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WHEN ATTENTION MATTERS MOST : INVESTOR FOCUS, RETURNS, AND VOLATILITY DURING COVID-19

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Investor Focus, Returns, and Volatility

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Abstract

One of the biggest worldwide disruptions in recent memory, the COVID-19 pandemic gives a rare chance to study how investor attention interacts with stock market dynamics in the face of high uncertainty. This study uses weekly data from January 2015 to December 2023 to examine the dynamic link between investor attention, stock returns, and volatility in the Indian market. Google Search Volume Index (GSVI), which is derived from market-specific questions pertaining to the BSE Sensex, serves as a stand-in for investor attention. While structural break tests detect regime transitions during the sample period, we use the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model to capture volatility persistence and asymmetric risk responses. Negative return shocks have a greater effect on future volatility than positive shocks of comparable magnitude, according to the EGARCH results, which also show a substantial leverage effect and significant volatility clustering. The sample is separated into pre-pandemic, pandemic, and post-pandemic phases using structural break analysis. The changing interdependence between attention, returns, and volatility throughout different regimes is then investigated using an impulse response analysis and a Vector Autoregressive (VAR) methodology. The results show that there is a strong regime-dependent link. Pre-pandemic market conditions were comparatively stable and efficient, as evidenced by the weak dynamic spillovers and rapid shock dissipation. The pandemic phase, on the other hand, shows greater durability, enhanced feedback effects, and more noticeable volatility reactions, indicating that amid systemic crises, investor attention becomes economically relevant. Shocks during this time are bigger and more persistent, especially for volatility, according to impulse response functions. While mean-reverting attention and quicker shock absorption are signs of partial normalization in the post-pandemic phase, downside risk sensitivity is still noticeable. Overall, the results demonstrate that while investor attentiveness has less of an impact in stable market conditions, it becomes a potent transmission channel during times of increased uncertainty. This has significant ramifications for investors, policymakers, and behavioral finance research, and it emphasizes how crucial attention is in enhancing market dynamics during crises.

Keywords: *Information Asymmetry, Investor Attention, Financial Crisis and Behavior; Volatility Clustering; Structural Breaks; Leverage Effect*

1 Introduction

Over the past decades, the emergence and flourishing of the internet have created a platform for information gathering, processing and interaction. In the stock market, the relevance of the internet creates new processes and interactions, like stock message boards, email and blogs. The efficiency of the stock market is attributable to the efficient and proper dissemination of information. So, the internet played an essential role in the stock market mechanism (Zhang et al., 2015). The internet's rise as the main tool for information processing, gathering, and interaction has created certain advantageous prospects for scholarly research. These characteristics are taken into consideration in the body of research in the fields of behavioral finance and finance when presenting the empirical question of whether or not open sources of information have an impact on investors' actions regarding stock market activities and information transmission. Kahneman's (1973) studies gained greater attention in the areas of investor attention and the importance of the stock market mechanism. According to traditional finance theories, new information about markets will instantaneously be incorporated into the market mechanism, especially in prices. The renowned theory called the Efficient Market Hypothesis (EMH) (Samuelson & Fama; 1960) noted that the market prices of securities always accurately reflect all the public information available. Among this, traditional asset pricing models like CAPM[1] and APT[2] explain that expected returns are defined through the behavior of other returns. Still, these theories failed to explain the capturing of variation in expected returns (Statman, 2014). Looking back at previous research, we observed that the discipline of behavioral finance has made substantial discoveries on investors' attention spans and stock market phenomena. These studies highlight the inadequacies of traditional theories in elucidating how behavioral factors influence market performance.

Here, we'll look into how investor attitudes and preferences account for stock market activity. Investors' search behavior and attention towards market-relevant activities and events can somehow explain how much these trends reflect in market activities (Chaudhuri & Kayal, 2022). Investment barriers are lessened by the modern, technologically enhanced environment, which makes it simpler to obtain cutting-edge applications. This study looks at the interactions between volatility, investor attention, and market performance during the pandemic in Indian stock market. The main argument is that market return increases investors' attention to news and information, whereas volatility and return vary according to investors' attention. Investor attention is measured using the Google Search Volume Index (GSVI) provided by Google Trends[3]. The

[1]Capital Asset Pricing Model by Sharpe Sharpe (1964) and Lintner (1965)

[2]Arbitrage Pricing Theory by Stephen Ross (1976)

[3]https://trends.google.com/trends/

most widely used search engine, Google, keeps track of search keywords for which it has received more than a specific number of queries. We are analyzing the extent to which investor attention and preference to market activities can explain market return and volatility using data from Google Trends. The objective of the study is to evaluate how investors' attention dynamics explain market return and volatility and vice versa. The way that investors focus on equities and their favorite portfolios may reveal something about them. Additionally, attempting to assess whether investor response stays constant during the pandemic.

The primary emphasis of this study was the behavior of investors in the Indian stock market, particularly those who trade on the Bombay Stock Exchange (BSE). India's markets are completely different from those in developed countries for a number of reasons, including high retail involvement, heightened susceptibility to sentiment-driven trading, increased information asymmetry, frequent changes in regulation and liquidity, and so on. The post-COVID retail trade in India has skyrocketed, mobile trading apps have grown significantly, and Google search traffic has increased. Investor attention has a greater effect on returns in emerging markets, according to sentiment effects in the markets. Developed markets effectively absorb the information, but emerging markets overreact and take longer to rectify. Because of its rising market characteristics, growing retail investor engagement, and increased susceptibility to information shocks, the Indian stock market offers a unique laboratory for studying the dynamics between investor behavior and market mechanism. Based on the statistics, about 3% of the world's market value comes from India, which reflects its growing influence in international finance (SEBI). The nation's economy has shifted from being savings-oriented to being investment-driven (World Bank, 2019), helped along by an increase in domestic participation from institutions and retail investors (Indian Brand Equity Foundation, 2022). Domestic investors helped maintain stability during the COVID-19 pandemic, even though international investors withdrew (Motilal Oswal, 2022). With 5–6 million new demat accounts opened in 2021 alone, technological developments and the expansion of internet trading platforms have greatly enhanced retail involvement. Market volatility has increased as a result of this boom, and dependence on digital information sources has grown.

Our study examines the relationship between market return and volatility from 2015 to 2023 and the internet search query used to obtain information, taking into account the pandemic's variations. By using GSVI as a direct proxy to measure investor attention, we will get the percentage of investors' queries to certain words in Google. The weekly closing price[4] of the BSE Sensex is used to measure market returns, and the Exponential GARCH method is used to construct volatility series. The sample period runs from 2015 to 2023 and is further divided into pre-pandemic, pandemic, and

[4]The daily frequency of GSVI is not available for long period of time

post-pandemic phases based on structural breaks. This study will help to understand how investors' reactions and behavior towards the market mechanism during normal trading conditions and the period of an epidemic. The empirical results show a significant and time-varying correlation between market volatility, stock returns, and investor attention. Returns and volatility are strongly correlated with investor attentiveness, suggesting that it takes into account pertinent data regarding anticipated market moves. According to the EGARCH results, there is a noticeable leverage effect and volatility clustering, with negative shocks having a greater influence on future volatility than positive shocks of comparable size. Particularly around significant economic events like demonetization and the COVID-19 epidemic, structural break analysis identifies discrete sub-periods where the dynamics of attention, returns, and volatility significantly shift. Further demonstrating the changing role of investor attention during times of economic uncertainty, the VAR analysis reveals that the strength and direction of these associations vary throughout the pre-pandemic and post-pandemic. In pre-pandemic period, the market were mainly functioned based on fundamental values rather than behavioral amplification. During crises, limits to arbitrage, heightened risk aversion, and constant media coverage amplify return reversals and persistent volatility as uncertainty evolves over time. The significant mean reversion in attention indicates that attention spikes are short-lived, suggesting improved information processing and reduced panic-driven behavior.

Investor attention is becoming a more significant role in financial market behavior as a result of the rising accessibility of online information, which has changed how investors obtain and analyze market-related information. Investors frequently rely on online searches to get up-to-date information about market conditions, investment opportunities, and economic developments in today's financial markets, where information flows quickly through digital platforms. Because of this, search activity might be a good indicator of investor interest and information demand. In the context of behavioral finance, which highlights that investor decisions are not always entirely rational and may be influenced by attention constraints and information-processing limitations, understanding how investor attention interacts with stock market returns and volatility has become especially pertinent. Furthermore, times of increased uncertainty, like the COVID-19 pandemic, have drastically changed market dynamics and investor behavior, which may increase the importance of attentiveness in financial markets. In light of this, analyzing the relationship between investor attention and stock market dynamics in the Indian context—using search activity associated with important benchmark indices like the BSE Sensex and the NIFTY 50—offers insightful information about how information search behavior reflects and may impact market movements in various economic regimes.

There are two primary ways in which this study contributes to the existing literature regarding investor attention. First, although a lot of study has been done on the financial effects of COVID-19, little is known about the connection between investor attention, stock returns, and market volatility in India during the epidemic. The study illustrates how changes in investor search behavior and the spike in retail participation affected market dynamics by contrasting pre-pandemic, pandemic, and post-pandemic periods. Second, the study expands our knowledge of behavioral reactions in emerging markets by using a VAR framework to investigate the relationships between investor attention, returns, and volatility and by estimating volatility using the EGARCH model to account for leverage and asymmetric effects. In keeping with Shiller's (1996) concept of "*irrational exuberance*," the pandemic era might represent more speculative activity fueled by increased information flows and psychological contagion.

The rest of the paper is organized as follows: Section 2 provides a literature review. Section 3 introduces data source, variables and empirical models. Section 4 reports the results of our empirical analysis, following with section 5 provide robustness check for the results. In section 6 we provide the concluding remarks and policy implications of our study.

2 Literature Review

Conventional asset pricing theories, which at first assumed completely rational investors and efficient markets, gave rise to behavioral finance. The Efficient Market Hypothesis (EMH), which was established by Fama & Samuelson (1970) and influenced by previous theoretical underpinnings, is the basis for traditional models. It asserts that securities prices accurately and instantly reflect all information that is available to the public. Investors were supposed to base their choices only on risk and expected rewards under this paradigm. Subsequent studies, however, refuted this notion by showing that cognitive biases, behavioral characteristics, and psychological factors consistently affect financial decision-making. Investors' attention is selective, constrained, and frequently influenced by salience, media coverage, or increased uncertainty rather than processing information consistently. In addition to increasing trading activity and amplifying specific news events, this selective attention can also cause short-term price movements that diverge from fundamental values. By elucidating anomalies that conventional rational models find difficult to explain, a behavioral framework enhances traditional finance. Therefore, in increasingly information-driven financial contexts, researching investor attention not only broadens our understanding of how markets behave under uncertainty but also has useful implications for risk management, volatility forecasting, and regulatory policy.

Scholars have discovered a number of significant behavioral biases that affects the stock market operation. A substantial amount of research indicates that while assessing financial assets, investors frequently stray from complete rationality. These abnormalities result from cognitive biases and behavioral mistakes that consistently impair judgment and decision-making. Important psychological biases which leads to limited attention have been previously observed, including the disposition effect[5], procrastination, overreaction and under-reaction, anchoring bias, status quo prejudice, conservatism, representativeness bias, and limited attention[6].

2.1 Investor Attention and Stock market activities

The value of web search data, especially Google search activity, as a stand-in for investor attention has been highlighted in a large body of literature (e.g., Bank et al., 2011; Ekinci & Bulut, 2021; Joseph et al., 2011; Klemola et al., 2016; Padungsaksawasdi et al., 2019). Several stock market phenomena, such as price pressure, trading volume, and return predictability, may be explained by changes in investor attention,

[5]Barber, B. M., & Odean, T. (2013). The behaviour of individual investors. The Handbook of the Economics of Finance (Vol. 2, pp. 1533-1570). Elsevier.

[6]Barber, B. M., & Odean, T. (2011). News on the buying behavior of individual. The Handbook of News Analytics in Finance, 173.

according to empirical research (DellaVigna & Pollet, 2009; Hasler & Ornthanalai, 2018; Mondria & Quintana-Domeque, 2013; Seasholes & Wu, 2007). Specifically, Peng and Xiong (2006) show that investors are prone to concentrate more on information at the market and sector levels than on firm-specific data because of information overload. Similar to this, Hirshleifer, Lim, and Teoh (2010) offer a model of restricted investor attention that explains anomalies like post-earnings announcement drift by taking into consideration both underreaction and overreaction to earnings components. All of these research point to the way that attentional limitations impact information processing, which in turn affects price dynamics, volatility trends, and the relationship between accruals and cash flows. Investors may ignore pertinent profitability signs if attention is expensive or given selectively, which could result in short-term mispricing and market inefficiencies. The fast growth of internet usage worldwide in recent years has greatly accelerated the analysis of investor behavior using internet-based data. Da et al. (2011) make a groundbreaking addition in this field by showing that the intensity of internet searches is a timely and accurate indicator of investor interest. In the finance literature, Barber and Odean (2008) contend that investors are more likely to buy companies that catch their eye because of their limited cognitive ability. Selling decisions are usually less restricted since investors usually sell equities that are already in their portfolios, but purchasing decisions are frequently motivated by attention. Attention-grabbing stocks are subject to net purchasing pressure due to this imbalance in attention allocation, which may lead to short-term price fluctuations and possible mispricing. The significance of attention-based metrics in comprehending trading behavior and market dynamics is highlighted by these findings taken together.

The assessment of investor attentiveness has been a major methodological difficulty in this literature. Indirect proxies including media coverage[7], advertising spending[8], extreme returns[9], trading volume, consumer confidence indexes[10], or headline frequency were used in early research. For example, DellaVigna and Pollet (2009) and Barber and Odean (2008) study the impact of media exposure and news distribution on asset returns, showing that stocks that receive more media coverage typically undergo aberrant trading activity and short-term price pressure. Da et al. (2011), however, make a crucial contribution by contending that because not all publicized information is actively absorbed or digested by investors, media coverage may not accurately reflect true investor interest. They suggest that the Google Search Volume Index (GSVI), which reflects

[7]Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. The journal of finance, 64(5), 2023-2052.

[8]Grullon, G., Kanatas, G., & Weston, J. P. (2004). Advertising, breadth of ownership, and liquidity. The Review of Financial Studies, 17(2), 439-461.

[9]Barber, B. M., Odean, T., & Zhu, N. (2008). Do retail trades move markets? The Review of Financial Studies, 22(1), 151-186.

[10]Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. Journal of empirical finance, 16(3), 394-408.

real-time information demand rather than passive exposure, is a more immediate and direct indicator of investor attention. According to their research, the Search Volume Index (SVI) provides better immediacy than conventional proxies and has a good correlation with investor attentiveness. The empirical examination of attention-driven market behavior has been greatly improved by this move toward internet-based metrics, which has allowed academics to more fully understand how information demand contributes to return dynamics and volatility swings. The Google Search Volume Index (GSVI), which they used to gauge investor attention, has since expanded the field of empirical research to include marketing, public health, economics, and finance (e.g., Carneiro & Mylonakis, 2009; Choi & Varian, 2012; Ginsberg et al., 2009; Guzman, 2011; Vosen & Schmidt, 2011; Yang et al., 2015).

2.2 Interaction between attention and return - volatility

It is crucial to look at how the current study is informed by earlier research on investor attentiveness, market volatility, and stock returns. According to a number of studies, market efficiency increases when investors focus more on information. The connection between volatility, returns, and investor interest is complicated, though. Trading activity usually increases as investors pay more attention to market-related news and events, which raises volatility (Andrei & Hasler, 2015). According to Wang, Xu, and Sharma (2021), there is a unidirectional relationship between predicted investor attention and volatility, indicating that market conditions influence anticipated attention. On the other hand, unanticipated investor attention might destabilize the stock market because it contains fresh information. Additionally, the literature makes a distinction between retail and institutional investors. News announcements typically elicit large reactions from retail investors, which raises the volatility of returns after the announcement (Ding & Hou, 2015). Institutional investors, on the other hand, are typically less sensitive to such news, which has a slight but detrimental impact on future volatility (Ballinari, Audrino, & Sigrist, 2022). Additionally, it has been demonstrated that investor attention has the ability to predict realized volatility, which has a short-term beneficial effect on future volatility (Said & Slim, 2022). When taken as a whole, these results demonstrate how important investor attentiveness is in determining return dynamics and financial market volatility patterns. According to Padungsaksawasdi et al. (2023), there is negative correlation exist between investor attention and stock performances in nations were investors exhibit higher level of uncertainty. Investors' information preferences may change as a result of a pandemic, with focus shifting from news about the industry as a whole to events pertaining to individual firms (Shear, Ashraf, & Sadaqat, 2020; Xu, Zhang, & Zhao, 2022). To measure volatility and investigate how investor behavior was quickly reflected in stock returns during the epidemic, a number of studies used econometric models including GARCH and EGARCH (Iyke & Ho, 2021; Jiang et al., 2021).

Since its introduction by Sims in 1980, the Vector Autoregressive (VAR) model has grown to be a fundamental framework for examining the dynamic interactions between financial and macroeconomic factors. To illustrate its utility in capturing return dynamics, volatility transmission, and information spillovers, Hamilton (1994), Cuthbertson (1996), Campbell et al. (1997), Tsay (2001), and Mills and Markellos (2008) have examined its application to financial time series in great detail. VAR models are very useful in financial market research because they allow for a thorough analysis of the feedback effects between returns, volatility, and investor behavior by treating all variables as endogenous. The classic VAR framework has been expanded in later research to incorporate regime transitions and structural identification. Researchers can identify shocks and track their dynamic consequences by imposing economically significant limits using structural VAR (SVAR) models (Lütkepohl, 2005). Additionally, as Galvão (2006) discusses, structural break VAR models allow for parameter instability over time, which is particularly important during economic crisis or pandemic outbreaks when market dynamics may shift suddenly.

3 Data & Methodology

This study is based on the Bombay Stock Exchange (BSE). We specifically employ investor attention metrics from Google Trends and weekly data for the S&P BSE Sensex from CMIE ProwessIQ. The data covers the first week of January 2015 to the final week of December 2023. The BSE was chosen as the study's subject because it is one of Asia's oldest and most well-known stock exchanges, and the S&P BSE Sensex is a benchmark index that represents big, established businesses in important areas of the Indian economy.

Two main reasons exist for using weekly data. First off, for a long period of time, the Google Search Volume Index (GSVI), which is utilized as a stand-in for investor interest, is not regularly accessible at a daily frequency. Second, weekly aggregation provides more reliable estimates of the correlation between investor attention, stock returns, and volatility by mitigating the short-term noise and microstructure effects found in daily data. However, the weekly frequency maintains enough variance to record dynamic interactions and transient market changes.

3.1 Description of Variables

3.1.1 Investor Attention

Investor attention was measured using the proxy i.e., GSVI from Google Trends, which offers the online search volume for any query term submitted to Google since 2004. The value was scaled between 0 to 100, where the topic's percentage of all searches on all topics within the specific location. In this study we are using the search term "Sensex" within India from the section of Finance.

Both theoretical and practical factors led to the selection of ”Sensex” as the search term. First, as a gauge of overall market performance, the S&P BSE Sensex is the most well-known benchmark index in India. The Indian stock market is commonly referred to as the ”Sensex” by the general public, media, and retail investors. Therefore, rather than focusing on specific companies or industries, search intensity for the phrase ”Sensex” is likely to catch attention at the market level. Second, use a benchmark index keyword is consistent with the goal of gauging investor attention generally rather than firm-specifically. Because this study looks at the relationship between investor attention, market returns, and volatility at the index level, using ”Sensex” guarantees conceptual coherence between the attention proxy and the dependent variable (market performance). Third, in the Indian context, ”Sensex” is more accurate and less vague than other phrases like ”stock market,” ”share market,” or particular firm names. Measurement noise may be introduced by generic queries that capture curiosity about non-investment-related topics, international markets, or educational searches. On the other hand, searches for ”Sensex” are more likely to indicate a direct interest in changes in the Indian equity market.

An indicator of investor interest is the Google Search Volume Index (SVI) for the term ”Sensex.” The Bombay Stock Exchange’s benchmark index, or ”Sensex,” is directly linked to the success of the Indian stock market. The need for market-related information, such as index movements, market trends, and investment choices, is usually reflected in searches associated with this phrase. Non-investor searches may be included in Google search activity, but overall market attention is captured by the aggregated search intensity. According to the restricted attention theory (Da et al., 2011), higher search activity indicates higher investor attention, which could affect market dynamics and trading behavior.

3.1.2 Stock Returns

The returns of S&P BSE Sensex is calculated as;

$$R_t = Ln(\frac{P_t}{P_{t-1}}) * 100 \tag{1}$$

where P_t is the weekly close price of BSE Sensex.

3.1.3 Stock market volatility

Nelson’s (1991) Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model is used to estimate stock market volatility in order to capture and examine the conditional variance of returns. Because it permits volatility to react asymmetrically to both positive and negative shocks, the EGARCH framework is especially well-suited for financial time series. The leverage effect is the term used to describe the tendency for negative news to have a greater effect on volatility in equities markets than positive news of comparable magnitude. In contrast to symmetric GARCH models, the EGARCH specification clearly accounts for this asymmetry, allowing us to investigate the ways in which both positive and negative changes in investor focus impact the volatility of stock returns. Due to a number of methodological benefits, EGARCH is favored over traditional volatility models. EGARCH captures asymmetric effects that are especially important during times of market stress, in contrast to ARCH (Engle, 1982) and GARCH (Bollerslev, 1986), which assume symmetric responses of volatility to shocks. The EGARCH model improves estimation stability by guaranteeing positive volatility estimates without requiring non-negativity requirements on parameters by representing the conditional variance in logarithmic form. Additionally, EGARCH successfully captures important stylistic characteristics of financial return series, such as volatility clustering, fat tails, and persistence.

To examine the dynamic behavior of stock returns and volatility this study employs the ARMA-EGARCH model, which allows simultaneous modeling of the conditional mean and conditional variance of the return series. The ARMA component captures the linear dependence in returns, while EGARCH model captures volatility clustering and asymmetric responses of volatility to market shocks.

The testable EGARCH (1,1) model has been represented as follows:

$$R_t = \mu + \phi R_{t-1} + \theta_{t-1} + \epsilon_t \tag{2}$$

where, R_t is stock return at time t; μ is constant mean return; ϕ is autoregressive parameter; θ is the moving average parameter; ϵ_t is the error term with conditional variance h_t. The ARMA structure captures the influence of past returns and past shocks on current returns.

The EGARCH model follows as;

$$ln(h_t) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}| + \gamma\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta.ln(h_{t-1}) \tag{3}$$

where, h_t = conditional variance of returns; ω = constant term in variance equation; α = magnitude effect of shocks (ARCH effect); γ = asymmetric or leverage effect parameter and β = persistence of volatility.

The asymmetric response of conditional volatility to positive and negative shocks is captured by the parameter γ from Equation (3). Positive and negative shocks have symmetric effects on volatility for $\gamma = 0$. The existence of a leverage effect is shown by a negative value of $\gamma(\gamma < 0)$, which suggests that negative shocks ("bad news") raise volatility more than positive shocks ("good news") of same magnitude. On the other hand, a high value of γ indicates that positive shocks have a bigger impact on volatility than negative shocks. The logarithmic specification permits asymmetric volatility responses while guaranteeing the positivity of the conditional variance without placing non-negativity limitations on the model parameters. The logarithmic specification ensures the positivity of conditional variance without imposing non-negativity constraints on parameters and allows for asymmetric responses of volatility to positive and negative shocks.

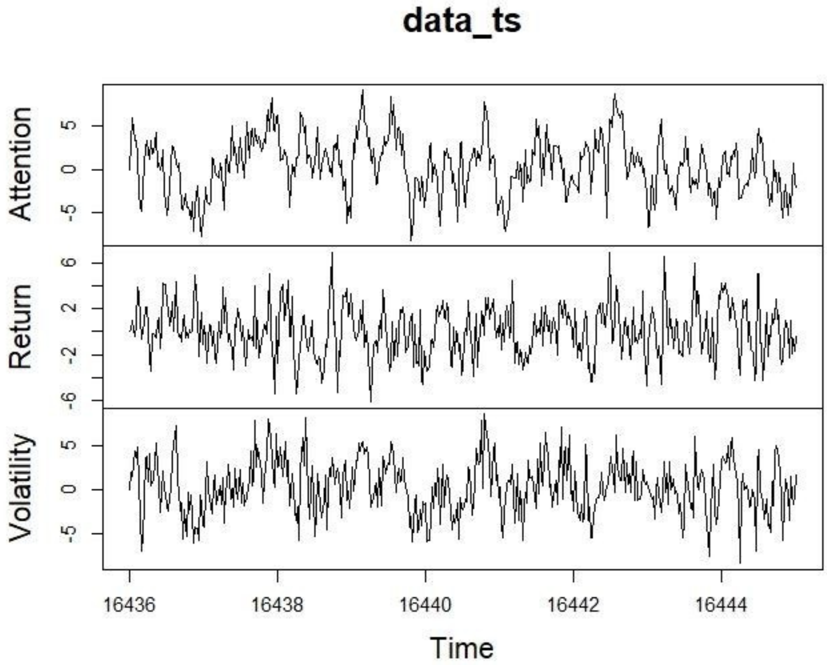

Figure 1: Plot of the variables

3.2 Methodology

3.2.1 Stationarity and Correlation

The Augmented Dickey–Fuller (ADF) unit root test is used to check for stationarity. The ADF test's alternative hypothesis contends that the series is stationary, while the null hypothesis asserts that the series has a unit root, i.e., is non-stationary. To investigate the initial linear relationship between variables, such as stock returns, volatility, and investor interest, correlation analysis is performed in addition to unit root testing. Before estimating multivariate models, correlation analysis is an experimental phase that helps determine the strength and direction of pairwise correlations. The use of more complex dynamic modeling tools is justified by the preliminary evidence that correlation, while not implying causality, offers valuable insights into whether investor attention tends to move favorably or negatively with returns and volatility.

3.2.2 Baseline Regression model

Before estimating the VAR model, a baseline regression model is estimated to examine the direct relationship between investor attention and stock market variables. This preliminary analysis helps to identify the basic association between variables and provide motivation for employing a dynamic multivariate framework such as VAR to capture feedback effects.

The model 1 in equation (4) states the relation between investor attention and market returns.

$$R_t = \alpha + \beta Attn_t + \epsilon_t \tag{4}$$

The model 2 in equation (5)identifies the relation between investor attention and market volatility.

$$Vol_t = \alpha + \beta Attn_t + \epsilon_t \tag{5}$$

3.2.3 Structural break

Bai and Perron (1998, 2003) developed the structural break test based on Weighted Double Maximum (WDmax) test as a structural break test to identify numerous structural breakdowns at uncertain dates in a regression framework. A variant of the Double Maximum (Dmax) test, the WDmax statistic is intended to enhance finite-sample performance and offer balanced inference across varying numbers of possible break points. In structural break analysis, individual Wald tests are computed for models with varying numbers of breaks (eg., m = 1,2,... M). To make sure that the marginal p-values of these separate test statistics are consistent throughout a range of values of *m*, the WDmax test applies weights to them. The robustness of inference is improved by this weighting approach, which accounts for variations in asymptotic distributions that occur when testing for varying numbers of structural breakdowns. Unlike the unweighted Dmax statistic, the WDmax appropriately controls the chance of rejecting the null hypothesis by adjusting the contribution of each individual sup-Wald statistic.

Formally, the WDmax statistic is defined as the maximum of the weighted sup-Wald statistics across all admissible break numbers:

$$WD_{max} = max_{1 \leq m \leq M}(a_m.supF_T(m)) \tag{6}$$

where, $supF_T(m)$ denotes the sup-Wald statistic for *m* structural breaks and a_m represents the corresponding weight and M is the pre-specified upper bound on the number of breaks. Thus as the critical values drop for higher levels of m, the weight assigned to that 'maximum' F statistic rises. Thus as the critical values drop for higher levels of *m*, the weight assigned to that *'maximum'* F statistic rises.

In the presence of *m* structural breaks, where $m = 1, 2, ..M$, the model becomes;

$$y_t = X_{it}\beta_j + u_t; t = T_{j-1} + 1...T_j; j = 1, 2..m + 1 \tag{7}$$

where, T_j represents the unknown breakpoints.

The WDmax test is used in this study to investigate whether there are any structural breaks in the correlation between volatility, stock returns, and investor attentiveness across the data period. There is at least one structural break in the model parameters when the WDmax statistic is statistically significant, indicating that the underlying linkages may vary between regimes, such as pre-pandemic and pandemic times.

3.2.4 Vector Autogressive Model

When analyzing multivariate time series data, vector autoregressive (VAR) models are frequently employed, especially in financial econometrics and macroeconomics. Every variable in the system is treated as endogenous in a VAR model, which represents each variable as a linear function of both its own historical values and the historical values of every other variable in the system. Without imposing significant theoretical constraints, this paradigm enables researchers to capture the dynamic interrelationships and feedback effects among numerous time series. Formally, each variable in a VAR(*p*) model with *k* endogenous variables is regressed on *p* lags of each other variable in the system as well as *p* lags of these variables. The model may take into consideration co-movements, lagged transmission mechanisms, and inter-dependencies across variables like stock returns, volatility, and investor attention thanks to this structure. VAR is especially well-suited for financial market analysis, where variables frequently affect one another at the same time, because it does not necessitate the a priori classification of variables as strictly exogenous or endogenous, unlike single-equation models. Additionally, VAR models offer a helpful foundation for forecast error variance decomposition and impulse response analysis, which aid in tracking the impact of shocks to a single variable on the system as a whole over time. In order to provide insights into how shocks in one dimension spread throughout the market, the VAR framework is utilized in this study to investigate the dynamic relationships among investor attention, stock returns, and volatility.

The model follows as;

Let the vector of endogenous variables be defined as;

$$Y_t = \begin{bmatrix} r_t \\ vol_t \\ A_t \end{bmatrix} \tag{8}$$

A VAR (*p*) can be written in compact matrix form as;

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + .. + \phi_p Y_{t-p} + u_t \tag{9}$$

where, c is a 3×1 vector of intercept terms; ϕ_i for (i = 1,..*p*) are 3×3 coefficient matrices; u_t is a 3×1 vector of white-noise disturbances.

The system can be written explicitly as;

1. Return Equation:

$$r_t = c_1 + \sum_{i=1}^{p} \alpha_{1i} r_{t-i} + \sum_{i=1}^{p} \beta_{1i} vol_{t-i} + \sum_{i=1}^{p} \gamma_{1i} A_{t-i} + u_{1t} \tag{10}$$

2. Volatility Equation:

$$vol_t = c_2 + \sum_{i=1}^{p} \alpha_{2i} r_{t-i} + \sum_{i=1}^{p} \beta_{2i} vol_{t-i} + \sum_{i=1}^{p} \gamma_{2i} A_{t-i} + u_{2t} \tag{11}$$

3. Attention Equation:

$$A_t = c_3 + \sum_{i=1}^{p} \alpha_{3i} r_{t-i} + \sum_{i=1}^{p} \beta_{3i} vol_{t-i} + \sum_{i=1}^{p} \gamma_{3i} A_{t-i} + u_{3t} \tag{12}$$

With the use of the VAR model, we can investigate the dynamic and interconnected interactions between market volatility over time, stock returns (Sensex returns), and investor attentiveness (GSVI). The model does not assume a one-way causal link; instead, it incorporates feedback effects because all variables are viewed as endogenous. Investor attention's significant lagged coefficients in the return equation suggest that shifts in search intensity affect market returns in the future. Greater investor attention is linked to better future returns, presumably as a result of increased trading activity or knowledge dissemination, according to a positive and significant coefficient. On the other hand, overreaction or trade noise that results in return reversals could be indicated by a negative coefficient. Significant lagged attention factors in the volatility equation show whether or not investor attentiveness raises market uncertainty. Increased search activity, particularly during times of crisis, may intensify market swings if investor attention has a favorable impact on volatility. This would lend credence to the idea that information shocks are transmitted through attention. Significant volatility coefficients or lagged returns in the attention equation suggest that investor attention is also sensitive to changes in the market. For instance, significant negative returns or volatility increases may lead to a surge in search traffic, indicating a demand for knowledge driven by panic.

4 Empirical Results

This section presents the empirical findings of the study.

Table 1: Descriptive Statistics of concept variables

Variables	n	Mean	Median	Std.dev	Skew.	Kurt.
Investor Attention	469	0.021	0.011	0.977	0.090	-0.010
Market return	469	0.027	0.031	1.004	0.006	-0.080
Volatility	469	-0.005	-0.010	0.994	0.180	0.084

Over the course of the sample, the Sensex produced positive average weekly returns. The significant variety in investor attention and volatility supports their applicability in elucidating market dynamics. At weekly intervals, the series exhibit near-normal distribution and approach symmetry. ADF testing, structural break analysis, EGARCH modeling, and VAR analysis are among the econometric estimations that are more reliable when there is no extreme skewness or kurtosis.

The findings of the ADF test in Table 2 verify that each of the three variables is level and stationary during the sample period.

Table 2: Unit root test

Unit root test	Return	Volatility	Attention
ADF Test	-7.954	-4.959	-10.504
	(0.01)	(0.01)	(0.01)

The Pearson correlation coefficients between investor attentiveness (GSVI), conditional volatility (EGARCH-based), and weekly market returns are shown in Table 3. The correlation results reveal several important insights: Investors pay more attention during periods of turbulence and volatility; market results are inversely correlated with attention, suggesting that investors pay more attention during recessions; and because volatility and attention are closely related, attention may increase or react to market uncertainty.

Table 3: Correlation

	Return	Volatility	Attention
Return	1.000	-0.266	-0.322
Volatility	-0.266	1.000	0.695
Attention	-0.322	0.695	1.000

4.1 Conditional Volatility

Table 4: Conditional Volatility

	Estimate	Std. Error	t-value	p-value
μ	0.003	0.0007	4.750	0.000
$\phi(AR_1)$	0.594	0.068	8.616	0.000
$\theta(MA_1)$	-0.532	0.070	-7.510	0.000
ω	-1.107	0.426	-2.597	0.009
α	-0.267	0.063	-4.224	0.000
β	0.860	0.054	15.894	0.000
γ	0.252	0.070	3.570	0.000

The estimation outcomes of the EGARCH (1,1) model applied to weekly Sensex returns are shown in Table 4. The model includes an asymmetric conditional variance specification and ARMA(1,1) dynamics in the mean equation. Strong model adequacy is indicated by all reported coefficients being statistically significant at the 1% level. The market produced positive average weekly returns during the study period, as indicated by the mean equation's positive and statistically significant constant ($\mu = 0.0033, p < 0.01$). The considerable negative θ coefficient (moving average) ($-0.5321, p < 0.01$) suggests partial correction of previous shocks, verifying dynamic changes in returns, while the positive and extremely significant ϕ coefficient (autoregressive) ($0.5942, p < 0.01$) suggests strong short-run return persistence or momentum effects. The long-run level of log volatility is determined by the constant term ($\omega = -1.1078, p < 0.01$) in the variance equation, which is statistically significant and suggests a stable volatility process. The presence of a leverage effect, in which negative shocks raise volatility more than positive shocks of the same size, is confirmed by the negative and significant asymmetry parameter ($\alpha_1 = -0.2676, p < 0.01$). Strong volatility clustering and a gradual decrease of volatility shocks over time are shown by the large and highly significant persistence parameter ($\beta_1 = 0.8605, p < 0.01$). Lastly, a positive and significant coefficient on investor attention ($\gamma_1 = 0.2524, p < 0.01$) indicates that increased search intensity greatly increases conditional market volatility.

Overall, the findings support the following: a statistically significant destabilizing effect of investor attention on market risk; persistent and asymmetric volatility behavior; and return dynamics.

The results point to a number of significant economic factors that underlie market behavior. The persistence of returns indicates that prices adjust gradually due to behavioral variables such under-reaction, momentum trading, and delayed information diffusion rather than instantly incorporating new information. Simultaneously, the partial adjustment of shocks suggests that markets eventually return to fundamentals. Volatility clustering, in which times of extreme uncertainty are followed by ongoing instability, is confirmed by the substantial persistence of volatility. This is a reflection of feedback mechanisms in financial markets since increased risk raises risk aversion, decreases liquidity, and promotes speculative or cautious trading. Negative news has a greater effect on market uncertainty than positive news, according to the evidence of asymmetric volatility responses. Significantly, the findings also imply that heightened information search can result in speculative behavior, a variety of expectations, and quick portfolio modifications, all of which could enhance market volatility, especially during uncertain times. Overall, the results suggest that behavioral reactions and market fundamentals influence market dynamics, with attention-driven processes significantly increasing volatility during difficult times.

4.2 Baseline model

The table 5 presents the results of baseline regression models examining the impact of investor attention on stock market return and volatility. According to the baseline regression results, stock market returns and volatility are not significantly impacted by investor attentiveness. Despite a small negative correlation between attentiveness and returns and a positive correlation with volatility, these effects are not statistically significant. Overall, the model only accounts for a relatively small percentage of the diversity in market behavior, suggesting that other factors probably have a greater impact on volatility and returns.

Table 5: Baseline regression model

	Dependent variables:	
	Return	Volatility
Attention	−0.027	0.010
	(0.048)	(0.047)
Constant	0.028	−0.006
	(0.046)	(0.046)
Observations	469	469
R^2	0.001	0.0001
Adjusted R^2	−0.001	−0.002
Residual Std. Error	1.005 (df = 467)	0.996 (df = 467)
F Statistic	0.326 (df = 1; 467)	0.043 (df = 1; 467)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Consequently, the feedback linkages between investor attention and stock market activity could not be adequately captured by a straightforward baseline regression. In order to overcome this restriction, the following analysis uses a Vector Auto-regression (VAR) model to investigate the dynamic interdependence between investor attention, returns, and volatility.

4.3 Structural Break Analysis

The table 6 reports the results of the sequential Bai- Perron multiple structural break test. The reported statistics correspond to the sequential supF test $seq(l|l-1)$ which examine whether an additional structural break significantly improve the model fit. The null hypothesis that there would be no further breaks is rejected in each instance since the computed test statistic is greater than the relevant 5% critical threshold. Consequently, four statistically significant structural breakdowns in the series during the sample period are confirmed by the results. The test statistic for the first break (22/05/2015) is 199.3973, which is significantly higher than the 5% critical value of 46.7108. The test statistics for the second break (02/09/2018), third break (28/02/2020), and fourth break (02/07/2021) are all much over their critical levels, making them extremely significant as well. The accurate estimation of the structural alterations is suggested by the small 95% confidence intervals surrounding each break date.

Table 6: Structural break test

Test	Test Statistic	5% critical values	Break dates	95% confidence interval
seq (1—0)	199.397	46.710	**22.05.2015**	71-77
seq (2—1)	109.224	33.452	**02.09.2018**	188-198
seq (3—2)	68.172	34.844	**28.02.2020**	270-272
seq (4—2)	49.915	35.779	**02.07.2021**	339-343

The structural break test identifies four significant breakpoints in the sample period, indicating changes in the underlying dynamics of the stock market. The first two breaks, occurring on 22 May 2015 and 2 September 2018, fall in the pre-pandemic period and reflect shifts associated with global financial instability, including concerns over China's economic slowdown, commodity price fluctuations, and volatility in emerging markets. The 2018 break also coincides with increased domestic financial stress, particularly the NBFC liquidity crisis such as the IL&FS collapse, which significantly affected market sentiment and volatility in India. This structural break coincides with the onset of the COVID-19 pandemic and the resulting global financial turmoil, which triggered sharp market declines, heightened volatility, and unprecedented uncertainty. The break reflects a clear regime shift in return dynamics, volatility persistence, and investor attention during the crisis period. The subsequent break in mid-2021 likely represents the transition toward recovery, marked by economic reopening, vaccine roll-outs, normalization of policy support, and improving market sentiment, indicating another shift in the relationship among returns, volatility, and investor attention.

Grouping the structural breaks into broader economic phases allows the analysis to capture changes in investor behavior and market dynamics across different regimes. The first two structural breaks are classified within the pre-pandemic period, because they occur before the pandemic and reflect market adjustments within the normal economic regime. Structural breaks occurring within same macroeconomic phase may capture temporary financial disturbances without indicating a fundamental shift in the broader economic environment.

4.4 Vector Autoregressive Model (VAR)

Three separate sub-periods:—pre-pandemic, during the pandemic, and post-pandemic are created using the findings of the structural break test. The pandemic period coincides with the worldwide COVID-19 epidemic, which was formally announced by the World Health Organization in March 2020. The structural break analysis's break dates show notable changes in the mechanism that generates the data, which supports distinct econometric modeling for each regime as opposed to estimating a single model for the whole sample.

We use a Vector Autoregressive (VAR) methodology to analyze the dynamic interrelationships between investor attention, stock returns, and volatility across different regimes. Because it regards all variables as endogenous and reflects their joint dynamics without imposing any theoretical constraints, the VAR model is suitable in this situation. This enables us to evaluate the temporal dependencies and feedback effects between volatility, returns, and investor attention. As a pre-requisite we have done the stationarity test of the variables (refer Table 10 in appendix)

4.4.1 Lag Length Criteria

Each of the three time periods has a separate set of lag length selection criteria (in table 11 to 20) (such as AIC, SIC, or HQIC). According to the lag criterion results, there is a single lag in the post-pandemic phase, a two-lag during the pandemic period, and a one-lag during the pre-pandemic period. Therefore, VAR model is estimated separately for each of the three sub-periods. For each period, three equations are estimated within the VAR system.

4.4.2 Pre-pandemic Period

All things considered, the pre-pandemic VAR(1) estimates in table 7 show a market environment with low endogenous feedback mechanisms between investor attention, returns, and volatility, modest behavioral distortions, and informational efficiency. The weak-form Efficient Market Hypothesis, which postulates that publicly available information, including attention-based signals, was quickly absorbed into asset prices, is supported by the return equation's lack of statistically meaningful predictive correlations. Furthermore, the minimal impact of investor attention on returns and volatility suggests that attention shocks during this time were either too minor to cause pricing pressure or were effectively offset by arbitrage activity. The leverage effect, which shows asymmetric risk reactions to negative price fluctuations, is consistent with the marginally negative influence of lagged returns on volatility, which is the only economically significant dynamic shown. Crucially, the system's overall low explanatory power suggests that the market functioned in a stable equilibrium regime with few spillovers and no indications of attention-driven or speculative amplification cycles. When considered collectively, these results imply that, prior to the pandemic, fundamental risk considerations rather than behavioral attention-based mechanisms dominated financial market dynamics, indicating a relatively peaceful and structurally efficient market phase.

Table 7: VAR(Pre-pandemic) Estimation Results

	Attention	Return	Volatility
Attention$_{t-1}$	-0.012	0.040	0.080
	(0.061)	(0.062)	(0.064)
Return$_{t-1}$	-0.068	-0.011	-0.119†
	(0.060)	(0.061)	(0.064)
Volatility$_{t-1}$	0.018	0.030	-0.059
	(0.057)	(0.058)	(0.060)
Constant	0.004	-0.042	0.003
	(0.058)	(0.058)	(0.061)
Observations		269	
Log Likelihood		-1116.451	
R^2	0.0052	0.0026	0.023
Adj. R^2	-0.0061	-0.0087	0.011
F-statistic	0.462	0.228	2.079
p-value (F)	0.708	0.876	0.103

Notes: Standard errors are reported in parentheses.
† $p < 0.10$.

This pattern shows a comparatively stable and information efficient market environment where pricing mostly took into account the information that was available without chronic behavioral biases. Financial markets did not show strong or persistent return predictability or attention-driven spillovers during the pre-pandemic period in India, despite a number of significant economic events, such as demonetization (2016), the implementation of GST (2017), the NBFC liquidity crisis following the IL&FS collapse in 2018, banking sector stress from rising NPAs, and global trade uncertainties. Instead of reacting with protracted panic, markets were able to gradually alter expectations because many of these shocks were policy-driven. Demonetization, for example, caused short-term liquidity problems, but equities markets were able to quickly discern between short-term shocks and long-term fundamentals. Similar to this, despite short-term adjustment costs, GST was generally seen as a structural reform with long-term benefits. Long-term market mispricing was reduced by strong macroeconomic fundamentals, reliable monetary policy, and active involvement from institutional investors. These factors also served to stabilize expectations and promote effective information absorption.

4.4.3 Pandemic Period

Table 8 shows stronger dynamic interactions among investor attention, returns, and volatility during the pandemic period compared to the pre-pandemic regime. The attention equation exhibits significant negative autoregressive coefficients, indicating strong persistence and mean-reverting behavior in investor attention, likely driven by heightened information demand during the crisis. In the return equation, the significant negative coefficients of lagged returns suggest return reversals rather than momentum, reflecting sharp corrections following large market movements. Additionally, the higher explanatory power of the attention and return equations indicates stronger endogenous relationships among the variables. The volatility equation also shows significant persistence, highlighting volatility clustering and prolonged uncertainty, which is typical during periods of financial crisis.

Table 8: VAR(Pandemic) Estimation Results

	Attention	Return	Volatility
Attention$_{t-1}$	-0.683***	0.190	0.001
	(0.122)	(0.126)	(0.100)
Return$_{t-1}$	-0.195	-0.668***	-0.101
	(0.118)	(0.122)	(0.097)
Volatility$_{t-1}$	0.118	-0.048	-0.710***
	(0.139)	(0.145)	(0.114)
Attention$_{t-2}$	-0.268*	0.108	0.075
	(0.122)	(0.126)	(0.100)
Return$_{t-2}$	-0.125	-0.283*	-0.130
	(0.119)	(0.124)	(0.098)
Volatility$_{t-2}$	0.071	0.099	-0.456***
	(0.141)	(0.146)	(0.115)
Constant	0.021	-0.035	0.012
	(0.145)	(0.150)	(0.119)
Observations		67	
Log Likelihood		-296.636	
R^2	0.360	0.393	–
Adj. R^2	0.296	0.332	–
F-statistic	5.640***	6.479***	–

Notes: Standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Sample size = 67. Deterministic component: constant.

The economic reasoning behind these findings is closely linked to the unprecedented uncertainty and systemic disruption caused by the COVID-19 pandemic. Unlike earlier policy-driven shocks such as demonetization or the implementation of GST, the pandemic was an exogenous health crisis with uncertain duration and economic consequences. Nationwide lockdowns, supply-chain disruptions, mobility restrictions, and a sharp contraction in economic activity significantly altered investor behavior and heightened uncertainty in financial markets. This environment led to increased investor attention, particularly through digital information sources, as investors closely followed pandemic developments, policy responses, and economic recovery measures. The significant negative return dynamics reflect market overreactions and subsequent corrections, consistent with panic-driven selling followed by recovery supported by fiscal stimulus, global liquidity injections, and monetary easing by the Reserve Bank of India. At the same time, the strong persistence of volatility indicates volatility clustering, where elevated risk perceptions, policy uncertainty, and repeated waves of infections kept market uncertainty high over an extended period. Overall, the pandemic period represents a structural shift in market dynamics, where extreme uncertainty and economic disruptions intensified the persistence and interdependence of returns, volatility, and investor attention.

Several economic developments further intensified these dynamics during the pandemic. The nationwide lockdown in March 2020 and the sharp global stock market decline triggered panic selling and capital outflows from emerging markets, including India. Uncertainty was heightened by the simultaneous global recession and the collapse in crude oil prices. In response, the Reserve Bank of India implemented aggressive monetary easing measures, including rate cuts, liquidity injections, loan moratoriums, and TLTRO operations, while the government introduced large fiscal stimulus packages under the Atmanirbhar Bharat program. Although these interventions helped stabilize financial markets, they also generated continuous information shocks as investors reassessed the effectiveness of stimulus measures, infection waves, vaccination progress, and economic reopening plans. Subsequent events such as the second COVID wave in 2021 and vaccination campaigns further increased information flow and market sensitivity to news. From a behavioral finance perspective, crises often tighten arbitrage constraints as institutions become more risk-averse and capital-constrained, allowing price adjustments and volatility to persist longer. Continuous media coverage and real-time monitoring of pandemic indicators also heightened investor attention, contributing to stronger feedback effects and sustained volatility in financial markets.

4.4.4 Post-Pandemic Period

Table 9 presents the VAR(1) estimation results for the post-pandemic period, indicating a transition toward a more normalized but still risk-sensitive market environment. Compared to the pandemic phase, the dynamic interactions among investor attention, returns, and volatility appear weaker, though not as subdued as in the pre-pandemic period. The attention equation shows a statistically significant negative coefficient on lagged attention, suggesting mean-reverting behavior where increases in attention tend to decline in subsequent periods, indicating that attention spikes were largely temporary during the recovery phase. Lagged volatility also has a marginally significant positive effect on attention, implying that investors continued to monitor the market more closely during periods of heightened uncertainty. The return equation exhibits limited explanatory power, with no statistically significant determinants, suggesting a partial return to weak-form market efficiency. In the volatility equation, the marginally significant negative effect of lagged returns is consistent with the leverage effect, where adverse price movements increase perceived risk and subsequent volatility. Overall, the relatively low R^2 values indicate only weak interdependence among attention, returns, and volatility during the post-pandemic period.

Table 9: VAR(Post-pandemic) Estimation Results

	Attention	Return	Volatility
Attention$_{t-1}$	-0.222**	-0.139	-0.052
	(0.086)	(0.089)	(0.085)
Return$_{t-1}$	-0.087	-0.017	-0.162*
	(0.084)	(0.087)	(0.083)
Volatility$_{t-1}$	0.154*	-0.062	0.145
	(0.089)	(0.092)	(0.088)
Constant	-0.005	0.093	-0.041
	(0.089)	(0.092)	(0.088)
Observations		128	
Log Likelihood		-541.832	
R^2	0.072	0.023	0.048
Adj. R^2	0.049	0.0001	0.025
F-statistic	3.205**	1.005	2.084
p-value (F)	0.025	0.393	0.105

Notes: Standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Deterministic component: constant.

The post-pandemic VAR results indicate a market environment that is gradually stabilizing but still influenced by structural adjustments and residual uncertainty. A key feature of this period is the significant negative coefficient of lagged attention, suggesting strong mean-reverting behavior where attention spikes are temporary rather than persistent. Unlike the pandemic phase, when continuous health updates and policy announcements sustained prolonged attention cycles, investor attention in the post-pandemic period appears to respond briefly to economic signals before returning to normal levels, reflecting more stable information processing. The return equation shows no statistically significant determinants and low explanatory power, indicating a partial restoration of weak-form market efficiency, where prices adjust more rapidly to available information and attention-driven predictability is limited. In contrast, the volatility equation remains sensitive to lagged returns, consistent with the leverage effect, where negative price movements increase perceived risk and subsequent volatility. This pattern reflects the broader post-pandemic macro-financial environment characterized by inflationary pressures, rising interest rates, global monetary tightening, and geopolitical tensions such as the Russia–Ukraine conflict, which continued to sustain risk perceptions despite the overall recovery of economic activity.

The economic reasoning behind these findings is closely linked to the post-pandemic adjustment and normalization of the economy. Following the severe disruptions caused by COVID-19, the period was characterized by economic reopening, vaccination campaigns, and a gradual recovery in production and consumption supported by earlier policy interventions. However, new macroeconomic challenges emerged, including supply chain disruptions, rising commodity prices, global inflationary pressures, and geopolitical tensions such as the Russia–Ukraine conflict. In response, central banks worldwide, including the Reserve Bank of India, shifted from accommodative policies to monetary tightening to control inflation. Unlike the sudden shock of the pandemic, these developments introduced a more structured and policy-driven form of uncertainty. As economic conditions improved, investors had clearer expectations regarding corporate earnings, policy frameworks, and recovery trends, leading to attention spikes that were more temporary than persistent. Improved liquidity conditions, stronger institutional participation, and clearer policy guidance also contributed to a partial restoration of market efficiency. Nevertheless, the persistence of the leverage effect suggests that markets remained cautious and sensitive to negative shocks amid inflation concerns and global monetary tightening. Overall, the post-pandemic period represents a transitional regime in which markets gradually stabilized after the crisis while continuing to adjust to evolving macroeconomic and geopolitical risks.

4.5 Impulse Response Function (IRF)

The impulse response functions (IRFs) in figure 2 indicate that during the pre-pandemic period, the dynamic linkages among investor attention, returns, and volatility were relatively weak and short-lived. Most shocks dissipate within one or two periods, suggesting a stable market environment with limited feedback effects among the variables. This pattern is consistent with a relatively efficient market structure where information is quickly incorporated into prices and arbitrage mechanisms limit behavioral amplification. Consequently, domestic economic reforms and financial sector disturbances during this period did not generate persistent inter-dependencies among attention, returns, and volatility.

In contrast, the pandemic-period IRFs reveal stronger and more persistent dynamic interactions among the variables. Shocks generate larger initial responses and take longer to dissipate, indicating heightened sensitivity and stronger feedback mechanisms during the crisis. This behavior reflects the high-uncertainty environment created by the COVID-19 pandemic, characterized by repeated lockdowns, policy interventions, global financial instability, and heightened investor risk aversion. As a result, investor attention, returns, and volatility became more closely interconnected, allowing shocks to propagate more strongly across the system.

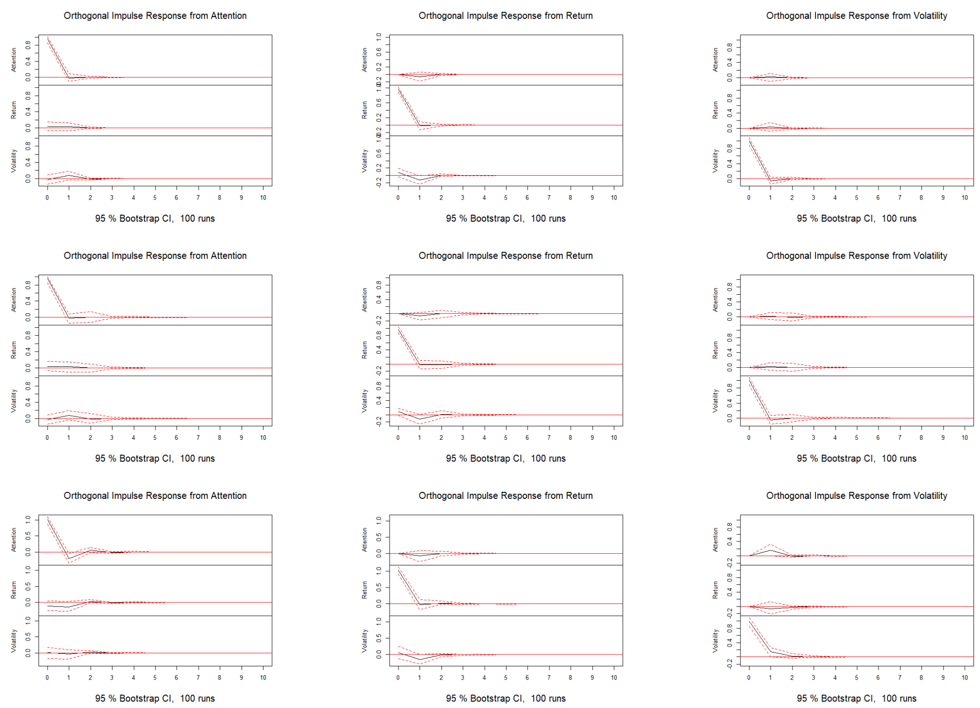

Figure 2: IRF in sub-sample

The impulse response functions (IRFs) for the post-pandemic period indicate that market dynamics have become more stable compared to the pandemic phase, although some sensitivity to risk shocks remains. Shocks are less persistent than during the crisis but slightly more interactive than in the relatively calm pre-pandemic period, suggesting moderate interdependence among investor attention, returns, and volatility during the normalization phase. This pattern implies that while markets are gradually moving back toward efficiency, they remain cautious in responding to risk signals. The faster absorption of shocks compared to the pandemic period reflects improved liquidity, stronger arbitrage activity, and clearer policy guidance. However, the persistence of short-run volatility responses indicates continued sensitivity to macroeconomic risks such as inflationary pressures, interest rate normalization, and global geopolitical tensions. Overall, the post-pandemic regime represents a transitional market structure that is more stable than the crisis period but still more risk-aware than the pre-pandemic equilibrium.

4.6 Granger Causality Analysis

The results in table 14 to 16 (in appendix) shows the Granger causality analysis. The VAR results may show dynamic interactions, while Granger causality test may still be insignificant, where this can be explaining the difference between dynamic interdependence and predictive causality. The Granger causality test particularly looks at whether historical values of one variable affect the prediction of another variable, even if the VAR model incorporates the dynamic interactions among investor attention, stock returns, and volatility. Therefore, historical investor attention values do not considerably improve the predictive potential for stock returns or volatility within the given lag structure, according to the insignificant Granger causality results. This does not, however, necessarily mean that there are no dynamic interactions between the variables. It is possible for market moves and investor interest to happen concurrently rather than sequentially. The usefulness of lagged attention factors to forecast future returns or volatility in the Granger causality paradigm is limited in these situations because market players may respond instantly to information searches and news events. The efficiency of financial markets, where publicly available information, including online search activity, is quickly absorbed into asset prices, may also be reflected in the negligible Granger causality results. The effective sample size in each subsample is decreased by splitting the sample into pre-pandemic, pandemic, and post-pandemic periods, which could limit the Granger causality tests' statistical power.

4.7 Discussion

Across the three regimes, the results reveal a clear structural shift in market dynamics reflecting how financial markets respond under conditions of stability, crisis, and recovery. During the pre-pandemic period, the VAR results show weak dynamic linkages among investor attention, returns, and volatility, with low explanatory power and mostly insignificant coefficients. This suggests a relatively stable market environment where information was efficiently incorporated into prices and behavioral distortions were limited. Despite major domestic events such as demonetization, GST implementation, and the NBFC liquidity crisis, these shocks were largely anticipated or gradually absorbed, supported by strong institutional participation, credible monetary policy, and improving financial infrastructure. Consequently, attention shocks did not significantly amplify volatility or generate persistent return predictability. In contrast, the pandemic period represents a clear regime shift characterized by stronger persistence and interdependence among the variables. The COVID-19 crisis generated unprecedented uncertainty through nationwide lock downs, economic contraction, and global financial instability. The VAR results indicate significant feedback mechanisms, where investor attention became highly persistent due to continuous monitoring of pandemic developments and policy responses. Returns exhibited reversal patterns consistent with panic-driven market reactions and subsequent policy-supported recoveries, while volatility showed strong clustering as risk perceptions remained elevated. These dynamics reflect a crisis-driven regime in which behavioral reactions, policy interventions, and heightened uncertainty intensified the interaction between attention, returns, and volatility. The post-pandemic period reflects a transitional normalization phase rather than a complete return to pre-crisis stability. As economic activity recovered and vaccination coverage expanded, investor attention became more mean-reverting and return predictability declined, indicating a partial restoration of market efficiency. However, volatility remained sensitive to negative return shocks, reflecting persistent leverage effects and heightened downside risk amid global inflation, monetary tightening, and geopolitical tensions. The moderate explanatory power of the system suggests that although endogenous feedback mechanisms weakened relative to the pandemic period, markets remained attentive to macroeconomic risks.

Overall, the comparison of the three regimes highlights a cyclical evolution in market behavior: a stable pre-pandemic equilibrium, a crisis-amplified pandemic regime characterized by strong feedback effects, and a post-pandemic adjustment phase where efficiency partially recovers but risk awareness persists. Consistent with this pattern, the Granger and instantaneous causality tests show no statistically significant causal relationship between investor attention, returns, and volatility across the three periods. The null hypothesis that investor attention does not Granger-cause returns or volatility cannot be rejected, indicating that past attention does not significantly improve the prediction of market movements. However, weak evidence of causality from returns to attention in the pre- and post-pandemic periods suggests that market fluctuations may attract investor attention and information-seeking behavior. Overall, the findings imply that investor attention primarily reflects market developments rather than exerting a strong predictive influence on stock returns or volatility across different economic regimes.

5 Robustness Check

For the robustness analysis, the study uses an alternative keyword, "Nifty", instead of relying solely on the Google search volume index (SVI) for "Sensex." Additional stock market–related search terms were employed to construct the investor attention index in order to verify whether the results depend on the specific keyword used. This approach provides a strong robustness strategy because both BSE Sensex and NIFTY 50 represent the overall Indian stock market and are widely followed by investors. In this robustness exercise, the attention variable was replaced from Sensex SVI to Nifty SVI, while the return and volatility series remained unchanged. The VAR analysis was then re-estimated using this alternative proxy, and the results remained qualitatively similar, indicating that the findings are not sensitive to the choice of search keyword used to measure investor attention.

Based on the stationarity test, all the variables are stationary at level (refer 17). According to the lag-length selection criteria (Section 8.4.2), the optimal lag order is three for the pre-pandemic and pandemic periods, and one for the post-pandemic period. This suggests that the pre-pandemic and pandemic regimes exhibit richer dynamic interactions among investor attention, stock returns, and volatility, whereas a shorter lag structure is sufficient to capture the relationships in the post-pandemic period.

Table 21 reports the VAR estimation results for the pre-pandemic period, where the Google search volume index for "Nifty 50" is used as the proxy for investor attention. The lagged values of attention are highly significant and negatively related to current attention, indicating strong mean-reverting behavior in investor attention. This implies that spikes in search activity tend to be followed by adjustments in subsequent periods. In contrast, the lagged values of returns and volatility do not significantly influence investor attention, suggesting that past market movements did not strongly affect search behavior during the pre-pandemic period. These findings are broadly consistent with the earlier VAR results where investor attention was measured using Sensex search activity. In both cases, lagged attention significantly influences current attention, while investor attention does not have a statistically significant effect on stock market returns or volatility. The similarity of the results indicates that the empirical conclusions are robust to the choice of search keyword. Since both Nifty and Sensex are major benchmark indices that move closely together, search activity related to either index appears to capture similar patterns of investor information demand. Overall, the results suggest that during the pre-pandemic period investor attention exhibited strong persistence and mean-reverting dynamics, with limited direct influence on stock market returns and volatility. The consistency of results obtained using both Nifty and Sensex search indices further strengthens the robustness of the empirical findings.

The VAR estimation results for the pandemic period in Table 22 indicate strong persistence and mean-reverting behavior in investor attention. Lagged returns suggest that previous market performance slightly reduces subsequent search activity, implying that investors tend to decrease information searches following positive market adjustments. Past returns also significantly influence current returns, reflecting heightened market dynamics during the crisis period. However, attention variables do not significantly affect stock returns, suggesting that investor attention does not directly drive market returns during the pandemic. Overall, these results are broadly consistent with the earlier VAR findings based on Sensex search activity. Although the direct impact of attention on returns remains insignificant, lagged attention significantly affects current attention in both cases. The Nifty-based results show a slightly stronger relationship between attention and volatility, suggesting that increased information search may have contributed to market stabilization during heightened uncertainty.

The post-pandemic VAR results in Table 23 show that increases in investor attention are followed by corrections in subsequent periods, indicating mean-reverting attention behavior. When market conditions improve, investors tend to reduce information search activity as uncertainty declines. Neither investor attention nor past market volatility significantly influences stock returns during this period, suggesting that returns are largely driven by factors outside the model. In the volatility equation, the positive coefficient of lagged volatility indicates volatility persistence, while the negative coefficient of lagged returns implies that higher previous returns reduce current volatility. The attention variable does not significantly affect volatility. These findings are consistent with the earlier VAR results using Sensex as the attention proxy, indicating that the empirical conclusions are robust to the choice of search keyword. Overall, the results suggest that investor attention mainly exhibits self-adjusting dynamics, while stock returns and volatility are largely influenced by their own past values rather than changes in search activity.

The impulse response functions in figure 3 show that investor attention, returns, and volatility interact weakly and transiently, with most responses stabilizing after a short while. Crucially, these trends are much in line with the previous IRF findings that were derived using the BSE Sensex's Google search volume index as a stand-in for investor attention. The response patterns' closeness indicates that the dynamic relationships between the variables are not affected by the search term chosen to gauge investor interest. Therefore, even when different measures of investor attention are used, the IRF analysis demonstrates that the study's primary conclusions—namely, the modest impact of investor attention on stock returns and volatility—remain consistent.

6 Conclusion

This study examines whether investor search behavior influences stock market activity during periods of economic disruption, particularly during the COVID-19 pandemic, or whether investor attention simply reflects market dynamics. Using weekly Google search data as a proxy for investor attention and applying time-series econometric techniques—including EGARCH for volatility estimation, VAR modeling, structural break analysis, and impulse response functions—the study analyzes the dynamic relationship between investor attention, stock returns, and volatility in the Indian equity market from 2015 to 2023.

The empirical findings reveal that the relationship between investor attention and market dynamics is strongly regime dependent. During the pre-pandemic period, the interaction between attention, returns, and volatility is weak, suggesting a relatively stable market environment where prices efficiently incorporate available information. Despite several major domestic economic events, shocks were largely absorbed quickly and investor attention did not significantly influence market movements.

In contrast, the pandemic period represents a structural shift characterized by heightened uncertainty and stronger feedback mechanisms. Investor attention became highly persistent as investors closely monitored pandemic developments, policy announcements, and economic recovery measures. Market volatility increased substantially and exhibited clustering, while returns showed reversal patterns consistent with panic-driven reactions followed by stimulus-supported recoveries. These findings highlight the stronger role of behavioral responses and information-seeking activity during crisis periods.

The post-pandemic period reflects a gradual normalization of market dynamics. Investor attention becomes mean-reverting and the dynamic interactions among attention, returns, and volatility weaken relative to the pandemic phase, suggesting a partial restoration of market efficiency. Nevertheless, volatility remains sensitive to negative return shocks, indicating continued macro-financial risk awareness in an environment shaped by inflationary pressures, global monetary tightening, and geopolitical uncertainty.

To ensure the robustness of the results, the analysis was repeated using an alternative proxy for investor attention based on Google search activity for NIFTY 50, replacing the original attention measure derived from searches for BSE Sensex. The VAR estimations and impulse response results obtained using this alternative keyword remain qualitatively similar to the baseline findings, confirming that the empirical conclusions are not sensitive to the specific search term used to measure investor attention. This robustness exercise strengthens the reliability of the results and supports the interpretation that search behavior associated with either benchmark index captures similar patterns of investor information demand.

Overall, the findings demonstrate that investor attention does not exert a constant influence on financial markets; rather, its impact varies across different economic regimes. Attention appears economically negligible during stable periods, highly influential during systemic crises, and moderately reactive during recovery phases. These results highlight the importance of incorporating structural breaks and behavioral dynamics when analyzing financial markets, particularly in emerging economies.

From a practical perspective, increased search intensity should not automatically be interpreted as a profitable trading signal, as it often reflects heightened uncertainty rather than market opportunities. Understanding how information flows interact with investor behavior can help policymakers improve communication strategies and design policies that mitigate volatility during periods of market stress. Overall, the study provides a comprehensive understanding of how information-seeking behavior interacts with financial market dynamics in India across different economic regimes.

7 References

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8 Appendix

8.1 ADF test

Table 10: Unit root test

Unit root test	Return	Volatility	Attention
Pre-pandemic	**-5.833**	**-6.544**	**-6.874**
	(0.01)	(0.01)	(0.01)
Pandemic	-3.268	-3.094	-3.423
	(0.084)	(0.130)	(0.059)
Pandemic (first-diff)	**-4.9703**	**-6.944**	**-5.186**
	(0.01)	(0.01)	(0.01)
Post- pandemic	**-4.421**	**-4.732**	**-4.797**
	(0.01)	(0.01)	(0.01)

8.2 Lag-length criteria

Table 11: Lag-length criteria for pre-pandemic

	1	2	3	4
AIC (n)	**-0.125**	-0.115	-0.070	-0.056
HQ(n)	**-0.059**	-0.0001	0.094	0.158
SC (n)	**0.039**	0.171	0.339	0.477

Table 12: Lag-length criteria for pandemic

	1	2	3	4
AIC (n)	**-0.125**	0.637	0.654	0.674
HQ(n)	1.134	**0.926**	1.066	1.210
SC (n)	1.391	**1.376**	1.710	2.047

Table 13: Lag-length criteria for post-pandemic

	1	2	3	4
AIC (n)	**0.144**	0.234	0.267	0.353
HQ(n)	**0.258**	0.433	0.551	0.722
SC (n)	**0.424**	0.725	0.968	1.263

8.3 Granger Causality

Table 14: Granger and Instantaneous Causality Test Results (Pre-pandemic)

	Granger Causality (F-Test)			Instantaneous Causality (χ^2)		
Null Hypothesis	Statistic	df	p-value	Statistic	df	p-value
Attention $\nrightarrow$ Return, Volatility	0.918	(2, 795)	0.399	0.714	2	0.699
Return $\nrightarrow$ Attention, Volatility	$2.442^{\dagger}$	(2, 795)	0.087	2.180	2	0.336
Volatility $\nrightarrow$ Attention, Return	0.180	(2, 795)	0.835	2.061	2	0.356

Notes: † indicates significance at the 10% level.

$\nrightarrow$ denotes "does not Granger-cause".

Table 15: Granger and Instantaneous Causality Results (Pandemic period)

	Granger Causality (F-Test)			Instantaneous Causality (χ^2)		
Null Hypothesis	Statistic	df	p-value	Statistic	df	p-value
Attention $\nrightarrow$ Return, Volatility	0.769	(4, 180)	0.546	1.515	2	0.468
Return $\nrightarrow$ Attention, Volatility	1.098	(4, 180)	0.358	1.890	2	0.388
Volatility $\nrightarrow$ Attention, Return	0.436	(4, 180)	0.782	1.209	2	0.546

Notes: $\nrightarrow$ denotes "does not Granger-cause".

No statistically significant causality detected at conventional levels.

VAR lag order = 2.

Table 16: Granger and Instantaneous Causality Results (Post-pandemic)

	Granger Causality (F-Test)			Instantaneous Causality (χ^2)		
Null Hypothesis	Statistic	df	p-value	Statistic	df	p-value
Attention $\nrightarrow$ Return, Volatility	1.351	(2, 372)	0.260	1.274	2	0.528
Return $\nrightarrow$ Attention, Volatility	2.40*	(2, 372)	0.091	1.618	2	0.445
Volatility $\nrightarrow$ Attention, Return	1.613	(2, 372)	0.200	0.409	2	0.814

Notes: $\nrightarrow$ denotes "does not Granger-cause".

* indicates significance at the 10% level.

No instantaneous causality detected at conventional significance levels.

8.4 Robustness Check

8.4.1 ADF Test

Table 17: Unit root test

Unit root test	Attention	Return	Volatility
Pre-pandemic	**-8.157**	**-5.833**	**-6.544**
	(0.01)	(0.01)	(0.01)
Pandemic	-5.263	-3.094	-3.423
	(0.01)	(0.130)	(0.059)
Pandemic (first-diff)	-5.532	**-6.944**	**-5.186**
	(0.01)	(0.01)	(0.01)
Post- pandemic	**-4.421**	**-4.732**	**-4.797**
	(0.01)	(0.01)	(0.01)

8.4.2 Lag-length criteria

Table 18: Lag-length criteria for pre- pandemic

	1	2	3	4	5
AIC (n)	-5.068	-5.087	**-5.093**	-5.056	-5.026
HQ(n)	-5.002	-4.971	**-4.927**	-4.842	-4.762
SC (n)	-4.904	4.799	**-4.682**	-4.522	-4.369

Table 19: Lag-length criteria for pandemic

	1	2	3	4
AIC (n)	-4.631	-5.591	**-5.701**	-5.454
HQ(n)	-4.466	-5.302	**-5.288**	-4.917
SC (n)	-4.209	-4.851	**-4.644**	-4.080

Table 20: Lag-length criteria for post-pandemic

	1	2	3
AIC (n)	**5.481**	-5.404	-5.351
HQ(n)	**-5.367**	-5.205	-5.067
SC (n)	**-5.201**	-4.913	-4.651

8.4.3 VAR Model

Table 21: Vector Autoregression (VAR) Results in Pre-pandemic period

	Dependent variable:		
	Attention	Return	Volatility
	(1)	(2)	(3)
Attention.l1	−0.314***	−0.439	−0.240
	(0.062)	(0.785)	(0.823)
Return.l1	0.006	0.004	−0.127*
	(0.005)	(0.062)	(0.066)
Volatility.l1	−0.007	0.024	−0.043
	(0.005)	(0.060)	(0.062)
Attention.l2	−0.268***	0.566	0.266
	(0.063)	(0.797)	(0.836)
Return.l2	0.004	−0.053	0.140**
	(0.005)	(0.062)	(0.065)
Volatility.l2	0.004	−0.126**	−0.054
	(0.005)	(0.059)	(0.062)
Attention.l3	−0.246***	−0.525	0.350
	(0.062)	(0.790)	(0.829)
Return.l3	0.003	−0.028	−0.073
	(0.005)	(0.062)	(0.065)
Volatility.l3	0.002	0.055	0.047
	(0.005)	(0.059)	(0.062)
const	0.001	−0.040	0.004
	(0.005)	(0.059)	(0.062)
Observations	269	269	269
R^2	0.152	0.032	0.046
Adjusted R^2	0.123	−0.002	0.012
Note:	*p<0.1; **p<0.05; ***p<0.01		

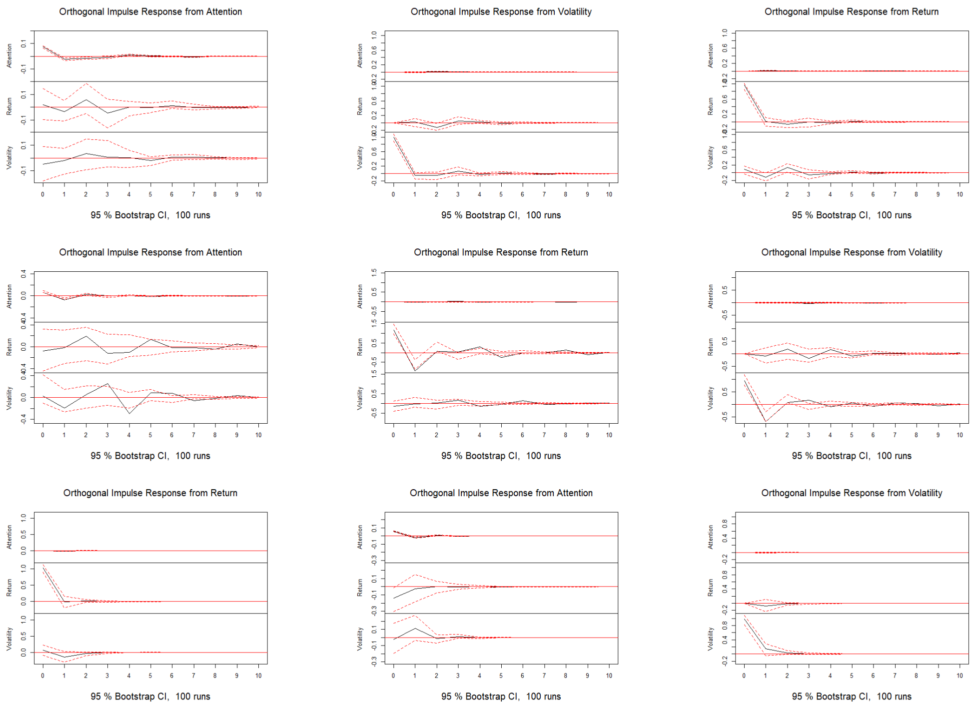
Table 22: VAR Estimation Results in pandemic period

	Dependent variable:		
	Attention	Return	Volatility
	(1)	(2)	(3)
Attention.l1	-1.132^{***}	-1.284	-2.860
	(0.122)	(2.275)	(1.852)
Return.l1	-0.007	-0.831^{***}	-0.107
	(0.007)	(0.122)	(0.099)
Volatility.l1	0.003	-0.103	-0.742^{***}
	(0.009)	(0.165)	(0.134)
Attention.l2	-0.864^{***}	0.345	-4.727^{**}
	(0.155)	(2.896)	(2.357)
Return.l2	-0.014^{*}	-0.631^{***}	-0.168
	(0.008)	(0.145)	(0.118)
Volatility.l2	0.016	0.031	-0.481^{***}
	(0.010)	(0.180)	(0.147)
Attention.l3	-0.400^{***}	1.132	-0.663
	(0.122)	(2.270)	(1.847)
Return.l3	0.002	-0.446^{***}	-0.046
	(0.007)	(0.128)	(0.104)
Volatility.l3	0.002	-0.065	-0.082
	(0.009)	(0.160)	(0.130)
const	0.004	-0.029	0.020
	(0.008)	(0.143)	(0.117)
Observations	67	67	67
R^2	0.677	0.487	0.478
Adjusted R^2	0.625	0.404	0.394
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 23: Vector Autoregression (VAR) Results in Post-pandemic period

	Dependent variable:		
	Attention	Return	Volatility
	(1)	(2)	(3)
Attention.l1	-0.355^{***}	-0.516	1.614
	(0.084)	(1.482)	(1.394)
Return.l1	-0.011^{**}	-0.009	-0.148^{*}
	(0.005)	(0.088)	(0.083)
Volatility.l1	-0.003	-0.072	0.146^{*}
	(0.005)	(0.093)	(0.088)
const	0.002	0.095	-0.042
	(0.005)	(0.093)	(0.088)
Observations	128	128	128
R^2	0.146	0.006	0.055
Adjusted R^2	0.125	-0.018	0.032
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 3: IRF for robustness



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