0.70	0.86
ULTRACEMCO	1.75	1.35	0.04	0.03	0.27	0.21	–0.50	–0.39	–0.91	–1.00
UPL	0.55	0.62	–0.37	–0.43	1.55	1.79	0.43	0.49	0.91	1.28
WIPRO	**2.30**	**1.91***	–1.84	–1.53	–0.71	–0.59	**2.11**	**1.76***	0.62	0.63

Note. Significant and positive values of security return lags are highlighted in bold. *Denotes significance at 10%, ** denotes 5% level of significance, and *** shows significance at 1% level.

Table 4. ***IRF Results of Stocks for the Period 2020–2021***

Sl. No.	Symbol	Duration of Effect	Peak day
1	ADANIPORTS	53	7
2	APOLLOHOSP	8	6
3	BAJFINANCE	35	7
4	COALINDIA	4	3
5	HCLTECH	3	1
6	HDFCBANK	5	2
7	HDFC	4	1
8	ICICIBANK	25	1
9	INFY	17	5
10	ITC	5	1
11	JSWSTEEL	35	5
12	KOTAKBANK	3	1
13	SUNPHARMA	27	6
14	TCS	4	1
15	TATACONSUM	11	6
16	TATASTEEL	36	6
17	TECHM	20	6
18	WIPRO	30	5

Neog, 2022). The competitive advantage of the financial services sector in India led to increased selling during this period, which is why disposition effects impact a larger number of stocks in this sector than during the white swan period (Kanojia & Malhotra, 2021). The average duration of bias in the stock market during the grey swan phase is 18.05 days, longer than the average of 10.37 days during the white swan phase. It was discovered that the bias had a more noticeable impact on the fourth day, with a peak day average of 3.89. Therefore, Table 4 of the IRF results leads us to the conclusion that there is a significant level of bias during the outbreak.

Table 5. *Output of Regression for the Year 2019*

Variables	Panel 1: Impact of the percentage of gaining days on anomalous trading volume			Panel 2: Impact of percentage of declining days on anomalous trading volume		
	Model I	Model II	Model III	Model I	Model II	Model III
Percentage of	–0.016	–0.010	–0.012	0.023	0.019	0.021
gaining days/	(–1.264)	(–0.808)	(–0.908)	(2.069)	(1.743)	(1.818)
declining days	[0.2126]	[0.423]	[0.368]	[0.044]	[0.088]	[0.075]
Volatility		0.332	0.386		0.308	0.373
		(1.736)	(1.794)		(1.679)	(1.789)
		[0.089]	[0.079]		[0.10]	[0.08]
Liquidity			1			1
			(0.565)			(0.670)
			[0.575]			[0.506]
Constant	1.210	0.529	0.360	1.107	0.498	0.290
	(23.46)	(1.339)	(0.722)	(24.55)	(1.363)	(0.602)
	[0.00]	[0.187]	[0.474]	[0.00]	[0.179]	[0.549]
Observations	49	49	49	49	49	49
R^2	0.033	0.092	0.099	0.083	0.136	0.145
Adjusted R^2	0.012	0.053	0.039	0.064	0.099	0.088

Note. Regression coefficients, *t*-statistic in parenthesis, and significance in square brackets.

As a result, H_{a1}: The incidence of the disposition effect differs significantly between the grey swan and white swan phases on the Indian stock market is accepted. The H_{01} was rejected because the study shows that the disposition effect is more prevalent during the pandemic phase. The second strategy used three regression models for two panels. Panel A examined the influence of gaining days on atypical trading volume, whereas Panel B examined the declining days. ABVOL is the dependent factor in all three models, whereas the independent factors are the percentage of gaining (declining) days in Model I, the percentage of gaining (declining) days, volatility in Model II, and liquidity also added in Model III. One of the 50 stocks had zero gaining and declining days in 2019. Table 5 shows the regression outputs.

Model 1 indicates the absence of a disposition effect as a significant and favorable relationship between anomalous trading volume and the percentage of gaining days would be expected if the disposition effect existed (Bharandev & Rao, 2020). This finding contradicts prior research by Bharandev and Rao (2020), Ganesh et al. (2020), and Prosad et al. (2018) on the Indian bourse, which reported the disposition effect. The coefficients of the percentage of gaining/declining days in Model II behave similarly to those in Model I, and the coefficients of volatility and liquidity are positive but insignificant. In Model III, the coefficient of the percentage of gaining days is negative, while the volatility and liquidity coefficients are positive but not significant. The coefficient of the percentage of declining days on trading volume is positive in all models.

One-way ANOVA was used to examine the mean of the percentage of gaining/declining days for each decile to determine the disposition effect. Once the ABVOL of all stocks is arranged in ascending order and clustered into ten deciles if disposition exists, the top deciles should represent a high percentage of gaining days and vice versa in low deciles because disposition-influenced investors cling on to declining shares and sell gaining shares too early. The mean proportion of gaining/declining days was not substantially different between deciles, contradicting this disposition explanation. No disposition effect is seen in the white swan phase in Table 6.

Table 6. ***ANOVA Results of 2019***

Variables	Decile. No.	Mean	*F*-value	*P*-value
Percentage of gaining days	1	2.938	1.311	0.262
	2	4.000		
	3	5.387		
	4	4.245		
	5	2.286		
	6	3.347		
	7	2.531		
	8	0.245		
	9	1.306		
	10	2.204		
Percentage of declining days	1	1.061	2.061	0.057
	2	0.653		
	3	1.633		
	4	0.245		
	5	0.816		
	6	3.265		
	7	2.531		
	8	6.286		
	9	3.429		
	10	3.755		

Using three regression models and an ANOVA test, no significant positive correlation was found between ABVOL and the percentage of gaining days in the COVID-19 phase (2020–2021). As a result, compared to reports before the COVID-19 phase, the disposition impact was not as widespread during the grey swan. The results are displayed in Table 7.

Table 7. ***The Results of Regression Estimate During 2020–2021***

Variables	Panel 1: Impact of percentage of gaining days on anomalous trading volume			Panel 2: Impact of percentage of declining days on anomalous trading volume		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Percentage of	–0.013	–0.013	–0.012	0.028	0.021	0.018
gaining days/	(–1.866)	(–1.933)	(–1.803)	(1.969)	(1.376)	(1.195)
declining days	[0.068]	[0.059]	[0.078]	[0.055]	[0.175]	[0.238]
Volatility		0.202	0.147		0.147	0.097
		(1.991)	(1.282)		(1.319)	(0.803)
		[0.052]	[0.206]		[0.193]	[0.426]
Liquidity			–1.000			–1.00
			(–1.04)			(–1.025)
			[0.303]			[0.311]

Constant	1.136	0.676	0.851	1.039	0.717	0.886
	(32.194)	(2.889)	(2.954)	(37.222)	(2.909)	(2.989)
	[0.000]	[0.006]	[0.005]	[0.000]	[0.006]	[0.005]
Observations	50	50	50	50	50	49
R^2	0.068	0.140	0.159	0.075	0.108	0.128
Adjusted R^2	0.048	0.104	0.105	0.055	0.069	0.071

Note. Regression coefficients, *t*-statistics in parenthesis, and significance in square brackets.

Table 8. ***The ANOVA Results of the 2020–2021 Period***

Variables	Decile. No.	Mean	*F*-value	*P*-value
Percentage of gaining days	1	6.04	1.14	0.36
	2	3.56		
	3	3.60		
	4	4.76		
	5	5.64		
	6	5.80		
	7	2.96		
	8	2.84		
	9	2.96		
	10	3.84		
Percentage of declining days	1	1.16	1.04	0.42
	2	0.68		
	3	1.64		
	4	1.28		
	5	1.20		
	6	0.64		
	7	1.56		
	8	1.48		
	9	2.40		
	10	2.36		

The study accepts the null hypothesis that there is no statistically significant difference in the proportion of improving and deteriorating days across the 10 deciles because the *F*-value in Table 8 is not statistically significant.

Bharandev and Rao's (2020) model accepted H_{01}: The incidence of the disposition effect does not differ significantly between the grey swan and white swan phases on the Indian stock market as it failed to capture the presence of bias over both periods. The study rejects H_{02} and accepts the H_{a2}: The S-VAR and Bharandev and Rao (2020) methodology significantly differs in identifying the presence of the disposition effect because the S-VAR traced out the prevalence of bias over two periods, whereas the Bharandev and Rao (2020) model could not identify the bias in the Indian stock market over these periods.

Conclusion and Practical Implications

The study investigates the disposition effect across the white swan and grey swan phases in the Indian bourse. The disposition effect is more pronounced during the pandemic, indicating heightened loss aversion bias among investors during uncertainty. After utilizing two testing methodologies, we discovered that the VAR model performed better in detecting bias than the Bharandev and Rao (2020) model. The major beneficiaries of this research are secondary market investors and researchers. Making sensible financial judgments requires emotional and psychological bias control. Investors can more successfully plan long-term and short-term strategies when they have a better understanding of how the disposition effect responds to various market conditions. Financial professionals and regulators should prioritize investor education and awareness campaigns to mitigate the adverse impact of emotional biases during uncertain periods. Comparison of SVAR and Bharandev and Rao's (2020) models guides researchers in understanding the effectiveness of these models in their study.

Limitations of the Study and Scope for Future Research

This study utilizes the benchmark index Nifty 50, and hence, future research encompassing a broader sample, like the Nifty 500, could provide deeper insights into investor behavior during challenging times. In addition to the disposition impact, the white-swan and grey-swan phases offer opportunities to resolve other biases.

Authors' Contribution

The authors have had a substantial influence on the design, execution, analysis, and interpretation of this research report. The concept for the paper was developed by Safeeda K. A., who also collected the data for the study. The methodology section's creation involved Dr. Ganesh R. using EViews and SPSS 26, and Safeeda K. A. carried out the study's analysis. The study has its roots in a joint project between the two authors. Together with Dr. Ganesh R., Safeeda K. A. wrote the paper.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript

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