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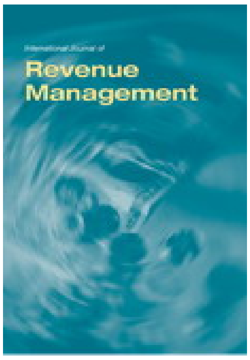

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An empirical analysis of overconfidence behaviour in the Indian ETF market

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Abstract: One of the most notable advances in contemporary financial markets is the creation of exchange-traded funds (ETFs). The rising demand for this asset class may induce overconfidence in investors, which may endanger the stability of financial markets. Overconfidence bias is an inclination to overestimate one's own abilities and underestimate their error variance while valuing securities. The present study aims to investigate the presence of the overconfidence bias in the Indian ETF market using a sample of 12 equity ETFs in both pre and during the pandemic period. Vector autoregression (VAR) and impulse response functions (IRFs) are used to understand the relation between past returns and the current transaction volume of the data. The study found that investors in ETF markets are overconfident, even in the crisis phase. This study contributes by addressing the knowledge gap on the overconfidence bias in the Indian ETF market. It sheds light on how the Indian banking industry maintained its faith in the investors' lobby. The findings of this research study have implications for investors, asset management companies, regulators, and policymakers.

Keywords: overconfidence; behavioural bias; behavioural finance; COVID-19; vector autoregression; impulse response function; IRF; exchange-traded funds; ETFs.

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1 Introduction

Proponents of behavioural finance argue that individuals are susceptible to behavioural biases while making investment decisions (Dhingra et al., 2023). These biases possess the potential to disrupt the stock market by influencing investors' investment choices. The extant literature has provided numerous biases, which can be broadly categorised into heuristic-driven and frame-dependent. Heuristics including overconfidence, availability, self-attribution, representativeness, etc. are mental shortcuts for making rapid judgements in uncertain and intricate financial scenarios (Kathpal et al., 2021). Investors use heuristics because of their limited skills to understand complex financial information (Ceschi et al., 2019; Fenzl and Pelzmann, 2012). Next, frame-dependent behavioural biases such as, disposition effect, loss aversion, mental accounting, etc. are based on the belief that there could be different responses and interpretations of a financial issue depending on how investors frame their available options (Kahneman and Tversky, 1979). Overconfidence is the most prevalent and widespread bias among investors worldwide (Boussaidi, 2020; Parhi and Pal, 2021).

According to Shrotryia and Kalra (2021), investors are more susceptible to behavioural biases under situations of extreme anxiety, turmoil, or emergency, like the most recent COVID-19 outbreak. World Health Organisation (WHO) has declared the COVID-19 a global pandemic and the largest crisis of this century (Chaudhary et al., 2020). This pandemic has repercussions for every sector of the economy, from healthcare to finance. This pandemic caused economies to undergo lockdown, which heightened market uncertainty. Indian government declared its first lockdown from 25 March 2020. There are several studies in the behavioural finance field considering the COVID-19 pandemic period.

Exchange-traded funds (ETFs) are one of the great bounties that financial markets have given to risk-averse investors, offering advantages such as the creation and redemption of shares, intraday trading, minimal costs, and tax efficiency in comparison to competing products (Chakrabarty et al., 2017; Charupat and Miu, 2013). ETFs offer investors exposure to the underlying stocks through a diversified portfolio of assets and were first developed to replicate broad stock indices. More recent developments in the industry have made it possible to gain exposure to various global markets, fixed-income instruments, commodities, and alternative investments (active, passive, leveraged, etc.). With the cumulative annual growth rate (CAGR) of 50.84% over the past decade, India's ETF market has achieved global prominence (Tripathi and Sethi, 2022). As a result, ETFs have gained popularity as an asset class due to their affordability (like mutual funds) and convenience (like equity) as a saving and investing tool (Kunjal and Peerbhai, 2021). This growth is mirrored on a global scale, with ETFs experiencing substantial investor engagement (Rompotis, 2020).

Market efficiency and investor rationality are key tenets of traditional finance theories. On the flip side, the irrationalities of equity markets can also be seen in ETF markets; for example, Ma et al. (2018) presented evidence of investor overreaction to ETFs in Asian countries. In their study, Bahadar et al. (2019) reported herd behaviour in ETF markets. As a result of these irrational decisions, investors may overtrade, engage in risky investments, or misjudge the likelihood of success (Chen et al., 2007). One of the greatest ways to explicate why investors act irrationally is via the lens of behavioural finance.

Despite the relevance of overconfidence bias in the financial market and the exponential rise of the ETF market in an emerging economy like India, the authors found that no study has ever tested investors' overconfidence in the Indian ETF market. Therefore, the authors take inspiration to investigate the existence of overconfidence bias in the Indian ETF market. In doing so, the current study seeks to address a series of research queries – whether Indian investors are overconfident while investing in ETFs? Do past positive returns of ETF investors result in a significant increase in trading volume of subsequent periods? Furthermore, the COVID-19 phase has brought turbulence in the stock markets, and therefore the study has a separate portion of analysis for the COVID-19 phase – how overconfident trading in the Indian ETF market is affected by the recent COVID-19 pandemic? Therefore, the present study intends to investigate the lead-lag relationship between transaction volume and return in the Indian ETF market, covering both pre and during the pandemic phases.

To answer the above research questions, the current study is based on the theoretical underpinnings of overconfidence hypothesis (Daniel et al., 1998; Gervais and Odean, 2001; Odean, 1998b). Overconfidence hypothesis has four testable implications: First, overconfident investors overreact to private information and underreact to public information (Daniel et al., 1998; Odean, 1998b). Second, market gains make overconfident investors trade more aggressively in subsequent periods (Gervais and Odean, 2001). Third, excessive trading by overconfident investors in securities markets contributes to the observed excessive volatility (Gervais and Odean, 2001; Odean, 1998b). Fourth, overconfident investors' under-estimate risk and trade more in riskier securities (Chuang and Lee, 2006). To examine the presence of overconfidence in Indian ETFs market, we empirically evaluate the second hypotheses using the daily data of the selected ETFs.

The empirical application in the current study involves data of 12 ETFs, especially those that have equity as an underlying asset and are traded in the domestic stock exchange of India. Vector autoregression (VAR) methodology is used to understand the relation between the lag returns and the volume of the data. Furthermore, to bolster the robustness of the study, we present how the transaction volume responds to one standard deviation shock in return for the ETFs by using the impulse response function (IRF). The findings indicated a significant overconfidence bias regarding BSLNIFTY, MOM100, KOTAKPSUBK, INFRABEES, JUNIORBEES, and MOM50 in the pre-pandemic period. In addition to these ETFs, investors gained overconfidence in PSUBNKBEES during the pandemic. This shows that investors were more optimistic about the banking sector of the Indian economy.

1.1 Motivation and contribution

The review of existing studies (Ahmad et al., 2017; Parveen et al., 2023; Prosad et al., 2018; Shrotryia and Kalra, 2021; Ul Abdin et al., 2022) reveals that understanding and addressing behavioural biases in financial markets is crucial due to their potential to disrupt investor decisions and financial and economic systems. Moreover, the literature signifies that the irrational tendencies observed in equity markets extend their presence into ETF markets as well (Bahadar et al., 2019; Ma et al., 2018). The CAGR of the ETF market in India over the past ten years was 50.84%, one of the highest rates in the world (Tripathi and Sethi, 2022). Despite the exponential growth of the Indian ETF market, the examination of overconfidence bias within this context remains unexplored.

Thus, grounded on the above issues and identified gaps, this study contributes to the existing literature by exploring the overconfidence bias in Indian ETF market and adding the latest findings to behavioural finance literature. Second, it provides insights into how the Indian banking sector did not lose its trust in the investors' lobby, which itself paved the way for further researchers to explore the factors that gain the investors' trust in the Indian banking system and how such factors can be exploited to retain and attract new investors in other sectors. Furthermore, recommendations are provided to regulators and policymakers to educate investors through investors' awareness programmes.

The story proceeds as follows: Section 2 deals with the review of the literature and hypothesis development. Section 3 introduces data and methodology. Section 4 provides the empirical results and discussions, and the paper is then concluded in Section 5.

2 Literature review and hypothesis formulation

Daniel Kahneman has cited overconfidence as the most hazardous bias in human investment behaviour (Pandey and Jessica, 2018). The existing body of research on the overconfidence bias is categorised into two principal streams: one delves into the overconfidence of managerial psychological characteristics and its impact on their decision-making processes (Chiu et al., 2022; El-Ansary and Ahmed, 2021; Hatoum et al., 2022), while the other stream concentrates on the psychological attributes of investors and their impact for investment choices. Within the latter stream, a significant portion of the literature focuses on primary data (Ansari et al., 2023; Baker et al., 2021; Ul Abdin et al., 2022), while another segment investigates the same subject using secondary data (focus of the present study) (Mushinada and Veluri, 2018; Shrotryia and Kalra, 2021; Statman et al., 2006). Additionally, there is a growing focus on exploring the influence of overconfidence on firm and stock market valuations in contemporary studies (Adebambo and Yan, 2017; Aljifri, 2023).

Overconfidence is an inclination to overestimate one's own abilities, probability of upcoming events and underestimate their error variance while valuing securities (Daniel et al., 1998; Guo et al., 2020). Overconfident people are overly optimistic and overestimate the precision of their knowledge and skills compared to their counterparts (Aljifri, 2023; Kansal and Singh, 2018; Odean, 1998b). This is shown in the abnormally high transaction volume or turnover in the financial markets (Prosad et al., 2018). According to Moore and Healy (2008), there are three manifestations of overconfidence: miscalibration, overplacement, and overestimation. Assigning extremely narrow confidence intervals to one's estimates leads to miscalibration, which is defined as having an excessive amount of certainty about one's beliefs and knowledge accuracy (Glaser and Weber, 2007). According to Pikulina et al. (2017), overplacement is when people believe they are better than others. Overestimation shows extreme confidence in one's abilities, level of control, etc. (Moore and Schatz, 2017). Understanding these various types of overconfidence is crucial because they have distinct implications for investors' behaviour (Broihanne et al., 2014; Glaser et al., 2013; Merkle, 2017). Overconfidence bias explains many market anomalies in financial markets (Abbes et al., 2009; Chuang and Lee, 2006; Mushinada, 2020; Sheikh and Riaz, 2012).

According to Odean (1998b) and Gervais and Odean (2001) model, investors mistakenly credit their stock-picking skills for the increase in their wealth, which is brought on by high market returns. Therefore, times of great market returns and the process of building wealth make investors overconfident. This increases the trading volume in the subsequent periods due to aggressive trading by overconfident investors. This is only one of the implications of the overconfidence model. Studies including Daniel et al. (2001), Kyle and Wang (1997), and Hirshleifer and Luo (2001) also supported the argument that trading increases with overconfidence. Statman et al. (2006) argued that the overconfidence model manifests the lead-lag relationship between trading activity and market returns when investors are overconfident. They have examined all NYSE common stocks to test the prediction of the model as mentioned above by using VAR and the IRFs. In line with the predictions, Statman et al. (2006) concluded that overconfidence bias is present in the stock market. The other testable implications of the overconfidence model are: First, overconfident investors overreact to their private information while underreacting to publicly available information (Daniel et al., 1998). Second, excessive trading by overconfident investors increases volatility (Odean, 1998a, 1998b). Next, they underestimate risk and hold an under-diversified (riskier) portfolio (De Long et al., 1990). Chuang and Lee (2006) and Abbes et al. (2009) have tested the various implications of the overconfidence model. Their results reported that excessive trading by overconfident investors leads to excessive volatility in the financial markets. Mushinada and Veluri (2018) and Boussaidi (2020) have probed these implications of the overconfidence model in the Indian and MENA stock markets, respectively. They agreed that overconfident investors overreact to their personal information and trade more, which adds to the market's excessive volatility. Kuranchie-pong and Forson (2021) found overconfidence bias and volatility in the Ghanaian stock market during the pre-pandemic and the pandemic period.

Chuang and Susmel (2011) reveal stronger positive causality from past returns to current volume in portfolios with minimal institutional ownership, demonstrating that individual investors are more overconfident in the Taiwan stock exchange. Similar results have been presented by Chen et al. (2007), and they also noted that investors might suffer multiple biases concurrently. Numerous studies have used primary surveys and qualitative research to compile a list of the factors that affect the overconfidence bias. The direct test of the hypothesis that investors' overconfidence promotes trading volume, which included a survey of 3,000 German investors, Glaser and Weber (2007) revealed that trading activity is influenced by better-than-average manifestation. The research by Antonelli-Filho et al. (2021) and Merkle (2017) further validated similar findings from a survey of UK investors and day traders in Brazil, respectively. Mishra and Metilda (2015) detected gender, education, experience, and self-attribution bias as the critical determinants of overconfidence bias. Based on a micro-world setting, Trejos et al. (2019) showed that gender and education contribute to overconfidence among investors. Age, experience, gender, and occupation are important factors affecting investors' behavioural biases (Baker et al., 2019).

Following Statman et al. (2006), the overconfidence bias has been studied by several research studies in numerous stock markets worldwide. For instance, Griffin et al. (2007) examined the relationship between trading activity and lagged returns in 46 nations and discovered convincing evidence of overconfidence bias in many of them. Similar evidence of overconfidence bias has been presented by Alsabban and Alarfaj (2020) and Prosad et al. (2018) for the Saudi and Indian stock markets, respectively. Using monthly observations of the common stocks traded on the Shenzhen Stock Exchange in China, Zaiane (2013) discovered compelling evidence of overconfidence bias. The relationship between current turnover and historical stock returns has been tested by Zia et al. (2017) and supported the overconfidence hypothesis in the Pakistani stock market. Metwally and Darwish (2015) strained this relationship in the Egyptian bourse for different market states and found the trading activity to be driven by investors' overconfidence when the market is trending upward. In contrast to these studies, Zaiane and Abaoub (2009) found little evidence of overconfidence bias among investors in Tunisia.

Moreover, there is still a paucity of research on whether investors are overconfident in different asset classes (Dhingra et al., 2023). In the study of US mutual fund investors, Bailey et al. (2011) discovered the influence of overconfidence bias on their trading choices. Lin et al. (2010) tested propositions of overconfidence models in the US REIT market and found results consistent with the investor overconfidence hypothesis. Similarly, Bao and Li (2020) have tested the overconfidence in the six REIT markets of the Asia Pacific region. They found that overconfidence only exists during market booms and is more prevalent in inefficient market settings. Chen and Sabherwal (2019) reported investor overconfidence in the options market of the USA. In the case of the ETF market, Kunjal and Peerbhai (2021) offered evidence of overconfidence bias for both ETFs (having domestic and international benchmarks). Given the importance of overconfidence bias and its implications on trading activity and volatility, there is not a single empirical study testing the overconfidence bias in the Indian ETF market. Therefore, this study fills a gap in the existing body of knowledge by examining the overconfidence bias in the investors of the Indian ETF market. Hence this study posits the following hypothesis:

- Hypothesis 1: Positive lagged market returns lead to increased trading activity in the subsequent periods among overconfident investors during the pre-pandemic/normal period.

Moreover, the financial markets have undergone unprecedentedly dramatic movement due to COVID-19 pandemic. This has raised the risk in the financial markets worldwide. FIIs were selling heavily in the majority of emerging economies and parking their assets in safe havens. The number of COVID-19 confirmed cases is negatively associated with emerging countries' financial markets' liquidity (Haroon and Rizvi, 2020). In their study, Shrotryia and Kalra (2021) examined the implications of the overconfidence model in global (developed, emerging, and frontier) stock markets by incorporating the COVID-19 phase. Their results showed the pandemic caused a drop in investor confidence in developed country stock markets. Investors in a few emerging and frontier markets were still overconfident during the pandemic. Azam et al. (2022) found significant overconfidence bias in the cyclical and defensive sectoral indices of the National Stock

Exchange during the pandemic period. Keeping this in mind, the second hypothesis for the study is as follows:

- Hypothesis 2: Positive lagged market returns lead to increased trading activity in the subsequent periods among overconfident investors during the pandemic period.

These hypotheses seek to examine the relation between current trading volume and historical returns of selected domestic equity ETFs during regular and pandemic periods. The results will help the authors compare the overconfidence bias among investors in a stable environment with the pandemic period.

3 Data and methodology

3.1 Data

The present study concentrates on ETFs which consist of only stocks within their underlying portfolio. In this regard, commodity-based funds (primarily gold ETFs) and funds containing fixed-income or money-market securities have been excluded. All Indian equity-index ETFs listed on the National Stock Exchange were identified for selecting the sample for the study. This resulted in removing the equity ETFs with an international benchmark, like HNGSNGBEES, MON100, etc. The sample period for the study spans from April 2012 to March 2022. This is the period of the astronomical rise in the Indian ETF market. Considering the sample period, we took ETFs listed before April 2012 and were still active by the end of the sample period. A few ETFs have been omitted due to a lack of continuous data. Therefore, a set of 12 domestic equity index ETFs has been considered for the study. The sample used in this study is comprised of the daily prices (high, low, and closing) and transaction volume for the selected ETFs. In the existing empirical literature, Alsabban and Alarfaj (2020), Metwally and Darwish (2015) and Statman et al. (2006) used monthly data to examine the overconfidence bias based on the assertion that shifts in investor overconfidence tend to unfold within monthly or yearly horizons (Gervais and Odean, 2001; Odean, 1998a, 1998b; Statman et al., 2006). In contrary to this, Abreu and Mendes (2012) and Tourani-rad and Kirkby (2005) studies have indicated that overconfident investors frequently engage in monitoring their portfolios, with daily assessment of investment strategies being a common practice. In addition to this, Bajzik (2021) highlighted that employing monthly data or VAR models makes the effect of trading volume on returns substantially more negative. Against this backdrop, the present study has used the daily data to examine the overconfidence bias in Indian ETF market. The whole sample period is divided into two eras: pre-COVID-19 and during COVID-19. The pandemic period is considered from 25 March 2020 to 31 March 2022, as the Indian government imposed the first nationwide lockdown on 25 March 2020. All of the ETFs included in the sample are listed in Table 1. Data for the study has been collected from the official website of the National stock exchange (http://www1.nseindia.com).

The daily ETF return is calculated using the following formula:

$$R_{i,t} = LN\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

where $R_{i,t}$ is the return of ETF i at time t; $P_{i,t}$ is the closing price of ETF i at time t; $P_{i,t-1}$ is the closing price of ETF i at time $t-1$.

Table 1 Sample for the study

Symbol	*Issuer name*	*Launch date*
BSLNIFTY	Birla Sun Life AMC	21-Jul-11
MOM100	Motilal Oswal AMC	31-Jan-11
KOTAKPSUBK	Kotak AMC	8-Nov-07
NIFTYBEES	Reliance Nippon Life Asset Management Limited	28-Dec-01
BANKBEES	Reliance Nippon Life Asset Management Limited	27-May-04
INFRABEES	Reliance Nippon Life Asset Management Limited	29-Sep-10
JUNIORBEES	Reliance Nippon Life Asset Management Limited	21-Feb-03
PSUBNKBEES	Reliance Nippon Life Asset Management Limited	25-Oct-07
KOTAKNIFTY	Kotak AMC	2-Feb-10
MOM50	Motilal Oswal AMC	28-Jul-10
QNIFTY	Quantum AMC	10-Jul-08
IVZINNIFTY	Religare AMC	13-Jun-2011

Following Prosad et al. (2018), the natural log of transaction volume ($V_{i,t}$) is considered for the study. In addition, daily volatility (VOLT) is added as a control variable to mitigate the potential effects of the contemporaneous relationship between volatility and volume (Shalen, 1993). For the calculation of volatility, the daily high and low values of an ETF are used (Prosad et al., 2018; Shrotryia and Kalra, 2021).

3.2 Methodology

Following Statman et al. (2006), the presence of overconfidence bias in the selected ETFs is tested using the bivariate market-wide VAR model and its associated IRFs. This approach is based on the relationship between current trading volume and past returns. The VAR model for the study has the following specification:

$$Z_t = \theta + \sum_{s=1}^{L} J_s Z_{t-s} + K_t X_t + \varepsilon_t$$

where Z_t is an $n \times 1$ vector of endogenous variables – return and transaction volume – at day t, X_t is an exogenous variable – volatility – at day t, J_s is the regression coefficient that measures how one endogenous variable interacts with its own, and another endogenous variable's lagged values, K_t is the regression coefficient that measures the interaction of endogenous with exogenous variable, θ is a constant and ε_t is an $n \times 1$ vector of residuals. This model demonstrates how one endogenous variable (volume/return) is a function of lagged values of its own (volume/return), another endogenous variable (return/volume), and residual term after controlling for the exogenous variable (volatility). The optimum lag length (L) for the VAR model is chosen using the Akaike information criterion (AIC). Individual VAR model is estimated for each of the selected ETFs.

Table 2 Descriptive statistics

			Mean	*Std. dev.*	*Skewness*	*Kurtosis*		*Mean*	*Std. dev.*	*Skewness*	*Kurtosis*
BSLNIFTY	Pre	Return	0.0005	0.0227	–0.0751	6.5499	JUNIORBEES	0.0003	0.0113	–0.8790	10.3153
		Volume	5.1015	1.6609	–0.1445	4.3720		9.6657	1.1099	0.3979	3.1132
		Volatility	0.0333	0.0356	2.0964	11.3596		0.0192	0.0144	4.5202	36.1281
	During	Return	–0.0084	0.1448	–15.6722	247.7458		0.0016	0.0111	–0.5409	6.9152
		Volume	8.4626	2.8836	0.8082	2.6528		11.3424	0.6165	0.9132	4.6445
		Volatility	0.0332	0.0313	2.8785	12.9722		0.0724	0.0612	1.3724	3.9936
MOM100	Pre	Return	0.0003	0.0129	–0.3567	5.8672	PSUBNKBEES	–0.0016	0.0561	–34.8768	1,431.1100
		Volume	10.2572	1.1783	0.3854	3.7862		7.3721	1.4727	0.4016	3.4411
		Volatility	0.0287	0.0234	3.9320	25.3913		0.0346	0.0255	3.0198	17.2297
	During	Return	0.0018	0.0140	–0.0868	6.5577		0.0014	0.0229	–0.1881	4.9936
		Volume	11.4029	0.7135	0.5490	4.4355		13.1064	1.2738	–0.1491	2.5967
		Volatility	0.0352	0.0255	3.2963	21.6243		0.0445	0.0290	2.8592	16.6433
KOTAKPSUBK	Pre	Return	–0.0005	0.0200	0.0348	6.9749	KOTAKNIFTY	–0.0009	0.0526	–42.3505	1,851.5780
		Volume	7.7063	1.5778	–0.4668	2.8069		9.0052	2.1087	–0.4380	2.8794
		Volatility	0.0307	0.0227	2.8377	17.1297		0.0149	0.0207	6.2323	53.5976
	During	Return	0.0014	0.0225	–0.2199	4.2065		0.0016	0.0111	–0.1652	7.2834
		Volume	9.7604	0.8847	–0.3875	2.7979		11.0578	1.0441	0.5235	2.7490
		Volatility	0.0411	0.0250	1.8760	7.8849		0.0251	0.0239	2.6400	11.1906

Table 2 Descriptive statistics (continued)

			Mean	*Std. dev.*	*Skewness*	*Kurtosis*		*Mean*	*Std. dev.*	*Skewness*	*Kurtosis*
NIFTYBEES	Pre	Return	−0.0009	0.0525	−42.2751	1,847.0800	MOM50	0.0001	0.0148	−8.3520	209.6106
		Volume	10.6440	0.9917	1.5047	8.1201		8.0034	1.4782	−0.3259	3.2223
		Volatility	0.0145	0.0163	7.8856	94.6432		0.0239	0.0176	3.6930	24.5248
	During	Return	0.0016	0.0115	−0.0352	7.0520		0.0015	0.0128	−0.1295	5.6172
		Volume	14.4044	0.5556	0.6432	3.7825		7.4882	0.9558	0.5882	6.2668
		Volatility	0.0521	0.0465	1.6874	6.0159		0.0309	0.0247	2.7431	12.7295
BANKBEES	Pre	Return	−0.0009	0.0535	−40.1635	1,724.8830	QNIFTY	0.0002	0.0087	−1.3023	15.3769
		Volume	8.3275	1.6841	0.8624	3.8013		3.1880	1.6210	0.1227	2.9266
		Volatility	0.0194	0.0160	3.5963	23.1448		0.0135	0.0363	3.3215	16.1576
	During	Return	0.0015	0.0187	0.1390	6.4567		0.0016	0.0125	0.6333	16.1183
		Volume	13.6015	0.6092	0.0306	3.3679		3.2839	1.5282	0.2174	3.1573
		Volatility	0.0309	0.0222	2.8087	14.6715		0.0144	0.0282	6.4483	58.8862
INFRABEES	Pre	Return	0.0000	0.0178	−0.1938	8.4647	IVZINNIFTY	0.0002	0.0185	−0.2750	21.5612
		Volume	6.1575	1.3637	−0.4525	4.3985		2.7979	1.4763	0.2014	3.0996
		Volatility	0.0286	0.0273	3.2025	20.2375		0.0171	0.0412	2.6085	14.8222
	During	Return	0.0016	0.0135	−0.3333	5.1959		0.0016	0.0176	0.9083	33.4201
		Volume	7.1660	1.1911	−0.1476	4.4891		2.7488	1.4237	0.1666	2.6432
		Volatility	0.0363	0.0320	2.6059	12.3296		0.0272	0.0493	3.0187	13.3373

4 Empirical results and discussion

4.1 Descriptive statistics

The descriptive statistics (Table 2) for ETF returns, volume, and volatility are studied to have a preliminary overview of the data and their behaviour for both pre and during the pandemic period. BSLNIFTY is found to be the ETF that has provided the highest mean return of 0.000503 in the pre-COVID-19 period. Some ETFs have reported negative average returns in the pre-pandemic period. During the pandemic period, M100 (0.001777) and IVZINNIFTY (0.001649) has the highest average return. Moreover, PSUBNKBEES has recorded the largest return deviation (0.056064) and mean volatility (0.034558) during the pre-COVID-19 phase.

Similarly, BSLNIFTY reveals the largest return deviation (0.14482) with mean volatility of 0.033241 in the pandemic phase. Most of the series are skewed and have leptokurtic distribution as their kurtosis value is greater than 3.[1]

4.2 Stationarity test

A time series is stationary if its statistical properties (mean, variance and covariance) are time-invaring. The return series and volume series of all the ETFs considered for the study are tested for stationarity using the Augmented Dickey-Fuller (ADF) test at a 5% significance level. The findings of the ADF test for each time series for both pre-and during-COVID-19 are covered in this section. The null hypothesis for the ADF test is that the time series [Y(t)] has a unit root. This null hypothesis needs to be rejected for the series to be stationary. The ADF test results in Tables 3 and 4 suggest that all the relevant series are stationary (p values are less than 0.05) for all the ETFs for both pre-and during-COVID-19.

Table 3 Stationarity test results for the pre-pandemic period

	Pre COVID-19			
Symbol	*Volume*		*Return*	
	t-stat	*p-value*	*t-stat*	*p-value*
BSLNIFTY	–21.71127	0	–31.2322	0
MOM100	–7.325615	0	–48.3739	0
KOTAKPSUBK	–7.380978	0	–42.0453	0
NIFTYBEES	–3.604754	0.0296	–44.5679	0
BANKBEES	–11.18436	0	–44.4442	0
INFRABEES	–9.743304	0	–36.6425	0
JUNIORBEES	–7.218233	0	–43.2855	0
PSUBNKBEES	–11.03194	0	–44.6163	0
KOTAKNIFTY	–9.750453	0	–44.3851	0
MOM50	–14.37607	0	–48.1436	0
QNIFTY	–29.91497	0	–26.8634	0
IVZINNIFTY	–18.87193	0	–30.6838	0

Table 4 Stationarity test results for the pandemic period

	During COVID-19			
Symbol	*Volume*		*Return*	
	t-stat	*p-value*	*t-stat*	*p-value*
BSLNIFTY	–5.197756	0.0001	–15.5739	0
MOM100	–15.93902	0	–25.524	0
KOTAKPSUBK	–6.002801	0	–21.0592	0
NIFTYBEES	–4.910802	0.0003	–22.3621	0
BANKBEES	–5.359653	0	–21.4056	0
INFRABEES	–8.967073	0	–25.9128	0
JUNIORBEES	–17.78225	0	–21.8699	0
PSUBNKBEES	–5.612499	0	–22.3732	0
KOTAKNIFTY	–17.3521	0	–21.9716	0
MOM50	–17.8385	0	–24.3555	0
QNIFTY	–18.60506	0	–22.9235	0
IVZINNIFTY	–11.68711	0	–16.4307	0

4.3 Pre COVID-19

Table 5 reports the results of VAR for all the ETFs considered for the study during the pre-COVID-19 period. Testing for statistical significance is done at 1%, 5%, and 10%. Results in the upper panel of Table 5 reveal that the transaction volume is autocorrelated with its lags, as shown by their highly significant coefficients. Furthermore, the coefficients of lagged transaction volume decrease with the increase in the number of lags. The IVZINNIFTY ETF has the largest autocorrelation coefficient at first lag [t value = 22.63559].

The lower panel of Table 5 shows the positive relationship between the transaction volume and lagged returns of some of the ETFs. This positive relationship is found to be significant at different lags, such as for BSLNIFTY (1, 2, 3 days), MOM100 (1, 4, 8, 15 days), KOTAKPSUBK (1, 2, 13 days), INFRABEES (1, 3, 6, 7, 8, 13 days), JUNIORBEES (2 days) and MOM50 (1, 2, 3, 4, 5 days) even after controlling for volume-volatility relationship. This confirms the positive relation between transaction volume and laggard returns, demonstrating the overconfidence bias in the above-mentioned ETFs in India. The relevant coefficients for NIFTYBEES, BANKBEES, PSUBNKBEES, and KOTAKNIFTY are significantly negative, showing the underconfident trading behaviour by investors during the pre-COVID-19 period. Furthermore, the results show that the investors of QNIFTY and IVZINNIFTY ETFs have no overconfidence bias. All of the ETFs included in the study show that volatility has a significant positive contemporaneous relationship with transaction volume.

Table 5 VAR results for the pre-pandemic period

Parameters	*BSLNIFTY*	*MOM100*	*KOTAKPSUBK*	*NIFTYBEES*	*BANKBEES*	*INFRA BEES*	*JUNIOR BEES*	*PSUBNKBEES*	*KOTAKNIFTY*	*MOM50*	*QNIFTY*	*IVZINNIFTY*
$V_{i,t-1}$	0.134***	0.176***	0.276***	0.329***	0.211***	0.189***	0.226***	0.255***	0.282***	0.176***	0.335***	0.509***
$V_{i,t-2}$	0.071***	0.079***	0.077***	0.093***	0.123***	0.076***	0.103***	0.118***	0.202***	0.066***	0.033	0.075***
$V_{i,t-3}$	0.051**	0.093***	0.122***	0.103***	0.105***	0.098***	0.117***	0.100***	0.069***	0.044*	0.018	0.048*
$V_{i,t-4}$	0.029	0.070***	0.070***	0.017	0.039*	0.054**	0.073***	0.108***	0.083***	0.097***	0.035	0.003
$V_{i,t-5}$	0.049**	0.036	0.020	0.062***	0.059**	0.009	0.025	0.054**	0.113***	0.073***	–0.009	0.039
$V_{i,t-6}$	–0.006	0.051**	0.033	0.039	0.054**	0.027	0.046**	0.024	0.048**	0.069***	0.037	0.005
$V_{i,t-7}$	0.044**	0.035	0.023	0.090***	0.053**	0.074***	0.106***	0.036	0.066***	0.065***	0.037*	0.005
$V_{i,t-8}$	0.054***	0.060***	0.071***	0.003	0.011	0.036	0.003	–0.001	0.068***	0.009		0.059***
$V_{i,t-9}$	0.065***	0.008	–0.010	0.041*	0.032	0.028	–0.008	0.039*		0.078***		
$V_{i,t-10}$		0.036	0.065***	0.078***	0.072***	0.015	0.069***	–0.007		0.036		
$V_{i,t-11}$		0.019	0.023		0.042*	–0.010	–0.045*	0.053**		0.067***		
$V_{i,t-12}$		0.030	–0.015		0.064***	0.061***	–0.017	0.075***		0.098***		
$V_{i,t-13}$		0.029	0.024			0.041*	0.017					
$V_{i,t-14}$		0.061***	0.039*			0.082***	0.036					
$V_{i,t-15}$		0.061***	0.065***				0.064***					
$V_{i,t-16}$							0.069***					
$R_{i,t-1}$	3.363**	4.258**	1.930*	–0.500*	–0.419	3.120**	1.694	–0.098	–0.526	3.867**	–0.660	0.785

Note: ***, ** and * represent the significant values at 1%, 5% and 10% significance level.

Table 5 VAR results for the pre-pandemic period (continued)

Parameters	*BSLNIFTY*	*MOM100*	*KOTAKPSUBK*	*NIFTYBEES*	*BANKBEES*	*INFRA BEES*	*JUNIOR BEES*	*PSUBNKBEES*	*KOTAKNIFTY*	*MOM50*	*QNIFTY*	*IVZINNIFTY*
$R_{i,t-2}$	3.858**	2.460	3.669***	–0.667**	–0.406	0.815	3.119*	–0.376	–0.883*	3.755**	–0.291	–1.513
$R_{i,t-3}$	2.735*	2.107	–0.976	–0.584*	–1.046*	3.821**	0.016	–0.139	–0.401	4.833***	–1.934	1.620
$R_{i,t-4}$	–1.821	4.477***	0.370	–0.241	–0.679	2.137	1.641	–0.048	–0.146	2.934*	–1.360	0.843
$R_{i,t-5}$	–0.433	–0.706	–0.025	–0.338	–0.680	1.480	1.035	–0.261	–0.267	4.233**	–5.960	0.773
$R_{i,t-6}$	–1.602	–0.210	1.376	–1.362***	–1.560***	2.812*	1.408	–1.269***	0.037	1.034	–3.218	0.781
$R_{i,t-7}$	–0.140	–1.063	–0.923	0.075	–0.915	4.839***	1.022	–0.328	0.121	–0.581	4.968	1.568
$R_{i,t-8}$	–0.269	4.014**	0.228	–0.055	0.430	3.004*	–0.879	0.272	–0.105	0.485		0.559
$R_{i,t-9}$	0.546	1.080	0.402	–0.047	–0.144	–0.714	–0.887	–0.264		0.114		
$R_{i,t-10}$		2.743	–0.214	–0.148	–1.609***	1.629	–1.121	–0.440		–2.510		
$R_{i,t-11}$		–0.328	1.432		–0.461	1.829	0.543	–0.766*		–0.418		
$R_{i,t-12}$		–0.503	–0.827		–1.080*	1.904	–1.348	–0.063		0.162		
$R_{i,t-13}$		–0.311	3.814***			–2.807*	–0.081					
$R_{i,t-14}$		0.295	–1.226			–0.283	–1.166					
$R_{i,t-15}$		2.984*	–1.235				1.419					
$R_{i,t-16}$							0.509					
Const	2.042***	1.333***	0.471***	1.433***	0.850***	0.950***	0.834***	0.675***	0.545***	0.631***	1.527***	0.620***
Volt	16.919***	10.123***	14.599***	8.049***	13.939***	14.371***	14.877***	11.452***	5.563***	14.877***	8.387***	5.775***

Note: ***, ** and * represent the significant values at 1%, 5% and 10% significance level.

Table 6 VAR results for the pandemic period

Parameters	*BSLNIFTY*	*M100*	*KOTAK PSU BK*	*NIFTYBEES*	*BANKBEES*	*INFRA BEES*	*JUNIOR BEES*	*PSUBNKBEES*	*KOTAKNIFTY*	*M50*	*QNIFTY*	*IVZINNIFTY*
$V_{i,t-1}$	0.471***	0.275***	0.154***	0.415***	0.214***	0.239***	0.210***	0.373***	0.244***	0.058	0.208***	0.201***
$V_{i,t-2}$	0.108	0.065	0.102**	0.087*	0.159***	0.086*	0.056	0.159***	0.101**	–0.131***		0.124***
$V_{i,t-3}$	0.030	0.071	0.089**	0.048	0.048	0.149***	0.140***	0.046	0.110**			0.056
$V_{i,t-4}$	0.080	0.053	0.103**	0.103**	0.070	0.029	0.029	0.213***	0.072			
$V_{i,t-5}$	0.020	0.113***	0.011	0.134***	0.082*	0.077*	0.123***	0.123***				
$V_{i,t-6}$	0.044		0.115***		0.065	0.113**						
$V_{i,t-7}$	0.185***		0.128***		0.088*	0.110**						
$V_{i,t-8}$					0.077*							
$R_{i,t-1}$	–0.204	6.178***	3.022**	–1.155	1.550	1.377	–4.061	3.229**	4.082	1.348	–2.465	5.799*
$R_{i,t-2}$	–0.375	2.857	2.118	–0.248	1.393	5.371	–0.836	1.559	8.741**	2.796		2.332
$R_{i,t-3}$	–0.861	3.940*	1.019	–3.273*	–1.493	8.577**	–3.283	–1.502	–1.589			–4.131
$R_{i,t-4}$	–0.022	3.332	2.470*	1.542	1.542	–0.838	3.395	–0.428	9.894**			
$R_{i,t-5}$	0.083	–0.540	2.595*	–0.551	–0.484	–2.621	–1.283	0.355				
$R_{i,t-6}$	0.029		0.018		–2.327*	0.132						
$R_{i,t-7}$	–1.390**		0.757		–2.433**	–1.892						
$R_{i,t-8}$					–0.768							
Const	0.262	4.481***	2.433***	3.058***	2.512***	1.157***	4.974***	0.805**	5.082***	7.679***	2.366***	1.403***
Volt	9.186***	8.658***	11.558***	0.442	5.365***	7.330***	0.490	7.346***	4.211**	11.482***	16.357***	10.974***

Note: ***, ** and * represent the significant values at 1%, 5% and 10% significance level.

Figure 1 IRFs of transaction volume to shock in the return of ETF (pre-pandemic period) (see online version for colours)

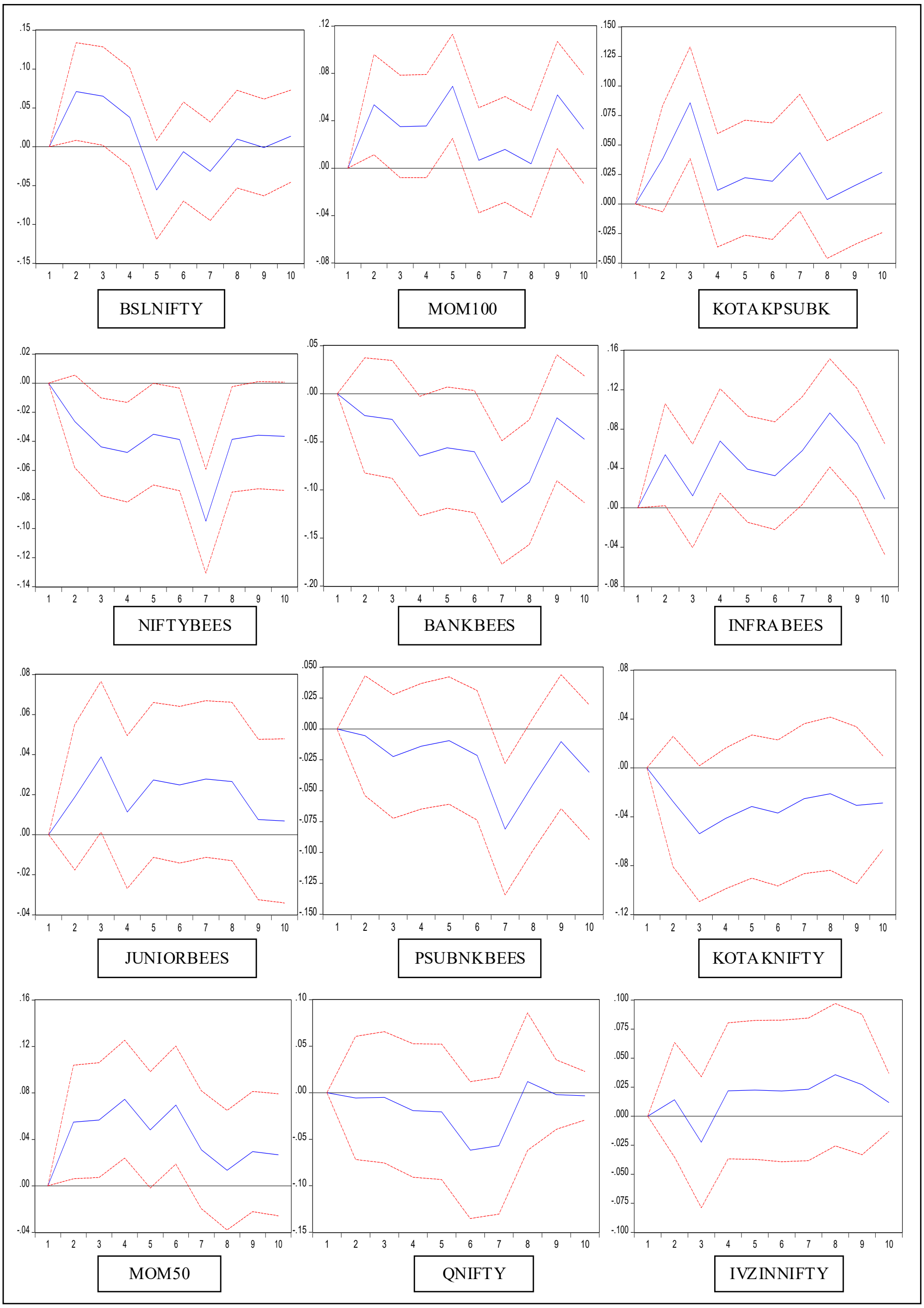
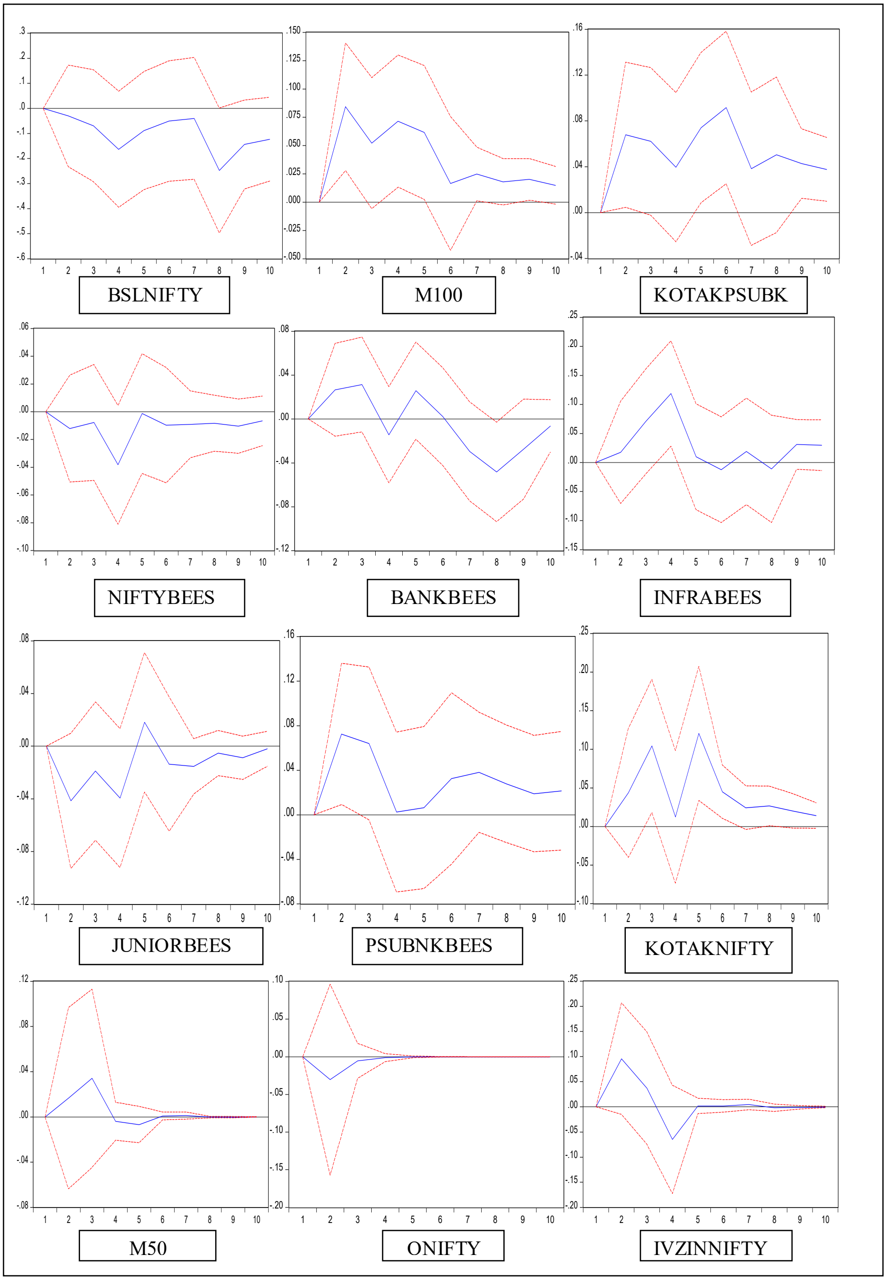


Figure 2 IRFs of transaction volume to shock in the return of ETF (pandemic period) (see online version for colours)



In addition, Figure 1 presents the response of transaction volume to one standard deviation shock in return for the ETFs. IRFs are plotted for ten days for all the ETFs. Figure 1 shows that a shock of one standard deviation in return leads to a positive response by the transaction volume for BSLNIFTY (7.118%), MOM100 (5.359%),

KOTAKPSUBK (3.856%), INFRABEES (5.391%), JUNIORBEES (1.873%) and MOM50 (5.5%) in the subsequent two days. Since the values are almost zero, the transaction volume's reaction to the market return shock is not reported for the first day. Moreover, for MOM100, KOTAKPSUBK, INFRABEES, JUNIORBEES, and MOM50, the positive IRFs persist for the entire ten-day period. INFRABEES ETF received the biggest total of responses (43.463%), followed by MOM50 (40.486%). These results demonstrate how returns affect investors' confidence and subsequent trading behaviour in these ETFs.

4.4 During COVID-19

Table 6 displays the VAR estimations for the COVID-19 period. With the exception of MOM50, transaction volume is significantly autocorrelated for all other ETFs. The majority of ETFs also exhibit the volatility-volume relationship. The VAR results show that there is a significant positive relationship between transaction volume and lagged returns for MOM100 (1, 3 lag(s)), KOTAKPSUBK (1, 4, 5 lag(s)), INFRABEES (3 lag(s)), PSUBNKBEES (1 lag), KOTAKNIFTY (2, 4 lag(s)) and IVZINNIFTY (1 lag). ETFs such as JUNIORBEES, MOM50, and QNIFTY witnessed no overconfidence bias during the COVID-19 period. Results for BSLNIFTY, NIFTYBEES, and BANKBEES show that their investors are underconfident.

Figure 2 shows the COVID-19 phase IRFs for ten days for all the ETFs. It shows that a shock of one standard deviation in return leads to a positive response by the transaction volume for MOM100 (8.434%), KOTAKPSUBK (6.794%), BANKBEES (2.662%), INFRABEES (1.772%), PSUBNKBEES (7.256%), KOTAKNIFTY (4.358%), MOM50 (1.657%) and IVZINNIFTY (9.57%) on the second day. Moreover, for MOM100, KOTAKPSUBK, PSUBNKBEES, and KOTAKNIFTY, the positive IRFs persist for the entire ten-day period. For ETFs such as JUNIORBEES, the positive response by the transaction volume is recorded for the fifth day (1.820%).

5 Conclusions, implications and limitations

ETFs have developed into one of the most successful ideas in the financial sector. Equity ETFs in India are expanding quickly due to increased interest from various investment sectors regardless of the COVID-19 pandemic's enhanced market volatility. A strand of literature has supported that irrationality is present in the financial markets. Therefore, ETF investors' trade choices may not always be rational. In light of the ETF markets' rapid expansion, irrationality in investment choices in ETF markets may endanger the stability of financial markets. As a result, the present study aims to investigate the overconfidence bias in the Indian ETF market using a sample of 12 equity ETFs in both pre and during the pandemic period. VAR and IRFs are used to understand the relation between the lag returns and the volume of the data.

The study's findings are twofold; first, we found that before the pandemic Indian retail investors were overconfident in BSLNIFTY, MOM100, KOTAKPSUBK, INFRABEES, JUNIORBEES, and MOM50 as indicated by the significant positive, relevant coefficients at different lags. Among these, only BSLNIFY has lost its attraction during COVID-19. The ETFs that do not contribute to investors' overconfidence in the pre-pandemic phase are NIFTYBEES, BANKBEES, PSUBNKBEES, KOTAKNIFTY, QNIFY, and IVZINNIFTY. This could be attributed to the differences in the various attributes of ETFs, including transaction costs, management fees, etc. Another reason could be the lack of liquidity in these ETFs, which is necessary to support quick and frequent trade.

However, we found that during COVID-19, investors gained overconfidence in PSUBNKBEES. The investors were more optimistic about the banking sector of the Indian economy as the banks are well capitalised, and the corporations that account for more than half of the banks' loans are also in a better financial position. Therefore, investors were taking their positions in banking sectors since banks are well positioned to recover from a long tenure of stress. All this implies that the unpredictable market movements in the Indian ETF market brought on by the current pandemic are explicable by behavioural finance. Similar results for the existence of overconfidence bias among investors are provided in the USA (Statman et al., 2006) and Indian (Mushinada and Veluri, 2018; Prosad et al., 2018) stock markets. Kunjal and Peerbhai (2021) demonstrated the presence of overconfidence bias in the South African ETF market. Overall in the case of Indian ETFs, we found no reason to say that there is a significant difference in the investors' overconfidence.

Overconfidence bias can lead to dramatic stock market reactions and significant risks to one's wealth. This study delves into the intricate mechanisms through which overconfidence can lead to excessive risk-taking. Among the numerous biases examined, overconfidence is rife in financial markets with profound implications for investment decision-making. The findings of this research study extend their significance to various stakeholders, including investors, asset management companies, regulators, and policymakers. This will help investors in counteracting the overconfidence bias and constructing more informed investment strategies to align their expectations with the actual return on their investment. By fostering a more realistic understanding of market dynamics, asset management companies educate their clients; assist them in managing their risk exposures effectively and enhancing their prospects of achieving optimum returns. Furthermore, regulators and policymakers should strategically intervene through investor awareness programmes to reduce investor overconfidence, promote informed and effective investment decisions. These measures enhance market efficiency and contribute to a stable and resilient financial market.

5.1 Limitations of the study

The primary focus of the current study is to examine the impact of lagged returns on current trading volume while controlling the impact of volatility. In this regard, the various other factors (such as expense ratio, liquidity, tracking errors, etc.) have been ignored. Thus, the future studies should encompass a broader spectrum of variables to comprehensively explore the multifaceted landscape that shape ETFs trading volume. In addition, the current study uses the daily prices and transaction volume for analyses. Future research can use high-frequency data to examine the overconfidence bias as it could provide more significant insights. Moreover, further researchers could explore the factors that gain the investors' trust in the Indian banking system and how such factors can be exploited to retain and attract new investors in other sectors. Further research can explore other biases (like anchoring, representativeness, mental accounting, etc.) in the Indian ETF market.

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Notes

1 Additionally, the correlation and variance inflation factors (VIFs) among the concerned variables are observed to be within the limits (correlation less than 0.7 and VIF less than 10), suggesting that multicollinearity is not problematic.