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How Does Investors' Attention Influence Equity Trading and Performance? Evidence from Listed Indian Companies

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Abstract

Purpose: The present study investigates the impact of investors' attention on both equity performance and trading. Besides, it also investigates the corporate affairs that attract more investors to a company.

Design/methodology/approach: The study uses a sample of 60,200 weekly observations of the companies from FY2014 to FY2022 (till November 2022) to assess the impact of investors' attention on both stock performance and trading.

Findings: The study finds that investors' attention is positively linked to stock performance. However, this link disappears shortly. On the other hand, the Volume has a positive relationship with the number of trades that do not change subsequently, but its ability to predict the future gets worse over time. The study further finds that some companies' events have fuelled investors' interest.

Practical implications: The Google Index could potentially be referred to show investors' interest. Further, AGTI is able to forecast a short-term shift in equity performance, which can result in short-term profits or help investors escape from getting short-term losses from their investments. Lastly, particularly corporate events can herald a shift in AGTI, and hence, in investors' interest.

Originality/value: The majority of earlier research has evaluated attention indirectly, using headlines and sensationalism, commercials, and upper and lower price limits. The present study, on the other hand, assesses investors' interest by using a simple and direct metric: the cumulative searching rate in a search engine, the data of which is provided by Google.

Keywords: Stock Performance, Trading volume, investors' attention, Panel data analysis.

JEL Classification: G11, G12, G34, G35, G41

1. Introduction

Theoretical approaches to finance presume that investors have access to useful data and pay adequate attention to it when they look at it and decide how to act on it (Hou et al., 2011). The Efficient Markets Hypothesis (EMH) posits investors evaluate stocks rationally by using the data they receive (Fama, 1965; Mangram, 2013). However, due to the restricted intellectual capacity of the human mind, concentration is a scarce intellectual asset. Because of the abundance of data available, retail investors can only give their decisions a limited amount of attention, particularly in the alleged information age that we live in. Accordingly, limited attentiveness might have an impact on the trading activities and stock returns of investors. Retail investors have traditionally played a significant role in India's economy, which is the major developing market in the world. India is witnessing an incredible increase (400% increase in the pace of opening Demat Accounts over the last six years[1]) in retail participation, particularly in the last three years. In developed nations, where there are often more institutional investors, this does not hold true. Individual investors' conduct is far more prone to cognitive bias than that of institutional investors because individual investors are less experienced. Over the past few years, investor awareness has been identified as a cause of variations in stock performances and is now increasingly commonplace (Bai et al., 2012; Johari et al., 2022; Ali et al., 2022**).** One illustration of this phenomenon is the online fame effect. The present inquiry will focus on India as it will attempt to answer two issues: Does the attention of investors have any bearing on the trading pattern of investors? Does the attention of investors have an effect on stock performance?

Assessing investor interest is challenging. The majority of earlier research has evaluated attention indirectly, using headlines (Yuan, 2015) and sensationalism (Ichev & Marinč, 2018), commercials (Chemmanur & Yan, 2012), and upper and lower limits (Seasholes & Wu, 2007). The indirect measurements primarily operate if investors really notice about particular stocks, for instance, when the particular stock appears in the headline, and investors notice it; if not, assessments introduce prejudice in the relationship between attention and investment. There have been several early attempts to use browsing habits to identify attention in numerous financial activities, including property sales, tourism, and the healthcare field (Choi & Varian, 2012; Ginsberg et al., 2009). Given that the act of searching for something implies an interest in and focus on the subject matter, these findings provide a straightforward method for gauging attention (Da et al., 2011).

Throughout this study, we assess investor interest using a simple and straightforward metric: the cumulative searching rate in a search engine, the data of which is provided by Google. As previously said, the Indian stock market is experiencing an unprecedented surge in retail participation, and retail investors are increasingly likely to use browsers, social media platforms, and the news to gather information. Specifically, the study collects investors' browsing data using the “Google Trend index”, which provides data on the activities of numerous users on Google. The index also provides daily data on a real-time basis and can best

[1] Source: SEBI, NSDL and CDSL

capture the attention of Internet users. Consequently, we use the weekly Google Trend Index (GTI) as a proxy for investor interest in India.

The study uses a sample of 60,200 weekly observations of the companies from FY2014 to FY2022 (till November 2022, the study finds that abnormal GTI, that is, AGTI indicates a favourable relationship with stock performance. However, this relationship is totally altered in the next period; and AGTI also shows a positive relationship with the trading volumes; however, this relationship has not changed in the next period. The results show that investors' attention has brief effects on the equity prices and the number of trades that happen. The study also shows that the aforementioned relationship is stronger for the NIFTY NEXT 50 market and for companies with a greater level of financial disclosure. The relationship between stock performance and trading volumes is stronger in an uptrend market than in a downtrend market (Chiang et al., 2010; Duong et al., 2021; Guimarães, et al., 2021). The study looks to see if the rise in AGTI is caused by certain company events to learn more about why investors are paying attention. It is found that four types of company events, such as declarations of financial performance results, annual general meetings' projections, market analyst ratings, mergers and amalgamations, and dividend payment decisions, are linked to an increase in the AGTI.

This study adds to the body of knowledge in three ways. First, it uses a direct measure to measure investors' attention. In contrast to previous research, which focused on indirect attention, that is, when investors learn about specific information across announcements, news, ads, or other media, the study uses browsed information to depict proactive attention. The present alternative makes up for the problems associated with indirect measures, since browsing behaviour is a clear sign of interest in and focus on the data gathered. The outcomes from the direct assessment relate to Kahneman's hypothesis of restricted attention (Donovan & Epstein, 1997). Besides, the findings of the study indicate the unpredictable economic effects of investor interest in a developing economy. The developing markets are generally portrayed as having a large number of retail investors and a few big investors. The conduct of retail investors is far more sensitive to psychological biases than that of large investors. The study documents the impact of investor attention on stock performance and trading volumes in India in the short run, as a corresponding contrast or diminution of influence has been documented.

The outcomes of the study align with those studies which are based on developed markets (Da et al., 2011; Tang & Zhu, 2017). Further, findings also demonstrate the moderating effect of institutional characteristics by demonstrating that the relationship between investors' attention and market performance differs among segments of the market, data environment, and market quotation. Besides, findings on segments of the market indicate that, throughout market segments, the search volume indicator is more effective in attracting the attention of inexperienced retail investors (Da et al., 2011). It further investigates company affairs that garner so much attention from investors and financial analysts. The findings, on the other hand, contradict the study (Drake et al., 2012) that focuses on S&P 500 equities in the United States. It indicates that amalgamation and take-over announcements have the largest correlation with investor interest, whereas financial statements and financial analyst interest have weaker correlations. One potential reason could be that Indian investors are less experienced or educated than their U.S. counterparts, and they depend largely on financial analysts and other experts. Consequently, the findings of the study add to the literature in the fields of data-driven attention and behavioral finance.

The rest of this study is structured as follows. The Literature section reviews some of the most associated literature and introduces our research hypotheses. The research methodology and data collection are described in the third section. The fourth section of this study summarises the outcomes of the primary interest. The fifth section contains an additional explanation. In the sixth section, we conclude the work.

2. Literature Review

Early studies have attempted to evaluate investor attention based on a variety of happenings, including ads, attention-inducing events, and coverage of media exposure (Chemmanur & Yan, 2012; Grullon et al., 2004; Hsu & Chen, 2019). They (Grullon et al., 2004) believe investors' knowledge of a company can be indicative of their interest in the company, and they use advertisements to determine a company's prominence among retail investors. Retail investors discover businesses with higher advertisement outlays induce more investors as well as more stock liquidity. A study conducted by Chemmanur & Yan (2012) hypothesizes by spending more on advertisements, the price of the stock can be manipulated by boosting investors' awareness of a company. The study demonstrates that enhanced investor familiarity is related to higher simultaneous stock yields, though worse future stock performance, and that the relationship is strong during the promotional period. Hsu & Chen (2019) employ a multi-variate Markov approach examining the differential influence of investor attention on Indian stock performance. In times of lower volatility, the portfolio with higher advertising earns a better above than average return than the portfolios of lower advertisements; nevertheless, during higher volatility, the excess return is negligible despite companies' raising their advertising outlays.

The research of Seasholes & Wu (2007) shows when the upper circuit of stock suddenly shifts, it attracts the attention of engaged retail investors, who then purchase stocks they have never purchased before. Nevertheless, this phenomenon is accompanied by an immediate price increase and a subsequent high-price average readjustment in the succeeding weeks. In addition, the study demonstrates that the price paid by shareholders determines the level of purchasing due to circulated information. Barber & Odean (2008) consider securities in the headlines, securities with unusual trading quantity, and securities with spectacular short-run performance as focus-inducing phenomena besides, it is also observed that retail investors are net purchasers of focus-grabbing stocks since the browsing process only occurs when they could possibly buy them. After attention determines the choice set, interests influence choices. Yuan (2015) examines Dow record levels and market articles as market-wide attention-grabbing events and finds that investors sell their stocks drastically when the share market is soaring.

In a study conducted by Gurun & Butler (2012), they tested to see if mainstream media reduces information-based divergences and changes the price of stocks. After taking risk elements into account, the study discovered that securities with no media exposure earn greater yields than securities with a lot of media exposure. This is especially true for small and penny stocks. Besides, it also holds true for securities with a lot of retail ownership, securities that financial analysts don't follow, and securities with a lot of idiosyncratic volatility.

The studies record the indirect attention paid by investors to newly given data. One big problem they have to deal with is that passive measures only work if investors really study the data and pay attention to it.

Recent research has used the amount of online search data to draw attention to a particular topic. Netizens typically engage in browsing activities to locate relevant data online, so the approach is fair. Eysenbach (2006) uses queries on the web to track influenza-like sickness in a community since the likelihood of specific inquiries is substantially connected with the proportion of clinic visits when a patient reports influenza-like symptoms. Several pieces of research reveal a substantial correlation between online activity and unemployment (Adachi et al., 2017), automobile sales, and individual spending (Vosen & Schmidt, 2011).

In finance, (Da et al., 2011) suggest using Google Trends' "Search Volume Index" to evaluate investor interest. (Vozlyublennaia, 2014) analyses if previous performance can predict future gains and volatility. They discover that growing investor attentiveness can enhance market efficiency by reducing price predictability. Using Google search traffic, Tang & Zhu (2017) are able to quantify the increase in investor interest and find a significant indication that it is associated with a favorable anomalous yield during the same day. After day zero, there doesn't seem to be a positive relationship between investor interest and share prices, and there doesn't seem to be a big difference between how ADRs from developing nations and those from developed nations react to an increase in investor interest. Adachi et al. (2017) examine the link between investor interest and fluctuations in the price of securities on Japanese start-up exchanges. Researchers discover a link between browsing rates, equity performance, and stock liquidity, especially in start-ups with an increased concentration of shareholders. Cornelli et al. (2006) also employ internet search traffic as a proxy for public investor interest and find that a rise in public investor interest post-initial filing, though before initial pricing, is positively correlated with the initial valuation.

Shen et al.(2017) presented data on developing nations, focusing on a market with small and newly listed companies, while Aouadi et al. (2013) found a strong correlation between investors' attention and trading volume. Andrei & Hasler, (2015) revealed that attention to news can increase stock market variance. Yang et al. (2021) examined the Chinese stock market, where retail investors dominate. However, the majority of earlier research (Chemmanur & Yan, 2012; Ichev & Marinč, 2018; Yuan, 2015)has evaluated attention indirectly, using measures such as headlines, sensationalism, commercials, and upper and lower limits.

In contrast, this present study uses a simple and straightforward method to directly measure investors' attention. Following a similar approach to Yang et al. (2021), the study aims to investigate the impact of investors' attention on equity performance and trading in India. It is important to note that there are notable differences between the Indian and Chinese markets. While institutional investors predominate in the Indian stock market, retail investors are dominant in China. Additionally, India has a more liberal stance towards social media, news platforms, and other online resources, whereas China has more restrictions on internet access.

Therefore, this study seeks to explore how investors' attention affects equity performance and trading in the unique context of the Indian stock market. By directly measuring investors' attention, this study aims to contribute to a more comprehensive understanding of the impact of attention on equity markets, particularly in the context of developing nations with low retail participation.

2.1. Research Hypothesis

In a theory of limited attention proposed by Kahneman (1973), focus on information is a precious asset of rationality, and restricted focus is an unavoidable consequence of accessing huge amounts of data and the limitations of data processing abilities. The theory might justify numerous discrepancies in conventional financial theories, such as irrational investors trading focusing on factors with zero intrinsic links to fundamental (Hirshleifer et al., 2006) and investors focusing on "obvious" data instead of "fuzzy" information, as attention must be selective and require effort. It is seen that as investors are confronted with numerous stocks, they rely on only a select few that spark their interest. When they pay heed to a certain set of securities, they seek detailed understanding and are likely to actively look for data about the equities. Since the information found would affect how investors make decisions and what kind of returns they expect, the amount of attention investors pay to the stocks becomes a factor that affects their prices and how much they trade.

Keeping in mind the above rationale, investors' focus on the available data may be positively related to stock value and trading volume, as investors' reactions to evident information can push stock prices and trading in the short-term (Kudryavtsev, 2020; Ravinagarajan & Sophia, 2022). On the other hand, such an influence could vanish or even correct itself in the long term, particularly the impact it has on stock performance (Bai et al., 2013; Lu et al., 2022; Mahmood et al., 2022). According to the theory of attention provided by (Barber & Odean, 2008), investors become net buyers of a stock when it is in the news for favourable reasons, putting upward pressure on the stock price. The rationale behind this is straightforward: while buying, investors have numerous options; when selling, they can only sell what they already own. This implies that retail attention disruptions might, on average, result in net purchases from ignorant traders. Positive investor attention within the context of (Barber & Odean, 2008) should forecast better stock performance in the short run and respond to downturns in the long run (Vieito et al., 2016; Niu et al., 2018; TajMazinani et al., 2022). The turnaround in stock returns may encourage investors to sell their stocks, preventing a turnaround in trading volumes in the upcoming time.

The present study has the following hypothesis:

H1: The attention of investors has a positive effect on equity performance in the short term but a negative effect in the long term;

H2: The attention of investors has a positive impact on trading volume both in the present and in the future.

3. Data and Methodology

3.1. Data

The study has taken a sample of 200 companies (NIFTY 50, NIFTY NEXT 50, and NIFTY Small Cap 100) listed on the National Stock Exchange (NSE) between FY 2014 to FY 2022 (till November 2022. The period of study comprises all the downtrend and uptrend phases in the market. The study further excludes the companies having insufficient financial data to execute our cross-sectional test.

Next, the study outlines the actions that it takes to collect the data. To begin, the study gathers the identity of the equities of a listed company on the Internet. On the web, investors browse stocks either by their full name or the code every stock has been given by NSE. The study chooses the full name of the company or its abbreviation instead of its code name as the keyword for browsing the company stock online.

The study further uses the R statistical package to get the index values of all the names or abbreviations of shares of the companies from "Google Trends," which gives information on how often each name is searched. The index is called the "Trend_Index," and it shows the average number of searches per week. "Trend_Index" gets investors to pay attention to a certain company, and consequently, we have 60,200 company-week observations of 200 listed (on NSE) Indian companies (NIFTY 50, NIFTY NEXT 50 and NIFTY Small Cap 100) during the study period.

We convert the "Google Trend Index" into a natural log of the Trend_index; that is, GTI = Ln(Trend_index), which is calculated as the logarithm of GTI in the present week less its average in the preceding six weeks as shown in the following:

$$AGTI_{x,t} = GTI - 1/4 \sum_{n=1}^{4} GTI_{x,t-n} \tag{1}$$

We note that AGTI is the primary focus of the current study. Likewise, the emphasis of the study is not on the normal returns rather on the abnormal returns generated by the stocks. The "anormal stock return" is calculated by deducting the average returns of the last four weeks from the returns of the current week. Similarly, the study focuses on "abnormal trading volume," which is calculated by deducting the average trading volume of the last four weeks from the trading volume of the current weeks. The study chooses abnormalities (abnormal stock returns and abnormal trading volumes) over a month (four weeks) so that less data is compromised during the data cleaning. The longer the period of abnormality, the greater the loss of data that would have impacted the study.

The database maintained by Capital IQ provides us with weekly stock returns as well as weekly trading volumes for the sample companies. The Moneycontrol database is the source of a variety of additional financial data, some of which include corporate factors, market segments, and the risk premiums on the market, amongst others.

3.2.Methodology

In order to prevent omitted variable bias, the primary OLS model follows Fama and French's (1993) three-factor CAPM. The study also includes other control variables, such as ratings from financial analysts and market indices from prior weeks. The research model is:

$$
\begin{aligned}
Y_{x,t} = v_x &+ \beta_1\, AGTI_{x,t} + \beta_2\, MCAP_{x,t} + \beta_3\, BP_{x,t} + \beta_4 MRP_t \\
&+\beta_5\, Institution_{x,t} + \beta_6 Ln\left(1 + \, Rat_{Analys} t_{i,t}\right) \\
&+\beta_7\, Retn_{x,t-1} + \beta_8 Trdv_{x,t-1} + \varepsilon_{x,t}\,,
\end{aligned} \tag{2}
$$

where $Y_{x,t}$ denotes Abnormal returns (Abn_Retn) of the stock and Abn_Trdv abnormal trading volume for stock x during week t. The study chooses Control variables considering the Fama-French 3-factor CAPM (FF3) and previous studies (Keim & Madhavan, 1997; Welagedara et al., 2017) as holding of the stock along with their trading influence the stock prices. Abnormal historical return and trading activity were once considered as indicators for investor attention (Barber & Odean, 2008); hence, the study include past variables (Retn $_{t-1}$, Trdv $_{t-1}$) in control variables, per Zhang & Wang (2015). Based on research by Welagedara et al., (2017) we find that the number of financial analysts rating in the current week (Rating_Analyst) has a substantial correlation with stock prices.

The study hypothesizes that investors' focus has a favorable effect on equity performance and trading volume during the going periods and anticipates a significant positive β_1 in the OLS model presented above. As the study further hypothesizes that equity performance could change in the following period, it anticipates a significant negative β_1 when the response variable is abnormal equity returns (Abn_Retn) when we use abnormal GTI in one previous term (AGTI $_{x,t}$) instead of abnormal GTI in the same period. Even though trading volume might not change in the next period, it considers β_1 that is higher than zero when the response variable is abnormal trading volumes (Abn_Trdv) (A1).

Conventional finance theories and studies implicitly deduce that when data are made public, market participants can access the data at a low cost and respond quickly (Chemmanur & Yan, 2012; McNichols & Trueman, 1994). However, they overlook a critical point to which investors pay either adequate or insufficient heed, depending on the patterns in which the data are publicly released. Grossman & Stiglitz (1980) contends that when arbitrage is costly, the notion that data are symmetrical and perfectly arbitraged is incompatible. They discover that valuations present the data of informed individuals partially; thus, those who devote resources to getting data are compensated, and the pricing system makes data publicly available and gathered by aware individuals to the unaware.

McNichols & Trueman (1994) examines how a shift in data requirement influences the stock market's reactions to earnings. They discover that irregular browsing for financial instruments goes up temporarily when revenues are announced. Hence, the study expects that there are potentially certain incidents that induce investors and make it easier for them to pay attention to them ahead of time. The current investigation makes the following suggestion for an additional research hypothesis:

H': Certain events associated with the listed companies help attract the attention of more investors.

The study follows Yang et al. (2021) for testing this hypothesis by focusing on six certain events: earnings releases, management projections, credit analyst’s ratings, mergers and amalgamations news, fresh stock offerings, and dividend declarations. The interest variable measurements are shown in Appendix A1.

The research model is developed as follows, with all variables' measurements provided in Appendix A1. When any of the correlation coefficients β_1 are strongly positive, the relevant event is critical in capturing the interest of investors.

$$\begin{aligned} \text{AGTI}_{x,t} = v_x &+ \beta_1 \text{ DeclarationEarn } t_{x,t} \\ &+\beta_2 \text{ Forecast } x,t + \beta_3 \text{CreditRat} t_{x,t} \\ &+\beta_4 \text{ MA}_{x,t} + \beta_5 \text{ FreshIssue}_{x,t} \\ &+\beta_6 \text{ DeclarationDiv}_{x,t} + \beta_7 \text{Abs}_{\text{ret}x,t} + \beta_8 \text{Trd}_{x,t} \\ &+\beta_9 \text{ MCAP}_{x,t} + \beta_{10} \text{ BP}_{x,t} + \beta_{11} \text{ Institution}_{x,t} + \varepsilon_{x,t}. \end{aligned} \tag{3}$$

4. Empirical results

Table 1 provides a statistical summary of the factors of key research significance. As mentioned, the minimum AGTI value is -0.681, and the maximum AGTI value is 1.021, indicating a significant level of attention variation among investors. The Google Trend Index for the present week may surpass (or fall below) the median GTI for the preceding eight weeks by 1.021 percent when the limits are reached (or 0.681). The median shareholding of institutions is 0.431 percent, indicating that around 43.1 percent of the market's shareholdings are owned by institutional investors, whereas the share of retail investors in the Indian stock market is on the continuous rise at an unprecedented rate, this also makes India an ideal setting for this study.

Table 1: Presents a statistical summary of the factors of key research significance.

Variables	Count	Mean	Standard Deviation	Minimum	P50	Maximum
Abn_Retn	60200	-0.034	5.936	-17.632	0.000	31.583
Abn_Trdv	60200	-0.033	2.829	-09.869	0.093	5.234
AGTI	60200	0.031	0.241	-0.681	0.000	1.021
BP	60200	0.411	0.314	0.029	0.118	1.020
MCAP	60200	9.326	0.863	8.143	9.326	9.995
MRP	60200	0.004	0.019	-0.095	0.001	0.063
Institution	60200	0.431	0.322	0.001	0.099	0.493
Rating_Analyst	60200	0.099	0.416	0.000	0.000	2.153
Retn	60200	0.438	8.168	-14.369	0.000	32.143
Trdv	60200	9.836	3.951	0.001	9.935	13.417

Table 2: Pearson's coefficient correlation

	AGTI	**Abn_Retn**	**Abn_Trdv**	**BP**	**MCAP**	**MRP**	**Institution**	**Rating_ Analyst**	**Retn $_{t-1}$**	**Trdv $_{t-1}$**
AGTI	1									
Abn_Retn	0.093***	1								
Abn_Trdv	0.286***	0.027***	1							
BP	-0.039***	0.001	0.000	1						
MCAP	0.187***	0.021***	0.106***	0.210***	1					
MRP	0.062***	0.424***	-0.026***	-0.027***	0.032***	1				
Institution	-0.025***	-0.000	0.010***	0.081***	0.021***	-0.016***	1			
Rating_Analyst	0.096***	0.024***	0.062***	-0.018***	0.059***	-0.006***	0.041***	1		
Retn $_{t-1}$	0.174***	-0.326***	0.052***	-0.048***	0.074***	0.035***	-0.017***	0.018***	1	
Trdv $_{t-1}$	0.007***	-0.516***	0.097***	0.087***	0.162***	0.041***	0.009***	0.052***	0.024***	1

Pearson correlation coefficients (see Table 2) between the most important factors in the investigation. Significantly positive correlation coefficients between AGTI and anomalous stock returns (Abn_Retn) indicate a co-movement in the same direction between the two variables. The correlation coefficients between AGTI and anomalous trading volume (Abn_Trdv) are likewise significantly positive and produce similarly positive results (0.286).

Taking into account the correlation coefficients between independent variables, the maximum value stands at 0.174 only, indicating that the regression models do not have a severe multi-collinearity issue.

Since the study sample contains substantial company-week observations and significant differences may exist among the intercepts through these observations, the study employs the Hausman test (F value) to determine if fixed evaluation is statistically acceptable. The tests reject the null hypothesis at a 0.01 significance level, indicating that significant differences are indeed present between the intercepts across the data; hence, the study employs an individual fixed-effect model in the primary panel regression analysis (Trang et al., 2022)

First, the study examines the relationship between investors' attention, simultaneous anomalous stock returns, and anomalous trading volumes. The findings from the research technique are presented in Table 3. Column (I), in particular, displays the outcomes when abnormal stock return is used as the explained factor. As stated, AGTI has a positive effect on abnormal stock returns (Abn_Retn) (1.994) at a significance level of 0.01, indicating that, after optimizing for many companies- and market-level characteristics, investor attentiveness has a favorable effect on contemporary stock returns. The results using abnormal trade volumes as the dependent variable are shown in column (IV). Similarly, AGTI shows a positive effect on abnormal trading volume (Abn_Trdv) (3.803) at a significant level of 0.01, implying that, after adjusting for other variables, investors' attentiveness has a positive impact on contemporary trading volume.

The second hypothesis the study examines is whether investor interest results in subsequent reversal of equity returns and trading volume. The outcomes with anomalous equity returns as the explained factor and $AGTI_{t-1}$ and $AGTI_{t-2}$ as the explanatory factors are presented in columns (II) and (III), respectively. As seen, both $AGTI_{t-1}$ and $AGTI_{t-2}$ have an adverse influence on abnormal stock returns (Abn_Retn) (-1.683, -1.091) at 0.01 significance level, indicating that there is a reversal of abnormal stock returns in the following periods. Similar to our hypothesis, the data indicates that retail investors, whose participation is increasing in the Indian stock market, tend to overtrade when confronted with visible occurrences; nevertheless, when attention wanes, a change in stock returns occurs.

Columns (V) and (VI) represent the results, with abnormal trading volume as the explained variable and $AGTI_{t-1}$ and $AGTI_{t-2}$ as the explanatory variables, respectively. $AGTI_{t-1}$ and $AGTI_{t-1}$ have a beneficial impact on abnormal trading volume (Abn_Trdv) (0.487, 0.293) at a significant level of 0.01, although the influences are significantly smaller than those of AGTI (3.803). The data shows that the change in equity returns can prompt investors to sell their stocks quickly, resulting in a temporary rise in trading activity. Despite the absence of a future reversal, the predictability of AGTI has a tendency to deteriorate. Unlike stock returns, trade volumes convey an indication of confidence (Albuquerque et al., 2020). In the event of unfavorable market confidence, equity performance, and trading volume may go in opposite directions. Chen (2012) employs a Markov-switch model to investigate the potential uneven return-volume relationship in uptrend and downtrend markets and finds significant confirmation that stock performance is inversely related to volume in downtrends but positively correlated with volumes in uptrends. In fact, the data are in agreement with this theory. In conclusion, the aforementioned results confirm our two hypotheses.

Table 3: Main Regression Results

Variable	**I Abn_Retn**	**II Abn_Retn**	**III Abn_Retn**	**IV Abn_Trdv**	**V Abn_Trdv**	**VI Abn_Trdv**
AGTI	1.994***			3.803***		
	(29.37)					
$AGTI_{t-1}$		-1.683***			0.487***	
		(-28.37)			(23.27)	
$AGTI_{t-2}$			-1.091***			0.293***
			(-22.35)			(19.39)
BP	0.517***	0.492***	0.608***	0.618***	0.629***	0.619***
	(14.21)	(14.23)	(9.79)	(19.30)	(19.35)	(19.39)
MCAP	-0.068***	0.193***	0.099***	-0.005	0.197***	0.414***
	(-7.83)	(12.83)	(0.91)	(-0.48)	(37.05)	(61.48)
MRP	73.210***	79.827***	68.810***	-4.321***	-4.359***	0.294***
	(190.75)	(195.32)	(197.23)	(-49.25)	(-41.21)	(27.41)
Institution	0.213***	-0.021	0.001	0.226***	0.197***	0.192***
	(8.17)	(-0.39)	(0.01)	(17.21)	(9.94)	(9.17)
Rating_ Analyst	0.517***	0.837***	0.519***	0.197***	0.621***	0.559***
	(19.63)	(41.32)	(27.26)	(13.26)	(57.29)	(53.17)
$Trdv_{t-1}$	-0.083***	-0.069***	-0.083***	0.109***	0.048***	0.061***
	(-37.43)	(30.03)	(-19.28)	(59.38)	(39.24)	(37.95)
$Retn_{t-1}$	-0.88***	-0.061***	-0.021***	-0.021***	0.009***	0.021***
	(-7.39)	(-7.81)	(-6.62)	(-5.12)	(0.59)	(7.21)
C	3.014***	-2.038***	-1.193***	-1.832***	-6.825***	-8.034***
	(15.19)	(-9.37)	(-5.92)	(-9.94)	(-59.47)	(-71.03)
Observations	60200	60199	60198	60200	60199	60198
Total Companies	200	200	200	200	200	200
Years	Yes	Yes	Yes	Yes	Yes	Yes
STOCKD	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.163	0.163	0.991	0.127	0.053	0.049

Note: Statistical significance at the 1%, 5%, and 10% levels is represented by ***, **, *, respectively.

The NIFTY 50, the NIFTY Small Cap Market, and the NIFTY NEXT 50 Market are the three sections of the National Stock Exchange. The listing standards, company size, and company valuations of the three sectors differ, as do their respective industries. As a result of the typical disparities between the market segments, the study anticipates that enterprises sold in different segments will differ considerably in their ability to capture data awareness and their information consumption.

Table 4 presents the findings of cross-sectional market segment tests. In terms of the effects of investors' attention (AGTI) on anomalous equity returns (Abn_Retn), the correlation is highest in the NIFTY NEXT 50 (2.846), lowest in the NIFTY Small Cap (1.873), and highest in the NIFTY 50 (2.016). AGTI on abnormal trading volumes (Abn_Trdv) shows a similar pattern, with the NIFTY NEXT 50 having the highest correlation coefficient (3.825), the NIFTY Small Cap having a lower correlation coefficient (3.841), and the main market having the lowest correlation coefficient (4.183).

The data show that the NIFTY NEXT 50 market has the best data efficiency and equity market reactivity to investors' data demand compared to the other two market segments. When comparing different market segments, the findings indicate that the search activity grabs the focus of retail investors and outperforms at grabbing the focus of low-skilled retail investors. Retail participants in the NIFTY NEXT 50 are obviously more inexperienced than those in the NIFTY50. The findings of the study are similar to those of Yang et al. (2021).

Table 4: Findings of cross-sectional analysis based on market segments

Variable	**NIFTY 50**		**NIFTY Small Cap**		**NIFTY NEXT 50**	
	Abn_Retn	**Abn_Trdv**	**Abn_Retn**	**Abn_Trdv**	**Abn_Retn**	**Abn_Trdv**
AGTI	2.016***	4.183***	1.873***	3.841***	2.846***	3.825***
	(32.12)	(51.24)	(14.35)	(37.47)	(31.02)	(27.36)
BP	0.325***	0.529***	0.587***	0.247***	0.991***	0.218**
	(8.35)	(14.35)	(4.89)	(3.84)	(6.18)	(1.99)
MCAP	-0.105***	0.0001	-0.039**	-0.032***	-0.206***	0.029**
	(-6.36)	(0.09)	(-1.78)	(-1.98)	(-4.36)	(1.99)
MRP	71.251***	-6.214***	69.124***	-4.897***	77.712***	-4.687***
	(168.31	(-42.25)	(99.48)	(-19.89)	(69.02)	(-19.89)
Institution	0.215***	0.391***	0.119**	0.426***	0.099	0.315***
	(9.01)	(20.14)	(1.73)	(9.15)	(0.09)	(3.15)
Rating_Analyst	0.615***	0.292***	0.293***	0.293***	0.328***	0.218***
	(23.14)	(19.35)	(9.91)	(12.28)	(5.14)	(9.78)
Trdv_1	-0.078***	0.078***	-0.098***	0.099***	-0.097***	0.207***
	(-19.89)	(43.37)	(-14.23)	(27.18)	(-14.89)	(29.89)
Retn_1	-0.061***	-0.021***	-0.103***	-0.021**	-0.104***	-0.019***
	(-7.25)	(-4.59)	(-1.91)	(-1.73)	(-17.29)	(-13.28)
C	1.935***	-2.041***	2.061***	-1.163***	4.027***	-1.937***
	(8.87)	(-8.01)	(5.89)	(-3.14)	(5.47)	(-7.36)
Observations	15200	15200	30400	30400	15200	15200
Total Companies	50	50	100	100	50	50
Years	Yes	Yes	Yes	Yes	Yes	Yes
STOCKD	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.162	0.148	0.141	0.181	0.129	0.196

Note: Statistical significance at the 1%, 5%, and 10% levels is represented by ***, **, *, respectively.

The Bloomberg database provides ratings based on the information transparency of the listed companies. We anticipate that enterprises with greater information transparency will have a more favorable information environment, and as a result, the stock market will respond with a greater degree of investor interest. In order to validate this hypothesis, we conduct additional tests based on the data environment.

The findings of the tests based on the data neutrality rating of companies are presented in Table 5. Here, the study exclusively examines the moderating influence of the information ecosystem on the link between AGTI and abnormal stock returns (Abn_Retn). As can be observed, the coefficient for the Order Q group (with greater data transparency) is the greatest (3.129); the coefficient for the Order P group (with the most data transparency) is somewhat lower (1.935), and the coefficients for the Order R group and the Order S group are significantly lower (2.187 and 0.634). The results match our hypothesis, and one potential ground is that retail investor is more prone to have a fear of incurring loss and therefore avoid risk, so the financial impact of their attention on enterprises with high financial risk, such as companies with poor information openness, is less substantial.

Table 5: Results of cross-sectional tests based on data environment.

Variables	**Order P Abn_Retn**	**Order Q Abn_Retn**	**Order R Abn_Retn**	**Order S Abn_Retn**	**Order PQ Abn_Retn**	**Order RS Abn_Retn**
AGTI	1.935***	3.129***	2.187***	0.634***	1.765***	1.162***
	(14.89)	(33.25)	(11.36)	(2.47)	(17.89)	(9.36)
BP	0.343***	0.705***	0.531***	2.035**	0.489***	0.915***
	(2.89)	(8.97)	(2.73)	(1.91)	(9.48)	(4.05)
MCAP	0.039*	-0.201***	0.048	0.289***	-0.063***	0.036
	(1.79)	(-5.89)	(0.99)	(1.96)	(-5.14)	(2.01)
MRP	59.489***	63.005***	62.283***	67.334***	77.340***	83.152***
	(63.38)	(119.29)	(29.38)	(11.35)	(139.26)	(29.54)
Institution	-0.019	0.051	0.093	-0.065	0.018	0.019
	(0.19)	(0.69)	(0.78)	(-0.08)	(0.38)	(0.09)
Rating_Analyst	0.534***	0.391***	0.489***	1.835***	0.362***	0.426***
	(7.32)	(9.93)	(3.89)	(2.49)	(12.36)	(3.48)
Trdv_1	-0.987***	-0.098***	-0.059***	-0.029**	-0.097***	-0.042***
	(-12.01)	(-19.42)	(-5.43)	(-1.26)	(-24.36)	(-5.89)
Retn_1	-0.099***	-0.394***	-0.091***	-0.039***	-0.058***	-0.102***
	(-19.93)	(-5.01)	(-9.83)	(-2.76)	(-3.56)	(-9.01)
C	0.519	2.953***	-0.197	-6.293***	3.024***	-0.425
	(1.19)	(8.94)	(-028)	(-2.33)	(9.93)	(-0.52)
Observations	8618	20301	4602	2307	176911	10476
Total Companies	62	101	49	32	72	78
Years	Yes	Yes	Yes	Yes	Yes	Yes
STOCKD	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.153	0.134	0.118	0.103	0.142	0.121

Note: Statistical significance at the 1%, 5%, and 10% levels is represented by ***, **, *, respectively.

As an additional robust check, columns (5) and (6) categorize the publicly traded companies into only two groups: those with strong information accessibility (order P or Q) and those with poor information accessibility (order R or S). As indicated, the coefficient value for the group with good information accessibility (1.765) is still greater than the coefficient for the group with poor information accessibility (1.162). The preceding explanation demonstrates conclusively that the information environment moderates the relationship between investor focus and unusual stock performance.

In India, the market quotes talk about an uptrend, a downtrend, and a shock market. As for how uptrend and downtrend markets are defined, the available studies usually look at how the market index returns compare to a certain target level. A downtrend or uptrend market exists when the index return is less than or greater than the threshold hold. Or else it's called a "shock market." Taking into account the "short uptrend, long downtrend" characteristics of the Indian exchanges and the actual trend of the exchanges, the study also defines an uptrend/downtrend as the yearly fluctuation of the "Wind All Share Index" being around 20% higher from the previous high to the subsequent through given the time period is around a year; alternatively, it is a crisis period in the market. Table 7 shows how the market stage is split up.

Table 6: The periods between 2014 and 2022 in India.

Market	**Downtrend**	**Crisis**	**Uptrend**	**Downtrend**	**Crisis**	**Uptrend**
Start	01/04/2014	01/12/2015	01/12/2016	01/07/2018	08/03/2020	13/04/2020
End	01/12/2015	01/02/2016	01/01/2018	01/10/2018	05/04/2020	01/03/2022

Table 7: Results of cross-sectional tests based on market quotations.

Variables	**UPTREND**		**CRISIS**		**DOWNTREND**	
	Abn_Retn	**Abn_Trdv**	**Abn_Retn**	**Abn_Trdv**	**Abn_Retn**	**Abn_Trdv**
AGTI	2.842***	1.785***	3.425***	3.946***	0.989***	6.154***
	(23.26)	(23.48)	(34.86)	(48.12)	(14.36)	(53.47)
BP	0.286***	0.329***	-2.943***	-0.063	0.175***	2.047***
	(3.21)	(5.18)	(-4.26)	(-2.01)	(3.15)	(26.36)
MCAP	-0.186***	-0.023	0.009	0.032	-0.003	0.062***
	(-5.14)	(-0.67)	(0.54)	(2.35)	(-0.41)	(6.14)
MRP	58.294***	-7.062***	48.612***	-0.393***	91.105***	-7.064***
	(84.32)	(-34.39)	(84.24)	(-1.84)	(129.23)	(-47.17)
Institution	2.005***	0.325***	-0.816***	0.415***	0.234	0.084
	(19.24)	(2.96)	(-17.41)	(11.52)	(2.25)	(2.14)
Rating_Analyst	1.054***	0.414***	0.189***	0.214***	0.412***	0.425***
	(16.26)	(17.21)	(8.14)	(17.14)	(6.254)	(23.46)
Trdv_1	-0.035***	0.235***	-0.204***	0.063***	-0.098***	0.071***
	(-9.26)	(36.14)	(-19.24)	(29.26)	(-21.15)	(31.47)
Retn_1	-0.098***	0.021***	-0.099***	-0.031***	-0.030***	-0.021***
	(21.54)	(9.47)	(-23.25)	(-19.89)	(-2.94)	(-4.25)
C	4.635***	-1.972***	3.026***	-2.364***	2.624***	-3.624***
	(4.28)	(-6.37)	(3.64)	(-9.05)	(6.145)	(-21.47)

Observations	14200	14200	25370	25370	16895	16895
Total Companies	200	200	174	174	157	157
Years	Yes	Yes	Yes	Yes	Yes	Yes
STOCKD	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.099	0.079	0.071	0.153	0.193	0.167

Note: Statistical significance at the 1%, 5%, and 10% levels is represented by ***, **, *, respectively.

Table 8 presents the findings of the primary model for various time periods. First, a substantial positive association exists between investors' interest (AGTI) and abnormal returns (Abn_Retn) and abnormal trading volume (Abn_Trdv) in market quotations, indicating that the linkages between them are strong in the sub-samples. Second, the effect of investors' attention on irregular returns is greatest in uptrends and smallest in downtrend markets (coefficients of 2.842 and 0.989, respectively). It shows that investors often have high greed during uptrends, causing positive market sentiments to continue to rise; hence, the increase in investor focus during uptrend markets results in greater market returns.

As a result of market volatility, it is challenging for ordinary investors to maintain stable market expectations in a shock market. High deviation from presumptions causes divergent opinions on market sentiments, and as risk avoidance rises, investors prefer to overtrade, resulting in an unusual spike in trading volume.

5. Further Analysis

The primary analysis of this research examines the relationship between investor attention, stock performance, and trading volumes. In this part, the study intends to provide additional insight into whether or not there are unique occurrences that encourage investors to pay attention to a company. The results could assist us in gaining a deeper understanding of how investor attention affects financial outcomes, and we may be able to rely on specific occurrences to detect investor attention shifts and predict stock market reactions.

Table 8 depicts the empirical findings of an additional study on specific incidents. Columns (I) through (VI) separately present the affirmation of six occurrences, and column (VII) incorporates them into the OLS. Declaration of Earnings (DeclarationEarn, 0.080), management forecasts (Forecast, 0.049), ratings by credit rating bodies (Ana Folldt, 0.091), mergers & amalgamations announcements (MA, 0.073), and declaration of dividend (DeclarationDiv, 0.062) have positive co-relation coefficients at 0.01 significance level, indicating that investor is likely to pay heed to those affairs. In the case of the issue of new equity (FreshIssue), the co-relation coefficients stand negligible in columns (V) and (VII), indicating a moderate relationship between corporate affairs and atypical browsing traffic (AGTI). If we compare the five corporate affairs, the credit rating bodies have the greatest influence, with significant coefficients of 0.091 in column (III) and 0.083 in column (VII). The findings contradict Drake et al. (2012) research of S&P 500 equities in the United States. Mergers and amalgamations announcements have the strongest correlation with investor attention in the United States, while earnings announcements and financial analyst following have the weakest correlations. Indian retail investors might not be as smart as their American counterparts, and investors who aren't as smart tend to rely on financial analysts and other experts.

Table 8: Results of Additional Analysis

Variables	I AGTI	II AGTI	III AGTI	IV AGTI	V AGTI	VI AGTI	VII AGTI
DeclarationEarn	0.080*** (61.01)						0.027*** (16.28)
Forecast		0.049*** (28.06)					0.021*** (9.06)
CreditRat			0.091*** (60.24)				0.083*** (53.48)
MA				0.073*** (31.15)			0.069*** (19.87)
FreshIssue					0.003 (0.006)		-0.007 (-0.76)
DeclarationDiv						0.062*** (34.26)	0.006*** (3.02)
Abs_ret	0.011*** (6.12)	0.011*** (6.10)	0.011*** (6.10)	0.011*** (6.10)	0.011*** (6.10)	0.011*** (6.10)	0.011*** (6.10)
Trdv	0.009*** (19.21)	0.009*** (19.23)	0.009*** (19.24)	0.009*** (19.21)	0.009*** (19.22)	0.009*** (19.20)	0.009*** (19.21)
MCAP	0.108*** (34.26)	0.108*** (34.27)	0.108*** (34.29)	0.108*** (34.21)	0.108*** (34.28)	0.108*** (34.22)	0.108*** (34.26)
BP	0.039*** (4.18)	0.041*** (3.97)	0.042*** (4.21)	0.038*** (4.19)	0.039*** (3.89)	0.043*** (4.22)	0.038*** (4.19)
Institution	-0.031*** (-6.63)	-0.028*** (-6.59)	-0.030*** (-6.61)	-0.029*** (-6.65)	-0.032*** (-6.58)	-0.028*** (-6.61)	-0.031*** (-6.60)
C	-2.016*** (-62.67)	-2.016***	-2.016***	-2.016***	-2.016***	-2.016***	-2.016***
Observations	60200	60200	60200	60200	60200	60200	60200
Total Companies	200	200	200	200	200	200	200
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes
STOCKD	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.138	0.132	0.147	0.132	0.142	0.147	0.149

Note: Statistical significance at the 1%, 5%, and 10% levels is represented by ***, **, *, respectively.

6. Conclusion

Attention is a limited mental resource, and this is especially true today when data is called the "new oil" and is easily accessible. The current study focuses on retail investors' interests, as India is experiencing an unprecedented surge in retail investor participation and the impact this will have on the economy. Due to the availability of a huge amount of data, the investors are using the internet to filter and use only relevant information. The research sample comprises Indian-listed companies from FY2014 to FY2022 (till November). The study relies on the "Google Index" to obtain people's proactive search actions because it provides a digital platform for the behaviours of Indian internet users.

The study demonstrates through an empirical study that the attention of investors has a considerable impact on short-term stock performance and trading volume. The study, in particular, finds that the AGTI has a significant and positive connection with stock performance, which reverses in the subsequent term completely, and the AGTI reflects a similar connection with trading volume, which does not have a subsequent reversal, however, whose predictability is deteriorating. The study further finds that stock market segments, data environments, and market quotations have a mitigating effect on the aforesaid association. The association is strongest in the NIFTY NEXT 50 (growth stocks) market, followed by the NIFTY Small Cap market segment, and finally the NIFTY 50 market segment, unlike the findings of Yang et al. (2021). This implies that retail investors in India pay special attention and react quickly, as there is information efficiency, to news related to growth stocks, as they have the potential to generate better returns than the market leader firms (NIFTY 50). Furthermore, the link is stronger in publicly traded companies with better transparency in financial matters. Furthermore, AGTI has the greatest impact on stock performance in an uptrend market and the highest impact on trading volume in a downtrend market. The study looks into whether specific corporate events are attracting more investor attention and discovers five types of corporate events, such as earnings announcements, management projections, analyst ratings, mergers and amalgamations decisions, and dividend pay-outs, have a significant and positive relationship with increased AGTI.

7. Policy Suggestions

The results have significant implications for equity investors. The Google Index, which provides daily and real-time data, could potentially be referred to show investors' interest. Further, AGTI is able to forecast a short-term shift in equity performance, which can result in short-term profits or help investors escape short-term losses from their investments. AGTI only leads to short-term swings in equity returns; hence, AGTI can help adjust investors' psychological deviation over the long run. Lastly, particular corporate events can herald a shift in AGTI and hence investors' interest. The study's findings suggest a possible extension concerning the impact of investors' attention on their decision-making process. Specifically, the significant focus on news has the potential to lead to overconfidence among retail investors, which can ultimately result in increased volatility in the equity market. This overconfidence can arise when retail investors believe that they possess more information and knowledge than they actually do, leading to a false sense of security in their decision-making. The overconfidence bias can then lead to excessive risk-taking, which can further exacerbate market volatility. Therefore, it is crucial to consider the potential impact of overconfidence among retail investors when studying the impact of attention on equity markets. This could provide insight into the factors that contribute to market instability and help develop effective strategies to manage and mitigate market risks.

However, the study faces two major limitations. Endogeneity is a significant challenge since the relationship between attention and performance may be driven by other unobserved factors like company fundamentals or macroeconomic conditions. Another limitation is measurement error, where the measures used to capture investor attention, such as trading volume, internet search volume, or media coverage, may not accurately reflect the true extent of investor attention.

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Appendix

A1: Definition of Variables

Variables	Measurements of Variables
GTI	The natural logarithm of the Google Trend is used to calculate the Google Trend Index.
AGTI	The abnormal Google Trend Index is calculated by subtracting the GTI for the present week from the median GTI for the prior eight weeks.
Retn	Weekly stock returns, taking into account the reinvestment of cash dividends during a specific week.
Trdv	The natural logarithm of a stock's initial trading volume for a given week is used to calculate its weekly trading volume.
Abn_Ret	Abnormal stock returns on weekly basis are calculated by taking the current week's returns after reinvesting cash dividends and subtracting the median returns from the last eight weeks.
Abn_Tr	The abnormal trading volume on weekly basis, computed by subtracting the current week's trading volume from the eight-week median trading volumes.
MCAP	Market value of the shares
BP	Book to Price ratio
MRP	The market risk premium is the difference between weekly stock returns and the weekly risk-free interest rate.
Institution	The percentage of shares owned by institution is calculated by dividing the value of the shares owned by institution by the total value of all shares.
Ln(1+Rating_Analyst)	The natural logarithm of one plus the number of financial analysts ratings on a equity during a given week is used to calculate the financial analyst rating.
DeclarationEarn	1 if financial results are declared during a particular week; otherwise, 0.
Forecast	1 if forecasts by the management are declared during a particular week; otherwise, 0.
CreditRat	1 if equity is being followed by the analysts during a particular week; otherwise, 0.
MA	1 if Mergers and Amalgamations are declared during a particular week; otherwise, 0.
FirstIssue	1 if fresh equities are issued during a particular week; otherwise, 0.
DeclarationDiv	1 if there is a dividend pay-out during a particular week; otherwise, 0.