Herding in the Indian Equity Market

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***Abstract*—This research investigates the influence of occurrences on the actions of Indian investors emphasizing herd behaviour and fluctuations, in the stock market. Traditional finance theories Efficient Market Hypothesis (EMH) Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM) presume investors act nonetheless geopolitical instability frequently causes behavioural irregularities. Therefore this study employs a Behavioural Finance approach to elucidate investment choices amid uncertainty.**

The research utilizes closing values of key Indian stock market indices spanning 2021 to 2025 encompassing times of notable domestic and international geopolitical occurrences. Herd behaviour is identified employing the CrossSectional Absolute Deviation (CSAD) approach whereas volatility clustering is assessed via Generalised Autoregressive Conditional Heteroscedasticity (GARCH) frameworks. The Granger causality test is applied to investigate the link between geopolitical risk and market returns.

The findings reveal that geopolitical events significantly increase stock market volatility in India. Cumulative evidence of herd mentality can be observed during times when Geopolitical risks are increased due to major world events causing a spike in stock prices or causing a temporary decline (extreme fear). There is also a typical bi-directional causal relationship between Geopolitical risks and stock prices. Hence the relationship mainly reflects the general population(or Investors) through their own emotions: therefore exhibiting Emotional and Rational Behaviours due to heightened irrational Psychology and increased volatility during Geopolitical stresses.

***Index Terms*—GARCH model, Herding, Indian capital market, Volatility**

I. INTRODUCTION

Finance is all about how money moves, how it is managed, and how it is used within the economy. It exists at every level, from small, everyday decisions like an individual choosing to save a part of their salary in a fixed deposit, to large-scale actions like a government borrowing billions to build highways or fund healthcare programs. At its core, finance studies the behaviour of money, currency, assets, and liabilities, as well as the decisions people, businesses, and governments make about them. It is both a practical and theoretical field that looks at how financial resources are raised, invested, divided, and managed over time.

On a personal level, finance plays a role in how individuals and households manage their money. This includes creating budgets, saving for the future, and investing in opportunities. Every choice, whether to spend on something now or set the money aside for later, is a financial decision. Personal finance is about using resources wisely to achieve both short-term goals, like buying a new phone or going on holiday, and long-term goals, like owning a house or retiring comfortably.

Investment is the core of finance. It helps individuals build wealth and helps companies finance their expansion. Savings are never enough; the potential of investing in financial markets will outweigh all the interest earned by savings, considering the high returns. Investments generate returns through interest or capital appreciation, which helps tackle inflation and maintain purchasing power. On a macroeconomic scale, investment drives capital formation, fosters innovation, and creates jobs, contributing to economic development. Compounding is the main concept of investment, where returns are reinvested to generate exponential growth, helping increase one's wealth. Investment can be done in stocks, bonds, mutual funds, or real estate, which are called investment vehicles. Understanding investment patterns will help calculate risk and estimate potential returns, which is vital for financial planning individually and on a broader scale. (Mirzaev Mirzabek Abdullaevich, 2020)

Investment platforms are services that allow investors to manage their investments. The diversification, or

variety, of different investment platforms has transformed the way individuals and institutions allocate capital, providing many opportunities for maximizing returns while managing risk. Traditional platforms such as stocks, bonds, and mutual funds are crucial for capital appreciation and income generation; however, there has been a surge in digital platforms due to advancements in technology. Robo-advisors, peer-to-peer lending, and cryptocurrency exchanges are examples of digital platforms that enable investors to increase their accessibility, leading to greater participation in the global market. Real estate investment platforms and exchange-traded funds (ETFs) help further diversify investment portfolios. Each platform has different characteristics and requires regulatory oversight. Evaluating these platforms helps analyze performance metrics and potential risks using technological adaptability. Analysis regarding the comparative advantages and limitations of each platform will help align investor objectives, leading to the feasibility of achieving high returns. (Zelda Brutti, 2022)

All of this activity takes place within financial systems—the interconnected networks of banks, stock markets, insurance companies, and other institutions that link those who have money with those who need it. These systems allow the exchange of financial instruments such as stocks, bonds, and derivatives, enabling individuals and organisations to grow their wealth while protecting themselves from potential losses. In the end, finance touches nearly every aspect of life. It helps people plan their futures, supports businesses in expanding and innovating, and allows governments to provide for their citizens. Without it, progress, stability, and growth would be nearly impossible to achieve.

Financial markets can be rational, or there may be some irrationalities, like the 2008 financial crisis. Rationality in financial markets can be known as the efficient market hypothesis theory. EMH is meant to suggest that all investors or financial agents use the adequate information available in asset or financial negotiations, creating a stereotype that portrays all economic aspects or the market situation as highlighted during these negotiations. Developed by Eugene Fama in the 1960s, this theory has been applied extensively to different models and in different price discovery processes (Sergio Roberto de Souza Junior). A rational decision is the product of a systematic decision-making process with the aim of maximizing profits. This behavior ensures any miscalculation in price is corrected through arbitrage (Subramaniam V.M., 2025). "The Behavior of Stock-Market Prices," published by Fama in 1965, discusses the hypothesis of efficiency, reflecting on statistical analysis of price behavior, which researches the successive changes in prices. The connection between EMH and rationality is integral in understanding the persistence of inefficiencies and predictive financial modeling, which highlights the stereotype that prices of financial instruments reflect the whole financial market, which is extremely rare due to high volatility (Thomas Delcey, 2019).

A more realistic theory of the financial market would be the irrationalities. It portrays the behavior and decisions that are driven by emotions, biases or cognitive theories leading to anomalies in the market. One of the most prominent examples can be the stock market bubble. In these cases, asset prices diverge greatly from their true values due to the overall mood of investors rather than fundamental factors.(Anders Johansen, 2010) Behavioral finance links such bubbles to cognitive biases, herd behavior, and overconfidence, which lead to excessive optimism and speculative trading. For example, during the dot-com bubble from 1995 to 2000, technology stocks saw rapid price increases driven by investor excitement over internet-based business models, even though many companies had no sustainable revenue streams. The market's collective enthusiasm created a cycle where rising prices attracted more investors, further pushing up valuations. This situation reflects the “greater fool theory,” where participants knowingly purchase overvalued assets, hoping to sell them to someone else at an even higher price.(Zou,Xuan, 2018) Eventually, when sentiment changes or reality does not meet expectations, the bubble pops. This leads to sharp drops in asset prices and significant loss of wealth. Such occurrences show the limits of the Efficient Market Hypothesis (EMH) in explaining extreme market changes. During these times, prices are not just influenced by information efficiency, but also by psychological and social factors. Understanding stock market bubbles is vital for policymakers, as they can upset economies and diminish investor confidence. Adding insights from

behavioral finance into financial models can enhance predictive accuracy. This can help spot early warning signs of irrational exuberance and reduce systemic risks through better regulation and investor education (Nicolas Huck, 2020).

This paper will focus on understanding the impact of recent geopolitical events on the Indian stock market.

II. LITERATURE REVIEW

Governing traditional finance was the idea that investors are rational, seek to maximize their expected utility of wealth, and live in markets that are informationally efficient (Ackert, 2014). Principles of modern finance are based on three core theories, namely: Modern Portfolio Theory (MPT) (Ferson & Riepe, 2017; Merton, 1983), leading to balancing of portfolios to achieve the best possible risk-return tradeoff; the Capital Asset Pricing Model (CAPM) (Lintner & Sharpe, 1964), relating expected returns with systematic risk; and the Efficient Markets Hypothesis (EMH), which stipulates that asset prices incorporate all available information at all times (Ackert, 2014; Finance Dictionary Pro, n.d.). In the conventional school of thought, risk is treated objectively and quantitatively, often assessed in terms of variables like beta or standard deviation, with a positive relationship between risk and expected return (Ricciardi, 2008). Researchers using such a method assume that markets and participants are acting rationally and in an effort to maximize utility, with deviations from the model's predictions attributable to random noise rather than systematic psychological effects (The MBA Institute, n.d.; Ricciardi, 2008). Such literature stresses mathematical rigor, statistical modelling, and application of formal tools to make inferences regarding capital placement, asset pricing, and financial risks. While these models have created a strong foundation for portfolio management and financial analysis, they are driven by assumptions such as rational agents, perfect information, and normally distributed returns, creating conflicts in academic discussions (Nik Maheran Nik Muhammad, 2009).

A Capital Asset Pricing Model (CAPM) portrays the relation between systematic risk and expected returns. It acts as a tool for investors to make better financial analysis in the market, considering the factors of volatility, uncertainty, complexity, and ambiguity (Wang & Liao, 2024). It highlighted that the expected return of a market can be shown as a linear function of its systematic risk, and that only market risk should be placed in equilibrium (Sharpe, 1964). This model provides a tractable equation that relates risk and return, enabling practitioners and researchers to estimate the cost of equity and assess portfolio performance (Black, Jensen, & Scholes, 1972). Its sophisticated simplicity is based on simplifying intricate financial behavior into a one-factor model, assuming rational investors, uniform expectations, and seamless markets (Lintner, 1964; Mossin, 1966). Early empirical studies, however, raised questions about the model's predictions. Black et al. (1972) discovered that, while beta is connected with returns, the relationship is flatter than predicted by the CAPM. Similarly, Fama and MacBeth (1973) used time-series regressions to argue that beta alone could not adequately reflect cross-sectional changes in stock returns. Roll (1977) went on to argue that the CAPM is empirically untestable because the genuine market portfolio—which includes all hazardous assets—is unobservable. These critiques paved the way for further investigation of anomalies and the development of alternative frameworks (Fama & French, 1992). The most prominent challenge to CAPM came from Fama and French (1992), who showed that firm size and book-to-market equity ratios explain average returns better than beta. Fama and French's results directly challenged the view that only systematic risk is relevant for expected return. In a subsequent study, Fama and French (2015) extended their analysis to a five-factor model that included profitability and investment policies, and found that profitability and investment policies explain average returns with much higher explanatory power than CAPM. They also reported the earnings-to-price ef(fect Basu, 1977), along with evidence regarding the size effect (Banz, 1981), which returned systematic bias from the CAPM. These empirical regularities prompted further scrutiny of the adequacy of single-factor models by the finance community (Jagannathan & Wang, 1996). Though the CAPM continues to come under criticism, it has survived because it is intuitive, widely used in finance courses, and thought to be useful for corporate finance, portfolio management, and capital budgeting (Sharpe, 1964; Lintner, 1965). For example, it continues to be the way firms calculate the cost of equity, used in discounted cash flow valuation, even when practitioners admit that it does

not tell the whole story (Jagannathan & Wang, 1996). Other extensions of the CAPM, like conditional models with time-varying risk premia, have tried to restore the model's empirical relevance (Jagannathan & Wang, 1996). Nonetheless, even under the CAPM framework, residual anomalies remain—for example, the momentum effect (Fama & French, 2015).

Rationality has historically occupied a significant place within the study of financial economics and the foundation of classical views of asset pricing theories and market efficiency. Traditionally, finance has assumed that investors act rationally, maximizing their expected utility in environments of uncertainty or risk. This notion of rationality appeared to be implicit in the thinking of Markowitz (1952) on portfolio selection and Sharpe (1964) in their development of the Capital Asset Pricing Model (CAPM). Furthermore, this notion of rationality lies at the basis of the Efficient Market Hypothesis (EMH), which posits that security prices reflect all available information quickly and completely, allowing little room for systematic mispricing (Fama, 1970). Moreover, the previously mentioned rationality assumes that agents adjust their beliefs over time based on a combination of new information observed through the exercise of rational processes in conjunction with Bayes's rule, and form unbiased expectations of future payoffs (Muth, 1961). Subsequently, in the wake of the previously mentioned research, findings indicated that actual investor concerns were often inconsistent with the predictions of rational models. To name several anomalies that elicited continued research: evidence on the size effect (Banz, 1981), stock prices that tend to overreact and underreact (De Bondt & Thaler, 1985), and excess volatility with stock market prices (Shiller, 1981). Ultimately, these anomalies to the assumptions of perfectly rational markets paved the way for behavioral finance which incorporates psychological and cognitive perspectives into financial decision-making (Barberis & Thaler, 2003).

Behavioral finance examines how cognitive and emotional biases systematically influence investor decision-making, thus abandoning the notion of rationality. Barberis & Thaler (2003) argue that behavioral finance diverges from rational finance by acknowledging the behavioral elements that influence investor bias. Anchoring, a cognitive bias that occurs when individuals put too much weight on initial reference points, impairs financial forecasting performance; Judijanto (2025) finds anchoring explains 34% of the variance in corporate forecasting errors in Indonesia. In equity markets, financial analysts' practice of anchoring earnings forecasts to previous values leads analysts to either underreact or overreact to changes in forecasts (see analysts in Tunisia; author, 2024) (Judijanto, 2025; Analyst study 2024). In an experimental feasibility trading context, Arora and Rajendran (2023) found anchoring persisted as a bias under stable market characteristics, while the disposition effect, which affects behavior to sell winners early and losers late, increases with volatility as anchoring has a greater influence on performance. The disposition effect was first observed by Shefrin and Statman (1985) and remains a strong pattern of investor behavior that exhibits stability over time. Ahn (2021) demonstrates that an investor's level of sophistication, gender, and level of loss aversion are the factors that account for the disposition effect among retail investors. Furthermore, Dorn and Strobl (2023) investigated disposition biases and questioned the notion that "rational disposition effects" might exist depending on the context, which would imply the action results from optimization as opposed to bias alone. Hincapié-Salazar and Agudelo (2020) broadened this framework to bonds and demonstrated a comparable magnitude disposition effect as in equities in an emerging markets context. Kahneman and Tversky's (1979) prospect theory still remains a theoretical base for anchoring and disposition biases, outlining how loss aversion and framing impair rationality in investor decision-making.

Herd behavior in financial markets refers to investor behavior that is consistent with relying on the actions of others rather than their independent analysis of the situation (Banerjee, 1992). This mass movement is often accompanied by a mispricing of the underlying assets, causing bubbles or crashes, as investors follow the decision-making process of others without evaluating the fundamentals behind the situation (Bikhchandani & Sharma, 2000). Herding is often seen when investors are faced with uncertainty; when investment decision-making under uncertainty occurs, there is a greater likelihood investors will copy other investors' behavior because the risk of diverging from what others are doing is too great (Devenow & Welch, 1996). As a result, herding behavior can increase volatility in the market when many investors make either a buying decision or a selling decision at the

same time (Nofsinger & Sias, 1999). One factor that contributes to herding behavior in stock markets is what has been referred to as informational cascades, that is, individuals who rationally imitate the actions of others, believing that their actions are based on superior information (Bikhchandani, Hirshleifer, & Welch, 1992). Additionally, demand for stocks is not based on the intrinsic value of a stock during herding behavior, but rather on perceived consensus (Christie & Huang, 1995). Institutional investors also participate in herding behavior since they will place large trades that other investors see as signaling information and can follow their lead (Wermers, 1999). Furthermore, this phenomenon often is stronger for emerging markets, in which less developed regulations and increased uncertainty expand the impacts of the herd (Lakonishok, Shleifer, & Vishny, 1992). Furthermore, herding behavior is classified as either intentional or unintentional. Intentional herding arises when fund managers intentionally follow the decisions of their peers to safeguard their own reputations, whereas unintentional herding occurs when investors respond independently to the same signals, which results in correlated trades (Scharfstein & Stein, 1990). Herding behavior has repercussions for market efficiency, as it can weaken the price discovery process and the usefulness of traditional valuation models in estimating prices (Chiang & Zheng, 2010). Overall, studying unique herding behavior is beneficial to both researchers and practitioners, as it illustrates the divergence from rational market theory with associated behavioral characteristics of economic decision-making (Cont & Bouchaud, 2000).

H1: Positive and significant relationship between herd behaviour and the stock market

H2: Positive and significant relationship between volatility and the stock market

H3: Positive and significant relationship between herding and volatility.

Data- Broadmarket indices were used to check the impact of geopolitical events on the Indian stock market between 1st July 2021 to 31st November 2025

Research gap:

1. The goal of this research article is to understand how geopolitical events affect investor behaviour and lead to price fluctuations within the Indian equity market.

2.The article analyzes historical and ongoing geopolitical occurrences, looking specifically for evidence of negative investor sentiment (panic) or uncertainty created by those events, which may lead to herding behaviour at times of great volatility.

3.While research conducted on Indian financial markets have pointed towards the existence of a link between panic among investors and increased market volatility, there is still very little empirical work done to look at whether herding behaviour (as seen through panic and volatility) is exhibited systemically after there is an external Geopolitical event. The absence of research in this area is very apparent when we consider Geopolitical Shocks to be isolated external triggers that influence investor activity.

4.To this end, this research aims to fill this gap by investigating empirically the presence, extent and timings of panic volatility, herd behavior to Geopolitical Shocks. If a relationship between herd behaviour and market volatility under Geopolitical Stress is established, then the research also aims to determine the directionality and interaction of causality between these two variables, thus enhancing our understanding of both the structure of the market dynamics and the psychological mechanisms of behaviour responsible for how investors respond to Geopolitical uncertainty.

III. RESEARCH METHODOLOGY

3.1 CSSD is popular for measuring herd behavior within financial markets, especially in times of stress and extreme (dis)ordering (Chang, Cheng, & Khorana, 2000). Essentially, it measures the dispersion of individual stock returns compared to the market return. This method indicates if investors are converging in their investment behaviours (Tan, Chiang, Mason, & Nelling, 2008).

CSSD is mathematically represented as:

$$CSSDt = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} \blacksquare (Ri,t - Rm,t)^2}$$

where Ri,t is stock i's return at time t, Rm,t is the average market return at time t, and N is the number of firms in the market (Chang et al., 2000). A lower CSSD value during times of market distress suggests that investors are gathering around the market consensus as opposed to pursuing independent signals (Chiang & Zheng, 2010). This methodology has been used in studies of both developed and emerging

markets, thus establishing CSSD as a mainstay in herd behavior studies (Economou, Kostakis & Philippas, 2011).

The Cross-Sectional Absolute Deviation (CSAD) was created to extend the CSSD to allow for possibly nonlinear relations between herd behavior and the return in markets (Chang et al., 2000). The main difference between CSSD and CSAD is that CSSD squares the deviations, while CSAD uses absolute deviations and accommodates asymmetric effects that can arise from extreme positive or negative returns (Chiang & Zheng, 2010).
CSAD is mathematically represented as:

$$CSADt = \frac{1}{N}\sum_{i=1}^{N} \blacksquare |Ri,t - Rm,t|$$

where Ri,t indicates individual stock returns and Rm,t is the market return at time t (Chang et al., 2000). To empirically test for herding behavior, the CSAD is typically regressed against the simple market return and squared market return, and the expectation would be a negative sign on the squared term, indicating herding (Tan et al., 2008). This approach is useful because it captures possible non-linear convergence of returns in a manner that other linear models may not (Economou et al., 2011). Consequently, CSAD has emerged as a primary measure used in the behavioral finance literature, especially when measuring herd behavior effects in varying market conditions (Yao, Ma, & He, 2014).

3.2 The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, created by Bollerslev (1986), generalizes the ARCH framework established by Engle (1982) and provides much more flexibility in modeling time-varying volatility in financial time series. For example, it enables the current conditional variance to be dependent on lagged squared residuals and lagged variances, so that both can explain conditional volatility over time. This provides a greater amount of flexibility in modeling the persistence or clustering of volatility (Engle, 1982; Bollerslev, 1986). The GARCH(1,1) model has been used widely in empirical research (Nelson, 1991); its success in empirically describing the dynamics of financial markets is largely responsible for its extensive use in economics and finance. The robustness of GARCH as an appropriate model for stock returns, exchange rates, or commodity price variation has been documented (Bollerslev, Chou, and Kroner, 1992). Researchers continue to apply GARCH and its extensions or modifications to evaluate risk, estimate volatility, and test for market efficiency (Hansen & Lunde, 2005). More recently, GARCH has prompted the introduction of new forms like EGARCH and TGARCH, which allow for asymmetric effects in volatility and have demonstrated greater predictive abilities in the face of extreme shocks (Glosten, Jagannathan, and Runkle, 1993; Li, Zhu, and Zhu, 2021). Overall, the GARCH framework plays an important role in econometric research, representing a reasonable compromise between the level of theory and its use as a model (Wang & Zhou, 2022).

3.3 The Granger causality test is a popular econometric method for rigorously evaluating predictive linkages between pairs of time series variables (Granger, 1969). In other words, it analyzes whether any information about the past values of one variable contributes any predictive content toward helping to forecast the subsequent value of a second variable, beyond that provided by the first variable's lagged values by themselves (Gujarati & Porter, 2009). It is worth noting that Granger causality is not implying anything akin to causation; rather, it is a statistical definition of predictability (Hamilton, 1994). The test is based on comparing two regression specifications given two time series variables: the first regression specification is a regression of one time series variable on its own lagged values; the second regression specification includes lagged values of the second variable as additional regressors (Enders, 2015). If the regressions with the lagged values of the second variable provide a joint relevant contribution to the robust specification, it is theorized that the second time series Granger-causes the first time series (Stock & Watson, 2019). An F-test is conducted by checking the joint contribution of the coefficient estimates on the lagged values of the second variable to the model as a whole (Wooldridge, 2016). This method is particularly interesting in studies looking at financial market effects, where investigators attempt to establish whether exogenous shocks to the market—including shocks from geopolitical events—Granger-cause changes in stock returns and/or changes to stock volatility (Bouri et al., 2017). By creating a directional linkage, the Granger causality test opens up the field to obtain considerably richer understandings of the

dynamic linkages between stock market behaviour and external stimuli (Chen, Roll, & Ross, 1986). (Since the objective of the research is to analyse if there is any relation between herding of the market and volatility in the financial market and vice versa.)

The main aim of this research project is to examine the extent to which external geopolitical events—acting as exogenous shocks—influence the behavior of the Indian financial market. Geopolitical events such as conflicts, policy adjustments, global trade tensions, or diplomatic stand-offs introduce uncertainty beyond national borders and have demonstrated economic consequences in emerging markets such as India. The aim of this research is to assess whether or not external shocks affect the Indian stock market and, importantly, the response of investors to these external events. More specifically, this research intends to assess the behavior of investors under these situations to determine if there is evidence of herd behavior, meaning that individuals will look to emulate or follow the behavior of the majority, rather than focus solely on their own independent decision-making. Another element of this objective is to test whether herding behavior is a source of volatility in the Indian financial system. Herding behavior can amplify short-term volatility and affect price formation by diminishing heterogeneity with respect to investment decision-making, and by extension, systemic risk. Analyzing both the broad market indices (combined, representing approximately 75% of all listed stocks) in India, this study, entitled "Behavioral Biases and Systemic Risk in Emerging Markets: Evidence from the Indian Stock Market," is expansive in determining whether certain sectors in particular, or the market structure in its entirety, are more or less responsive to external geopolitical conditions. The Broad market dimension also permits the identification of those sectors, such as energy, banking, or technology, that are differentially exacerbated in times of increased uncertainty. The primary objective of this study is to offer a reference point for future investors, policymakers, and academics that can fill an empirically documented knowledge gap for understanding the behavioral and structural reaction of the Indian economy to external shocks. This study will use econometric models in a manner that can mitigate methodological weaknesses while enhancing precision when measuring the complex interactions between geopolitical events, herding behavior, and market volatility. In the end, the study seeks to address the long-standing dialogue on financial stability and investor psychology by examining how a capital market in an emerging economy responds to global shocks, and whether those responses represent an opportunity or threat for investors.

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IV. DATA ANALYSIS AND DISCUSSION

4.1 CSAD-

Table 1: CSAD Analysis

Variable	Coefficient (γ)	Standard Error	t-statistic	P-value
Intercept (α)	0.0037	0.00014	25.65	0.000
Linear term	R_{m,t}		0.1164	0.0175
Squared term (R_{m,t}^2)	-0.1201	0.0177	-6.77	0.000

Indeed, there is proof of herding behaviour.

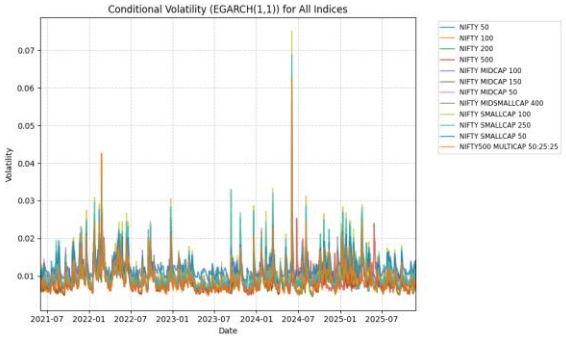
When the coefficient of the squared market return (γ) is statistically significant and negative, herding is recognised in financial literature.

Your γ is -0.1201, which is a negative sign. This indicates that the dispersion between indices (CSAD) does not rise linearly during times of significant market price fluctuations; rather, indices begin to move closer to the market.

Significance in Statistics: The P-value is 0.000 (more precisely, 2.06 \times 10^{-11}), which is significantly less than the typical cutoff of 0.05.

Interpretation: This finding implies that at times of extreme volatility, investors in various Indian market indexes tend to repress their personal opinions and follow the overall market trend, which results in a "convergence" of returns.

4.2 EGARCH-



4.3 Granger Causality-

We utilised the Granger Causality Test on the average conditional volatility (derived from the EGARCH models of all 12 indices) and the Cross-Sectional Absolute Deviation (CSAD) values to see if market volatility and herding behaviour (measured by CSAD) had a reciprocal effect.

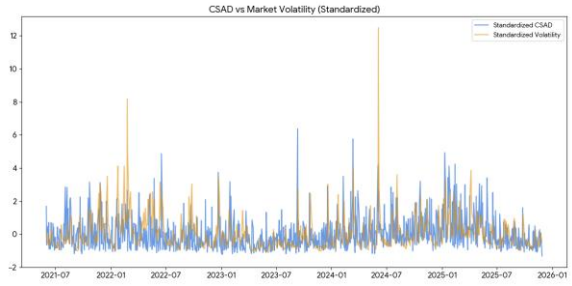
4.3.1. Stationarity and Data Preparation

The Augmented Dickey-Fuller (ADF) Test was used to determine the stationarity of both series before the Granger Causality test:

CSAD Stationarity: p-value 0.0001(Stationary)

Stationarity of Volatility: p-value 0.0000 (Stationary)

The Granger Causality test was applied straight to the initial values because the levels of both series are stationary.



Beyond what can be explained by the variable's own past, the test assesses whether past values of one variable aid in predicting the current value of the other. I looked for lags between 1 and 5, which correspond to about one trade week.

Direction 1: Does Volatility cause CSAD?

- Lag 1: p = 0.0001 (Significant)
- Lag 2: p = 0.0003 (Significant)
- Lag 3: p = 0.0221 (Significant)
- Lags 4-5: p > 0.05 (Not significant)
- In conclusion, at shorter delays (up to 3 days), market volatility Granger-causes herding (CSAD). This suggests that the degree to which individual index results diverge from the market average changes as market uncertainty rises.

Direction 2: Does CSAD impact Volatility?

- Lags 1-5: p = 0.0000 (Highly Significant)
- Conclusion: Across all studied lags, herding behaviour (CSAD) significantly Granger-causes market volatility. CSAD has a very strong ability to forecast future volatility.

The findings support a reciprocal relationship (feedback loop) between market volatility and herding behaviour:

Mutual Impact: There is a statistically significant relationship between the two variables.

Using CSAD as a Lead Indicator Compared to the opposite, CSAD has a far greater and longer-lasting effect on volatility. This implies that "dispersion" or herding behaviour in the market is a potent predictor of volatility in the future. The Short-Term Function of Volatility: Although volatility has an impact on CSAD, it usually only affects market dispersion for a period of one to three days.In conclusion, volatility and CSAD are closely related, with CSAD serving as a particularly potent predictor of future market risk.

V. CONCLUSION

According to the review of literature and aims of the research, this study puts forth the proposal that external geopolitical events trigger changes in the behavior of investors and changes in volatility in the Indian stock market. Geopolitical developments, such as wars, trade conflicts, and changes in diplomacy, create uncertainty within financial systems, which means investors do not only depend on fundamental analysis but also on other investors in the market. Because of this, behavioral economics definitions can be provided. This behavior, referred to as herding behavior, means investors depend on what the majority of investors do, meaning investors base their decisions on what is the de facto major decision of financial economics instead of making decisions based on rational expectations. Herding behavior causes stock returns to converge and causes mispricing and the emergence of bubbles and crashes of stock returns. Therefore, herding behavior reduces the efficiency of price discovery in the financial markets and will compound poor decisions by investors. In addition, the study proposes that geopolitical shocks will increase volatility in the stock market due to sudden changes in investor sentiment. Increased uncertainty means irrational trading, which causes the short-term changes of asset prices to be much more variable. Increased uncertainty also means that herding behavior will be exacerbated as investors safely depend on the consensus as a hedge against uncertainty, whether that uncertainty is caused by the geopolitical environment or within the stock market. Increased herding behavior is the interconnectedness of behavioral bias to systemic risk caused by additional volatility in the stock market. Consequently, the study proposes that herding behavior and volatility are connected; as one increases, so does the other. The study uses statistical techniques for examining herding, namely CSSD and CSAD; the GARCH method for volatility clustering analysis; and Granger causality techniques to assess directionality of causation. The purpose of the study was to empirically explore whether events of geopolitical significance Granger-cause changing herding intensity and market volatility in India. Ultimately, this hypothesis maintains that investor irrationality driven by external shocks is important in generating dynamic behavior in emerging financial markets like India.

Financial activities, especially concerning the stock market, are greatly impacted by geopolitical events, as they affect investor sentiment, risk perception, and international capital flows (Bekaert et al., 2014). Political unrest and uncertainty from wars, trade disputes, and diplomatic tensions often cause equity markets to fluctuate and alter investment allocations (Pastor & Veronesi, 2012). For example, wars or sanctions disrupt global supply chains, which impact firm profits and stock valuation, especially in industries that rely on some aspect of international trade (Barro & Ursúa, 2017). Geopolitical risk events typically lead investors toward “safe-haven” assets like gold or government bonds, which leads to outflows from equities (Caldara & Iacoviello, 2022). Geopolitical event risk also affects monetary and fiscal policies, potentially leading to governmental responses with interventions that have indirect impacts on market liquidity and investor confidence (Bussière et al., 2015). Global capital market integration also enhances these shocks, as events in one country can trigger similar effects or sentiments in another country's capital market, which is why their economies are so integrated into the global financial markets (Diebold & Yilmaz, 2014). The implications of geopolitical events on financial markets are important to consider in contemporary finance research, as they have the potential to help analysts and policymakers measure risks, forecast volatility, and plan mitigations to limit negative reactions in their respective markets (Antonakakis et al., 2017).

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