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Grey Swans and Investor Delusions in the Indian Stock Market

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Abstract

This study extensively investigated the investor delusion in the Indian securities market over ten years (2013-2023), focusing on the grey swan period of 2020-23 using Nifty50 index data. The study fully addresses overconfidence bias at many levels. It initially checks for market-level overconfidence bias and then confirms it across NIFTY50 Index sectors. The study analyses industry overconfidence levels to reveal behavioural bias variances across Indian economic sectors. The study sheds light on overconfidence bias in three phases: pre-COVID (2013-19), Grey swan phase of COVID-19 (2020-23), and 2020 alone when India suffered unprecedented pandemic instability. By studying each era separately, the research illuminates the complicated dynamics of overconfidence bias during different market conditions and pandemic upheavals. Over the period, industries such as services, metals and minerals, and FMCG exhibited overconfident behaviour. Examining the impact of the grey swan phase of COVID-19 revealed an overconfidence bias in the Indian stock market, while the challenging period of 2020 demonstrated a loss aversion bias. We also detected a tendency in trading behaviour to overreact to private information signals, regarded as a component of overconfidence bias. This research shows how psychological prejudices impair market effectiveness and have implications for investors, regulators, and lawmakers. Investors can make better judgments and avoid behavioral biases by understanding overconfidence bias and its effects. Lawmakers and regulators can utilize these findings to create investor protection and market efficiency measures.

Keywords: Covid-19, Grey Swan, Overconfidence Bias, Private and Public Information, Sectoral Overconfidence Bias, Stock Price Over and Under Reaction.

Introduction

From the seventeenth-century tulip craze to the twentieth-century dot-com bubble, literature is rife with examples of overconfidence causing exhilarating highs and catastrophic stock market disasters. In stock market investing, overconfidence becomes a double-edged sword, capable of fueling ambitious pursuits while blinding individuals to the perils of their unwarranted optimism. Experiments demonstrate that people underestimate prediction error variance and overestimate their forecasts compared to other forecasters (1). This overwhelming faith in one's cognitive ability and intuitive reasoning is a sign of overconfidence bias (2). These biases drive investors to excessively trade high-potential securities, lowering profits (3). They value and react to confidential information above the public (4). Overconfidence bias can cause stock market inefficiencies and asset mispricing (5), creating bubbles or devaluing equities, and affecting market efficiency and equilibrium. Overconfidence is widespread and hard to "de-bias" (6). This emphasizes the importance of examining bias. The vibrant and diverse Indian stock market is ideal for studying behavioral biases including overconfidence bias. Indian stock markets offer access to a large, fast-growing economy with investment potential (7). The market is often considered emerging and promising. Emerging markets have outperformed established ones over the long run, generating investment opportunities (8). The Indian market exposes significant worldwide industries like technology, pharmaceuticals, financial services, and consumer products where foreign investors seeking industry diversity like these durable, expandable industries (9). The Ghana stock exchange had overconfidence prejudice during the COVID-19 pandemic, where, weekly swings during Covid-19 were caused by overconfident traders' aggressive trading (10). Higher-income individuals are more impacted by the beneficial effects of this mood gap, according to an analysis of the impact of US consumers overestimating

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their own risk in comparison to the public's risk versus COVID-19 on abnormal market returns (11). Investor overconfidence bias during pre-crisis (2006–2008), distress (2008–2010), and recovery (2010–2015, 2015–2020, 2020–2021) market circumstances, including COVID-19 were examined in the BSE100 index. Investor confidence was high before the 2008 global market catastrophe and between 2015 and March 2020, but not during COVID-19 (12). Instances of self-attribution and overconfidence fallacies were identified, with a notable correlation between overconfidence and self-attribution, suggesting interconnectedness between these two cognitive biases. Behavioural biases were shaped by factors such as income, age, occupation, gender, and trading experience (13). Overconfident Indian investors overreact to private information (14). Investors with more money, trade more often, and are more experienced are more prone to overconfidence (15). However, demographics did not alter overconfidence bias. Overconfidence in the equities market can reverse stock values (16). Male, younger, low-income, and less educated investors have smaller portfolio values and are more overconfident. Overconfidence hurts portfolio value (17). There is a paucity of exhaustive reviews of the consequences of excessive confidence on stock market sectors in the existing literature on the Indian share market, particularly in light of recent regulatory reforms, market structure changes, and increased investor engagement. Examining a current sample of Indian equities allows us to assess how these developments have impacted market dynamics as well as the veracity of previous results. Indian equities widen the scope of investigation as global financial markets are influenced by cultural, economic, and regulatory variables. Revisiting study subjects with Indian stocks increases cross-validation and external validity due to investors' unique challenges and opportunities. To be reliable, research must be robust and adaptable. We may ask the same questions about Indian stocks to see if there are any market-specific differences. The consequences of overconfidence bias on stock market sectors have yet to be investigated. Investor reactions to private and public information signals should be researched since overconfidence bias and information processing might influence investing decisions. In view of the specific circumstances surrounding the COVID-19 outbreak, overconfidence bias and its consequences on the Indian capital market appear dubious. This study fills these gaps by shedding light on the presumptuous behavior in the Indian equity exchange before and upon pandemics. Hence this study examines the existence and effects of investor delusion in the Indian bourse. The study takes a complete stance by addressing overconfidence bias at distinct levels. It first looks at whether overconfidence bias exists at the market level and then confirms its occurrence across different sectors that are included in the NIFTY50 Index. The study offers insights into behavioral bias differences across various Indian economic sectors by analyzing variations in overconfidence levels among industries. The study offers insightful information on the existence of overconfidence bias in different phases: the white swan phase of the pre-COVID phase (2013-19), the grey swan phase amidst COVID-19 (2020-23), and the year 2020 alone, when India experienced unprecedented pandemic turmoil. The research clarifies the complex dynamics of overconfidence bias at various phases of market circumstances and disruptions brought on by the pandemic by looking at each era independently. We study the way prideful investors use public and private information to make investing decisions. The research examines the stock market's reaction to private and public information signals to see if overconfidence bias impacts it. This research shows how psychological prejudices impair market effectiveness and have implications for investors, regulators, and lawmakers. Investors can make better judgments and avoid behavioral biases by understanding overconfidence bias and its effects. Lawmakers and regulators can utilize these findings to create investor protection and market efficiency measures. Regulators should educate investors about cognitive biases including overconfidence and the significance of caution in volatile markets. These programs can help investors avoid psychological pitfalls that lead to bad financial decisions, especially in uncertain times. Policymakers can improve financial literacy by adopting behavioural finance concepts to help people make smarter investing decisions. They should also develop tools to detect and handle market bubbles, such as speculative activity monitoring and market stability measures. Section 2 delineates the study's data sources and variables. In Section 3 the methodological framework is given. Section 4 goes with the results, and the culminating section closes the article.

Methodology

To research stock market overconfidence bias, Nifty50 index trading data was collected for a decade from 1st April 2013, to 31st March 2023. The official website of the NSE provides daily trading information, such as high price, low price, closing price, and volume. The study utilizes the Nifty50 index because, it is the benchmark index that acts as the proxy for the health of the Indian stock market, comprising 50 large-cap stocks from numerous industries. The Indian stock market is accurately reflected by the Nifty50 index, which includes a variety of corporate entities. It measures market health and displays equity market trends in India. The 10-year timeframe permits long-term analysis and market cycles. This length of time encompasses bull markets, bear markets, and turbulent periods caused by the introduction of GST, demonetization, the COVID-19 epidemic, the IPO surge, banking sector changes, etc., allowing for a comprehensive examination of investor performance and behavior. Additionally, the National Stock Exchange's (NSE) industry classification system is used to divide the 50 component stocks into several industries to analyse the effect of overconfidence bias among different sectors. The study period spans from 2013 to 2023, with the pre-COVID period covering 2013 to 2019, the COVID period from 2020 to 2023, and the COVID breakout period 2020, which reflected a global crisis.

Methodological Framework

Hypotheses

$H0_a$: The Indian equity market is not affected by overconfidence bias.

$H0_b$: The magnitude of overconfidence bias is the same for all periods.

$H0_c$: The magnitude of overconfidence bias does not vary from sector to sector.

$H0_d$: Overconfident investors react identically to private and public information.

The following part discusses the four research hypotheses and the methodology used to test them.

$H0_a$: The Indian equity market is not affected by overconfidence bias

This analytical study applied the VAR (Vector Auto regression) model to evaluate the overconfidence in the equity market. This model brings forth a framework for investigating the relation between volume traded in the market, market return lag, lag of volume traded, and idiosyncratic volatility. Equation [1] is used to calculate the market return, while equation [2] is used to calculate idiosyncratic volatility;

Return = ln(current closing price/previous closing price) ------------- [1]

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

$$\text{Volatility} = \sqrt{250} * \sqrt{\frac{1}{4*\ln(2)} * \ln\left(\frac{h}{l}\right)^2} \text{------------- [2]}$$

h - the highest price in a day

l- the lowest price in a day.

Stationarity is a requirement for any regression model applied to time-ordered data. Unit roots are identified using the ADF (Augmented Dickey-Fuller) along with PP (Phillips-Perron) tests. The data is regarded as stationary in the absence of a unit root, and regression models may be implemented. Once the unit root is eliminated from the time series data, the investigation can proceed with VAR. Using VAR on market-wide transaction volume and market returns, investors' overconfidence is detected. The daily volatility, lagged market return and lagged market turnover values are independent factors, while the logarithmic value of turnover and daily market return of the Nifty50 are dependent factors.

$$\text{LogT}_{t=} \propto +\Sigma_{j=1}^{k}\beta_j \text{LogT}_{t-1} + \Sigma_{j=1}^{k}\gamma_j \text{LogRm}_{t-1} + \nu \text{LogVol}_t + \varepsilon_{1t} \text{----------------- [3]}$$

$$\text{LogRm}_{t=} \propto ' + \Sigma_{j=1}^{k}\beta_j' \text{LogT}_{t-1} + \Sigma_{j=1}^{k}\gamma_j' \text{LogRm}_{t-1} + \nu' \text{LogVol}_t + \varepsilon_{2t} \text{----------- [4]}$$

LogT: the natural log of the turnover of the index, Log Rm: the logarithmic value of daily index return, Log Vol: the idiosyncratic volatility of the index, k: the length of lags, j: lag summation index, t: the number of observations and ε: the residual disturbances. The lag length (k) is decided with AIC (Akaike Information Criterion) as well as the SIC (Schwarz Information Criterion). The regression values β and γ are used to figure out how the dependent factors and the independent factors change over time. The prevalence of overconfidence in the Indian stock market is shown if the volume of the Nifty 50 index has a positive relation with the lags of the index return. i.e., positive and significant values of γ denote the existence of overconfidence bias. Then IRF (Impulse response function) is used to discover the extent of bias in the market.

$H0_b$: The magnitude of overconfidence bias is same for all periods.

India encountered an unprecedented obstacle caused by COVID-19. Given the country's size, the economy's unstable position in the financial industry and its dependence on an unstructured workforce, the economy proved to be exceedingly disruptive. Lockdowns and other forms of social segregation have also been shown to be quite disruptive (18). In order to enquire into the influence of overconfidence bias over various time periods, a VAR model and IRF analysis were employed. AIC and SIC were used to decide the length of lag for running VAR. In the first stage, an analysis was conducted prior Covid epoch, specifically focusing on the timeframe spanning from 1st April 2013 to 31st December 2019. Subsequently, a distinct examination was conducted on the timeframe spanning from 1st January 2020 to 31st March 2023, which coincided with the COVID-19 era. The year 2020 was specifically chosen to examine the impact of the pandemic's tumults phase which resulted in a nationwide lockdown and caused global anxiety and uncertainty too.

$H0_c$: The magnitude of overconfidence bias does not vary from sector to sector.

In addition, the study classifies the constituent equities of the Nifty50 into thirteen distinct industries based on the NSE's classification. The study adopted the VAR and IRF techniques to detect overconfidence bias in these various industries.

$H0_d$: Overconfident investors react identically to private and public information.

It has been observed that an increase in trading volume can be attributed primarily to the tendency of overconfident investors to put greater importance on private information while undervaluing public information (4). To explore this tendency in the context of the stock market in India, the Structural VAR model is used (19). Bivariate Moving Average Representation (BMAR) tests the relation between volume and return. Private information shock and public information shock are included in the BMAR model. Shocks are orthonormalized to ensure their variances equal the identity matrix. The identifying restriction is imposed to differentiate between the sensitivity of private and public information disruptions on volume traded. According to the restriction, the private information shock ($\varepsilon_t^{private}$) has an immediate effect on the volume traded, whereas the public information shock (ε_t^{public}) does not. Empirical and theoretical data show that private knowledge drives the volume exchanged more than publicly accessible information. After the initial period, the restriction still permits the public information shock to affect trading volume.

A restricted Bivariate Vector Autoregression (BVAR) model is employed to estimate the model. The BVAR model defines a link between the volume of trading and returns on stocks, taking into account their lagged values and non-normalized shocks. The BVAR model coefficients capture the dynamic effects of disturbances on stock returns and trading volume.

$$\text{LogT}_{t=} \propto +\Sigma_{j=1}^{k}\beta_j \text{LogT}_{t-1} + \Sigma_{j=1}^{k}\gamma_j \text{LogRm}_{t-1} + \varepsilon_t^{private} \text{ ----------------------- [5]}$$

$$\text{LogRm}_{t=} \propto ' + \Sigma_{j=1}^{k}\beta_j' \text{LogT}_{t-1} + \Sigma_{j=1}^{k}\gamma_j' \text{LogRm}_{t-1} + \varepsilon_t^{public} \text{ ------------------- [6]}$$

The logarithmic value of volume traded is denoted by LogT, Rm_t is the log value of return in the market on the day. $\varepsilon_t^{private}$ is the private information signal ε_t^{public} is the public information signal. We apply AIC and SIC to decide the lag duration (k). A restricted BVAR of stock price and volume traded is developed once we estimate the restricted BVAR of volume and return. Analyzing the impulse response of these stock prices to private information shock and public information shock investors' responses can be addressed.

Diagnostic Checking: Diagnostic tests were conducted to confirm the sufficiency of the VAR model. The tests assessed autocorrelation, multicollinearity, heteroscedasticity, endogeneity, and residual normality.

Results and Discussion

The analytical findings of our inquiry on the presumptuous behavior by investors in the capital market and its effects on trading behavior are presented in this part. We start by looking at the descriptive statistics of the chosen variables, then we analyze each hypothesis.

Table 1: Descriptive Statistics

Variables	Average	S.D.	Median	Max.	Min
Log Volume	12.3	1.33	12.4	14.4	0.000
Log Return	0.000	0.011	0.000	0.084	-0.139
Volatility	1.41	0.388	1.34	5.57	0.666

The descriptive statistics (Table 1) provide valuable insights into the key variables, Volume, Return, and Volatility. The mean Log volume observed during the specified period was 12.3, exhibiting a minor degree of variability around this central tendency. The recorded logarithmic returns exhibited a marginally positive mean of 0.0004, indicating modest average profits. A volatility measure of 1.41 indicates the average size of price changes, together with a moderate level of variation. The study found very stable trade volumes, small gains, and moderate volatility within the timeframe. Understanding these statistics is essential for market dynamics and trend analysis. This study used many data diagnostics to evaluate the VAR model. Autocorrelation and residual correlations were tested using the Durbin-Watson test. Statistical methods like the Variance Inflation Factor assessed multi-collinearity. Heteroscedasticity was determined with White tests. The Jarque-Bera test assessed residual normalcy. In general, the outcomes of these diagnostic tests have substantiated the sufficiency of the VAR model, thereby signifying its dependability for subsequent examination and elucidation of the time series data.

$H0_A$: The Indian equity market is not affected by overconfidence bias.

The stationarity of the variables under investigation was demonstrated by conducting ADF and PP tests. The analysis assumed that the data was non-stationary, which is not accepted, as the p-values for all stocks in both periods were less than 0.01. Hence, the stationarity of the data has been established, and the decision on the ideal lag length for running the VAR was conducted using the SIC, resulting in the identification of 7 as the most suitable number of lags. The VAR output offers strong proof of the prevalence of overconfidence within the Indian stock market from 2013 to 2023 (Table 2).

Table 2: VAR Results (2013 to 2023)

Variable (Lag)	Coefficient	t-Stat.	Std. Error	Prob.
Rm_t (-1)	1.057	2.051	0.515	0.040**
Rm_t (-2)	0.772	1.502	0.514	0.133
Rm_t (-3)	-0.459	-0.897	0.512	0.369
Rm_t (-4)	-0.265	-0.518	0.512	0.604
Rm_t (-5)	-0.311	-0.606	0.513	0.544
Rm_t (-6)	0.010	0.019	0.514	0.984
Rm_t (-7)	0.163	0.316	0.516	0.752
Volatility	0.543	12.165	0.045	0.000***

Note: ** shows ∝ 5% and ***shows ∝ 1%

A significant positive coefficient for the lagged return variable supports this investor bias. This discovery supports overconfidence bias in this market, as it matches two previous findings (20, 21). A high coefficient indicates that investors overestimate their decision-making capabilities, resulting in an exaggerated reaction to their previous investment performance. The presence of overconfidence bias in the first lag is due to the priority given to the latest market updates in investment decisions. However, the subsequent six lags are devoid of bias, which is a remarkable attribute. Investors mitigate the impact of previous market performance on their decisions by adopting a more pragmatic and long-term outlook. The Indian stock market's T+2 settlements tailor the overconfidence bias. A two-day settlement window may cause investors to overreact to market events. As settlement deadlines approach, traders may become more determined, lowering overconfidence bias after delays. This interesting conclusion emphasizes the importance of understanding temporal patterns and market conditions that affect investor action for safe investment decisions and market adaptability. The VAR model shows overconfidence bias in the Indian bourse and volatility's significant impact. Market volatility affects investor behavior and market dynamics, making the volatility coefficient important. This discovery is consistent with the notion that heightened levels of volatility can result in heightened levels of uncertainty and risk, which in turn can affect investor sentiment and investors' decision-making processes (22).When volume is dependent, the R-squared shows that 76.99% of volume variability can be described by the lag of return, volume, and volatility, and the model yielded a high adjusted R-squared (0.768). A non-significant residual autocorrelation is confirmed by the Durbin-Watson statistic (1.948). When the return is the dependent variable, R squared and adjusted R squared is quite low (approx. 4%) reflecting the model's inability to explain dependent variable changes. We find the equation of Volume as a dependent variable more reliable for analysis. This means the Volume model correctly correlates past returns, market volatility, and market volume lag within the specified timeframe.

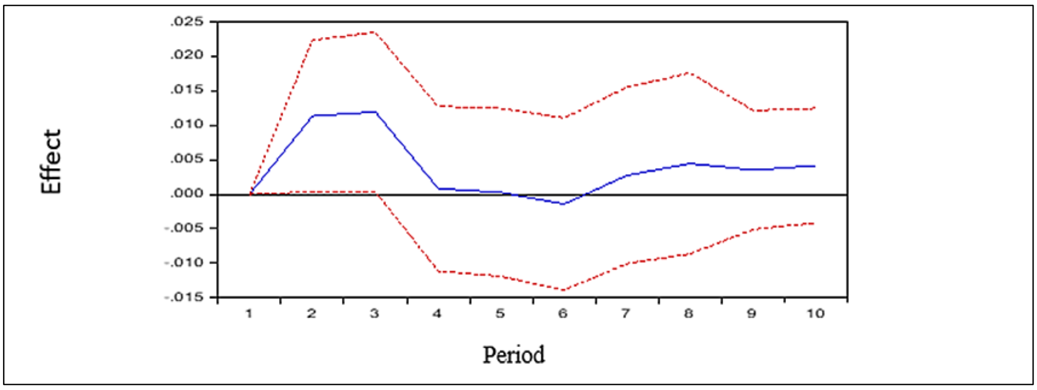


Figure 1: IRF- Volume to Return (2013-23)

The IRF in Figure 1 reveals that the effect of the stimulus on volume persists until the fifth day, indicating a sustained effect over this period. On the third day, the response reaches its peak, indicating the maximum level of increased trading volume. The effect then progressively diminishes, and by the fifth period, it has returned to breakeven. This shows the effect of bias has diminished after the 5th day.

$H0_b$: The magnitude of overconfidence bias is same for all periods. The VAR results for the pre-pandemic period (2013-2019) provide a fascinating insight into the market's overconfidence bias (Table 3).

Table 3: VAR Results during Pre-Pandemic

Variable (Lag)	Coefficient	t-Stat.	Std. Error	Prob.
Rm_t (-1)	1.895	2.313	0.819	0.021**
Rm_t (-2)	0.269	0.327	0.822	0.744
Rm_t (-3)	-1.046	-1.272	0.822	0.203
Rm_t (-4)	-0.590	-0.716	0.824	0.474
Rm_t (-5)	-0.925	-1.128	0.820	0.259
Volatility	0.594	9.062	0.065	0.000***

Note: ** shows ∝ 5% and ***shows ∝ 1%

Based on the SIC criterion and accounting for five lags, the model revealed a favorable and statistically significant coefficient in the first lag of returns at a five per cent level of significance. This observation reveals that investors tend to display an unwarranted level of confidence in their capacity to accurately forecast future market trends by relying solely on past performance (2). The presence of an overconfidence bias has the potential to exert an influence on investment decisions, which in turn may result in outcomes that are less than optimal (23). In addition, the volatility variable displayed a significant coefficient, indicating that it influences investor behavior. The model's robustness is indicated by the high R-squared (0.635) and adjusted R-squared values (0.633) of Volume as dependent, as well as the absence of substantial autocorrelation (Durbin-Watson 1.948). The R square value for return as dependent was found very low (0.033) which shows the incapability of the model to capture the variations of lag of volume, lag of return, and volatility. The IRF analysis contributes to a comprehensive comprehension of investor behavior and the persistence of overconfidence bias in the pre-pandemic market by shedding light on the duration of the bias's effects (Figure 2).

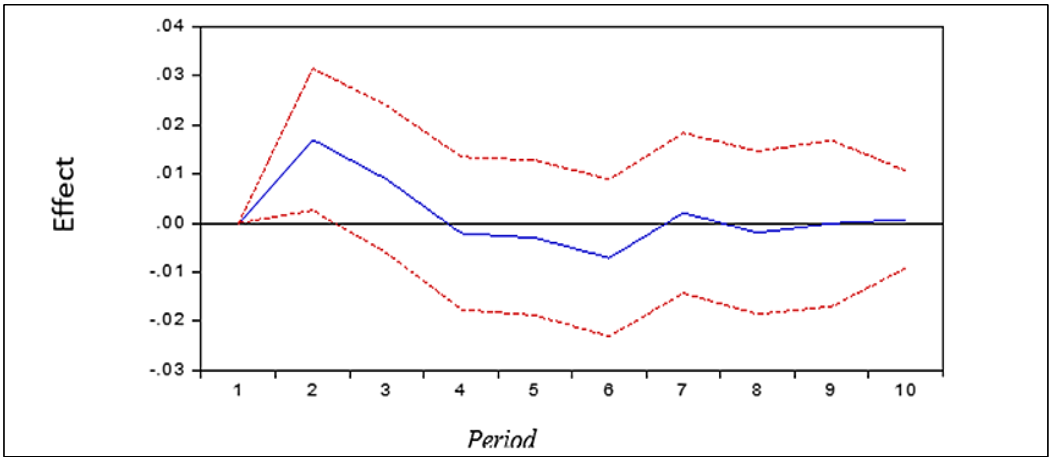


Figure 2: The impulse response of volume to return during pre-pandemic

The IRF shows the bias is at its peak on the second day and its presence is visible till the fourth day. This shows investors' immediate reaction to market information. Investors seem more overconfident in their choices in stable market conditions, which increase the volume in the short term. Market results may seem more predictable and controllable during periods of stability. Overconfidence bias has been exacerbated by the absence of major external shocks or disruptive events before the epidemic began. The bias's persistence until the fourth day shows how overconfidence affects market behavior and suggests investors should rethink their holdings and activities. The IRF findings underline the need to recognize and reduce overconfidence bias, particularly during market stability, to encourage informed and fair investment choices. The study analyzed the presence of overconfidence bias between 2020 and 2023 during the turbulent period of COVID-19 (Table 4).

Table 4: Result of VAR during the Pandemic Period

Variable (Lag)	Coefficient	t-Statistic	Std. Error	Prob.
Rm_t (-1)	0.246	0.419	0.586	0.675
Rm_t (-2)	1.087	1.883	0.577	0.059*
Rm_t (-3)	-0.126	-0.217	0.578	0.828
Rm_t (-4)	-0.116	-0.199	0.579	0.841
Rm_t -5)	0.210	0.361	0.581	0.718
Rm_t (-6)	-0.118	-0.201	0.588	0.841
Rm_t (-7)	0.246	0.419	0.586	0.675
Volatility	0.456	7.934	0.057	0.000***

Note: ** shows ∝ 5% and ***shows ∝ 1%

A favorable and statistically substantial coefficient for the second latency of returns revealed the existence of bias, albeit at a 10 percent level of significance. This indicates that investors were overconfident in their decision-making during this difficult period. In addition, it is essential to note that the absence of bias at 5 percent significance emphasizes the need for additional inquiry and analysis to fully grasp the impact of the pandemic on investor decisions. The R-squared score of 0.782 implies that the independent factors describe 78.2% of the variability in the dependent factor volume. The adjusted R-squared value of 0.778 improves model reliability and the Durbin-Watson value of 1.945 shows no significant autocorrelation in the residuals. Here also the equation for return is weak as it has R square and adjusted R square below 10 percent which shows only a small amount of dependent variable is explained by lag of return, lag of volume, and volatility.

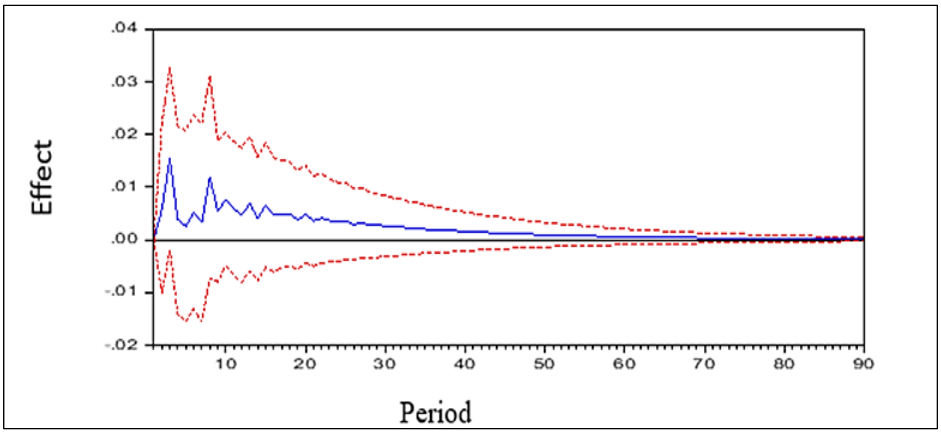


Figure 3: IRF of the pandemic phase

The analysis of the IRF for the pandemic period (Figure 3) revealed that the effect peaked on the third day and persisted until the 87th day for a significantly longer duration. The protracted duration of the bias amid the global epidemic can be attributed to increased market swings and unpredictability. The unforeseen and rapid evolution of the COVID-19 pandemic certainly heightened investors' emotions, resulting in a protracted overconfidence bias. As investors sought to understand the outbreak's rapid economic impact, bias may have persisted. Various government strategies and restrictions imposed on social living have changed the market pulse, affecting investor behavior and resulting in bias. Significant insights can be derived from comparing the outcomes of the overconfidence bias before and after the pandemic. The overconfidence bias was most pronounced on day three and gradually faded by day four before the epidemic. This indicates that the bias in the market is just momentary. Pandemic overconfidence was more pronounced and persisted for a longer period. From the third day bias rose until day 87. This shows how bias persisted on the Indian stock exchange during the outbreak, reflecting market players' fears and constraints. Different bias lengths show how market conditions and external shocks affect investor behavior. The COVID-19 pandemic resulted in substantial market volatility and economic uncertainty, which likely contributed to the heightened overconfidence bias as investors attempted to reestablish control and stability in their portfolios. In May 2020, the Indian government announced an economic package that included the Rs 20 lakh crore Atmanirbhar Bharat Abhiyan. The objective of this package was to revitalize the economy and provide investors with a sense of security. Furthermore, despite the ongoing economic challenges, the Nifty50 index's rapid return to pre-pandemic levels by the end of 2020 likely contributed to overconfidence by creating an illusion of market stability and recovery.

Table 5: VAR Results (2020)

Variable (Lag)	Coefficient	t-Statistic	Std. Error	Prob.
Return (-1)	0.091136	1.553042	0.058682	0.1211
Return (-2)	-1.486144	-2.210712	0.672247	0.0275**

Note: ** shows ∝ 5% and ***shows ∝ 1%

Table 5 indicates a negative correlation between return and trading volume on the Indian stock exchange, suggesting a clear tendency toward loss aversion bias. This confirms the existing body of work on investor behavior during uncertainties. This finding validates that market uncertainty and volatility can significantly increase loss aversion, especially during a pandemic (24, 25). Uncertainties of the market reduced the value of portfolios which in turn affected the investor confidence. This leads to a defensive approach, protecting existing portfolios and resulting in lower trading volume. In previous studies, the decrease in trading volume was reported due to the careful investment attitude of investors (26). The findings show the relevance of understanding behavioral biases during a crisis period to protect the market from fallacies.

$H0_c$: The magnitude of overconfidence bias does not vary from sector to sector. The observation of the overconfidence bias within the Nifty50 market over the past decade implies a prevailing tendency towards overconfidence among investors. Upon closer examination of bias at the industry level, it was observed that a mere three out of the total thirteen industries analyzed exhibited substantial indications of overconfidence bias. The services, FMCG (Fast-Moving Consumer Goods), and metals and minerals sectors exhibited notable indications of overconfidence bias. This suggests that the prevalence of overconfidence varies across different industries.

Table 6: VAR Result of Services Industry

Variable (Lag)	Coefficient	t-Statistic	Std. Error	Prob.
Rm_t (-1)	1.452	3.603	0.403	0.000**
Rm_t (-2)	0.671	1.671	0.401	0.094
Rm_t (-3)	0.407	1.014	0.402	0.311
Rm_t (-4)	-0.044	-0.109	0.400	0.913
Rm_t (-5)	0.423	1.057	0.399	0.290
Rm_t (-6)	0.317	0.795	0.398	0.427
Rm_t (-7)	0.412	1.036	0.398	0.300
Volatility	0.366	23.531	0.015	0.000***

Note: ** shows ∝ 5% and ***shows ∝ 1%

The VAR model outcomes (Table 6) indicated the presence of overconfidence bias at a 5 percent significance level in the services sector with Adani Ports and Special Economic Zone Ltd. being the sole trader in the industry. Because of its pivotal role in India's Sagarmala project, introduced in 2015 to support port-led development and trade infrastructure, investors might have excessive faith in the service sector, especially in Adani Ports and Special Economic Zone Ltd. Due to the company's strong market position, quick development, and apparent government support, investors could have overestimated its potential for expansion. The IRF analysis (Figure 4) revealed an increase on the second trading day, and the market remained biased until the 170th trading day.

Table 7: VAR Result of FMCG

Variable (Lag)	Coefficient	t-Statistic	Std. Error	Prob.
Return (-1)	-1.643	-1.524	1.078	0.128
Return (-2)	1.804	1.668	1.081	0.096*
Volatility	0.084	2.292	0.036	0.022**

Note: ** shows ∝ 5% and ***shows ∝ 1%

The FMCG sector made up of five equities of Nifty50 (HUL, Nestle, Tata Consumer Products Ltd., ITC, and Britannia) exhibited positive and significant return coefficients in the var model, (Table 7) indicating the presence of overconfidence bias. This can be tied to the growing demand for fast-moving consumer goods in India as a byproduct of a growing population, increased spending, and altering consumer preferences. FMCG has been seen as a safe investment due to consistent demand for essentials, thus investors overestimate its growth potential and disregard market saturation and increased competition. Over the last decade, aggressive rural market penetration, brand diversification, and product innovation have fuelled optimism and overconfidence in the sector's long-term prospects.

Table 8: VAR Results of the Metals and Minerals Industry

Variable (Lag)	Coefficient	t-Statistic	Std. Error	Prob.
Rm_t (-1)	0.992757	1.121056	0.885556	0.2628
Rm_t (-2)	2.213848	2.532388	0.874214	0.0116**
Volatility	0.570204	13.31014	0.042840	0.0000***

Note: ** shows ∝ 5% and ***shows ∝ 1%

In the metals and minerals industry, which consists of three equities (Hindalco, JSW, and Tata Steel), the VAR results revealed the existence of overconfidence bias (Table 8). The IRF analysis revealed a bias that peaked on the third day and lasted until the eighth day (Figure 4). Investors overestimated the stability of the metals and minerals sector during periods of high commodity prices brought on by global demand and India's expanding infrastructure. Many investors overestimated the long-term effects of government initiatives like "Make in India" and infrastructure development projects while underestimating supply chain difficulties and global market dynamics.

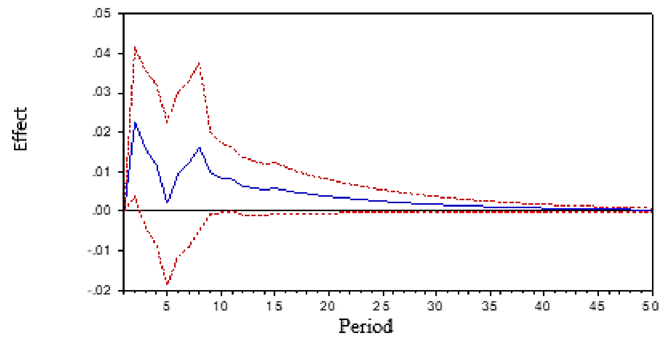
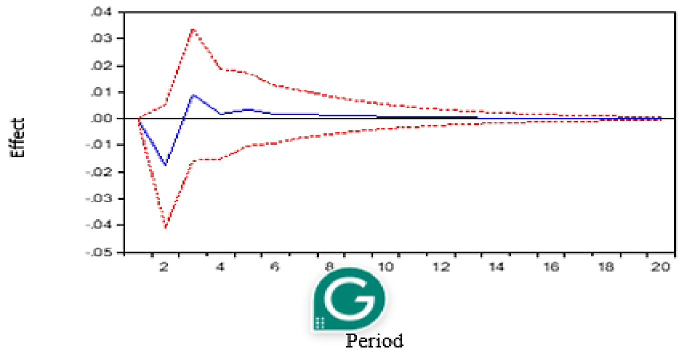
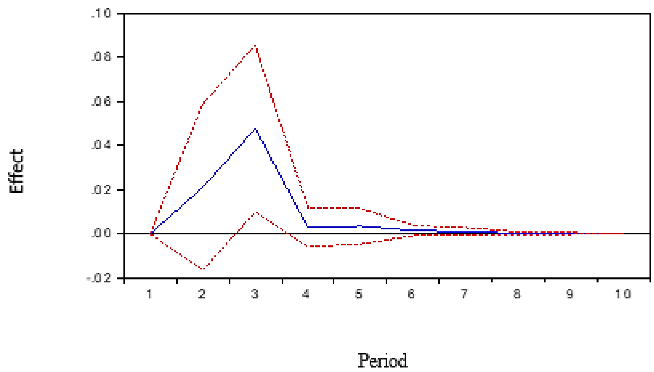
Industry	IRF
Services	
FMCG	
Metals and minerals	

Figure 4: IRF of Industries

H0d: Overconfident investors react identically to private and public information. As the presence of overconfidence bias is evident from the research, we examined whether this behavior is influenced by the proposition that overconfident investors respond quickly to private information and slowly to general information. The methodology for distinguishing between private and public information using an SVAR model is adopted (19).The number of lags as per AIC is 7. Using the BVAR, the reaction of share prices (pt) to private as well as public information was estimated. Figure 5 depicts the sensitivity of stock prices to confidential information over six days. Figure 6 illustrates the sensitivity of stock prices to public information over 6 days.

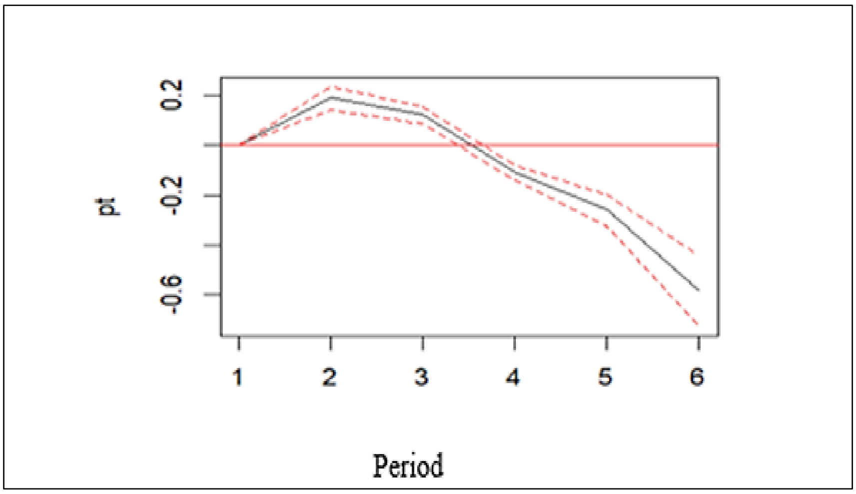


Figure 5: IRF - Stock Price to Private Information

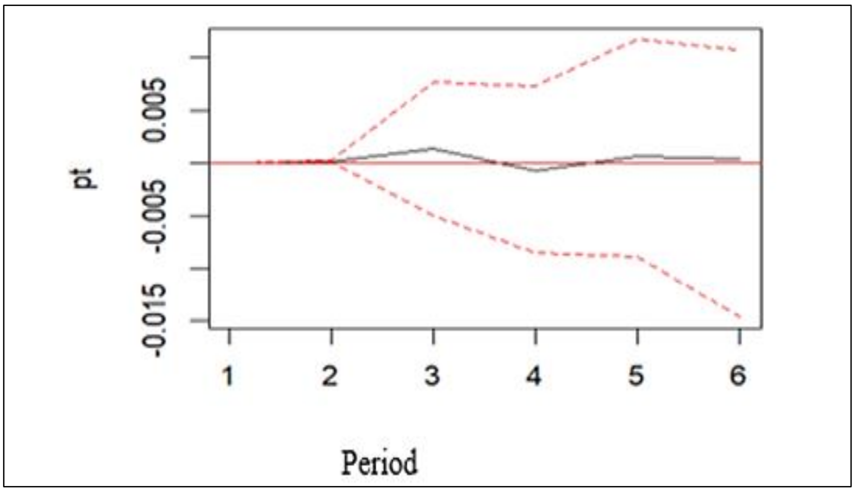


Figure 6: IRF-Stock Price to Public Information

The IRF demonstrates that stock prices are initially highly sensitive to private information, but by the third stage, the effect of private information becomes negative. Stock prices respond poorly to public information in the initial phase, only after the second period does public information begin to influence stock prices, albeit to a much lesser extent than private information. This study reveals evidence of sensitivity to private information and conservative response to public information on the part of overconfident investors similar to the findings of previous works (4, 14, 19, 27). Overreacting to private information implies that investors place disproportionate weight on their private signals when making investment decisions (27). Investors who react aggressively to private information are motivated by overconfidence or the desire to exploit perceived informational advantages. Consequently, stock prices could become more volatile and deviate from their fundamental values. On the other hand, the under reaction to public information indicates that investors do not completely incorporate the impact of widely available or market-wide news into their trading decisions. Under reaction to public information can result in delayed price adjustments, sluggish market reactions, and potential profit opportunities by exploiting mispricing caused by public information. This behavior can be attributed to self-attribution and confirmation biases too.

Conclusion

In conclusion, the quest of the current paper was to look into the manifestation of presumptive bias in the Indian bourse and to analyze its behavior across various periods and industry sectors. The study utilized trading data from 2013 to 2023 for the Nifty50 index and its constituent equities. The investigation revealed the prevalence of presumptuous behavior in the Indian bourse, which, curiously, persisted not only during normal periods but also during the grey swan phase. However, the effect of bias was found to be longer during uncertain market conditions, showing the significance of volatility on investment decisions. In the pandemic breakout year, investors turned more risk-averse to addressing a new phase. Overconfidence was present in the FMCG, services, and metals and minerals industries only demonstrating the heterogeneity of investor behavior across sectors and the significance of sector-specific characteristics when attempting to comprehend market dynamics. In addition, the analysis of investor reactions to private and public information revealed that overconfident investors are very sensitive to private information, which is in line with the prior research findings. Their under reaction to public information indicates they do not completely incorporate public information into their trading decisions. These insights can contribute to a greater comprehension of market efficiency, investor behavior, and the potential repercussions for market participants in various market environments. Even though this research provides insightful information, there are some limitations. The identification of overconfidence bias in a limited number of sectors demonstrates the need for a more diverse sectoral representation. While the analysis took the pandemic period into account, other external factors and events can be considered for further study. Although the daily trade data used in this study offers a comprehensive picture of market behaviour over a ten-year period, it might miss more subtle changes in investor psychology or more minute intraday swings. To learn more about these elements, future studies could look into employing intraday data or other methods. To curb overconfidence in investing plans, we recommend that investors use behavioural finance tools such as self-assessment questionnaires and decision-making frameworks and diversify their portfolios across asset classes. Regulators should pass laws requiring participants in the market to conduct regular risk assessments and stress testing, as well as to encourage transparency and information-sharing, to decrease information asymmetry. Policymakers can design educational programs that can help the public learn more about overconfidence bias and its effect on financial decisions. Financial literacy initiatives that combine principles of behavior finance can help individuals recognize these cognitive biases and techniques to overcome them, such as overconfidence. These steps are anticipated to lead to better decisions by all market players.

Abbreviations

VAR: Vector Auto regression, IRF: Impulse Response Function, FMCG: Fast-Moving Consumer Goods, IPO: Initial Public Offering.

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Author Contributions

Safeeda KA: Safeeda KA contributed to the development of the research idea, conducted data collection, designed the methodology, and performed the data analysis. Dr. Ganesh R: Dr. Ganesh R contributed to the analysis and interpretation of the data and was responsible for writing the literature review.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper. The authors have no financial or personal relationships that could inappropriately influence or bias the content of this work.

Ethics Approval

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