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Research paper

Market Volatility and Equity Risk Factors: Dynamic Interactions, Implications, and Evidence from India

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Abstract

This study examines the influence of investor sentiment, as captured by the India VIX, in conjunction with the Fama-French factors and Carhart's momentum factor, on equity risk premia in the Indian stock market. By focusing on periods of heightened uncertainty, specifically the subprime crisis and the COVID-19 pandemic, the research explores how market volatility and risk factors interact to shape stock returns. Using Granger causality tests, the analysis uncovers directional relationships between the India VIX and various equity risk premia, while Impulse Response Functions and Variance Decomposition are employed to understand shock transmission and the sources of volatility among factors. The findings indicate strong interconnectedness between market volatility (VIX) and key risk factors, particularly the market risk premium and momentum. Notably, the study identifies a bidirectional causality between the size and market risk premia, emphasizing the pivotal role of the size factor during periods of increased volatility. Variance decomposition results further reveal that, although risk premia are predominantly influenced by their own shocks, there are modest interactions across different factors, underscoring the broader influence of market sentiment. The results suggest that tracking market volatility can enhance portfolio adjustment strategies during turbulent times. This research is limited to the Indian context and specific asset pricing factors, suggesting future studies should consider cross-country analyses and incorporate additional behavioral variables. Overall, the study provides new insights into the dynamic interplay be-tween investor sentiment and asset pricing, offering valuable guidance for investors, financial strategists, and policymakers aiming to better understand and navigate periods of market stress.

Keywords: *Asset Pricing Factors; Equity Risk Factors; Granger Causality; Impulse Response Function; India VIX.*

1. Introduction

Market returns have long been at the heart of financial theory, reflecting the dynamic interplay between risk and reward. Merton (1980) presented a relationship between expected market return and market risk based on the seminal works of Lintner (1965), Mossin (1966), and Sharpe (1964). The author posits that increased volatility leads to higher expected returns and a higher risk premium. Based on Merton's work, Fama & French (1993) added two other factors into their asset pricing model, namely size and value. Size reflects the additional returns generated by small-cap stocks compared to large-cap stocks, while value captures the return premium associated with undervalued stocks relative to growth stocks. Carhart (1997) expanded the model further by introducing the momentum factor, which accounts for the short-term persistence in stock performance. Together, these three factors provide a more holistic approach to gaining insights into market dynamics and variations in risk premiums.

1.1. Investor Sentiment and Volatility Indices

An important dimension of this discussion is the measurement of investor sentiment, which directly impacts the risk premium. Investor sentiment is the most powerful driver of financial markets. The direction of the stock market depends on the sentiment of investors, and the volatility index, or VIX, reflects investor sentiment. VIX was introduced in 1993 by the Chicago Board Options Exchange to measure the expected volatility of the S&P 500. Whaley (2000) describes the VIX as the "investor fear gauge," which reflects its tendency to rise during market instability. Volatility increases when there is more uncertainty in the stock market. As a result, the VIX also rises, which leads to a decrease in stock market returns. Whaley (2000) explains that changes in the VIX are connected to fluctuations in market risk and the value premium. This shows that investor fear causes these changes, as also found by Durand, Lim, & Zumwalt (2011). Volatility index for India (India VIX) was introduced by the National Stock Exchange (NSE) in the year 2008. An elevated India VIX indicates greater market volatility, while a lowered India VIX suggests the opposite, as pointed out by Chandra & Thenmozhi (2015). India VIX is recognized as a proxy of risk, with its value reflecting the market's expectations of price changes and overall market risk. Understanding VIX helps in understanding investor sentiment and its impact on financial market movements (Whaley, 2009).

1.2. Research Context: Crisis Periods and Market Volatility in India

This study investigates the impact of investors' sentiment as measured by India VIX, along with two factors identified by Fama & French (1993), and the momentum factor described by Carhart (1997), on the risk premium. This study focuses on two major crisis periods: the subprime crisis and the COVID-19 pandemic, both with sharp increases in India's VIX. The average VIX index for India is around 20, but during the subprime crisis in 2008 and the uncertainty caused by the COVID-19 pandemic in 2020, the VIX surged by more than 400%, and the stock market experienced a downward trend during those periods. These observations are based on the analysis of the dataset used in this study. Uncertainty caused by events like the subprime crisis or COVID-19 significantly impacts investor sentiment, which in turn affects risk premia. This study attempts to explore the complex interactions between investor sentiment and stock market premia during the subprime Crisis and the COVID-19 pandemic.

1.3. Research Objectives and Questions

The aim is to identify interactions between variables, the type of impact they have, and whether any causation is present, assessed through causality analysis. This study investigates whether changes in the India VIX predict changes in stock market premia, including the overall market premium, size premium, value premium, and momentum premium, and whether changes in these stock market premiums can predict changes in the India VIX. The research examines how the current and past values of the India VIX and various stock market premia influence each other over time. Additionally, it explores what happens to the different stock market premia when there is a sudden change in the India VIX. Lastly, the study aims to determine the extent to which changes in each stock market premium can be explained by their own past values as well as by changes in the India VIX and other stock market factors.

1.4. Structure of The Paper

The rest of the paper is structured as follows. The second section gives a summary of the relevant literature. While third Section outlines the details of the data sources used and the methodology employed to analyze the research questions formulated in the last section. Results are discussed in the fourth Section, offering an analysis of the results and their broader significance. Lastly, the fifth Section wraps up the study by highlighting the key conclusions and proposing avenues for further investigation.

2. Literature review

All factor acronyms used in this section are defined in Table 1; we use only the abbreviation thereafter for clarity.

2.1. The Size Factor

The size factor is defined as the performance differential between smaller market-cap stocks and larger market-cap stocks (Fama & French, 1993). This factor captures the additional risk-adjusted returns investors can earn from investing in small market-cap companies, which have historically outperformed the larger companies. However, evidence from the Lisbon Exchange suggests a reverse size effect. Abnormal returns increase with firm size, driven by selling pressure and market trading patterns (Adelino & Kim, 1996). According to ROLL (1981), accurately measuring risk and assessing performance in the existence of a size premium is challenging. Variations in the size premium result from differences in investor preferences among small and large market-cap stocks. These differences can be explained by behavioural factors, including investor sentiment, with small stock premiums correlating with and being predictable through various sentiment measures (Deb & Mishra, 2019; Qadan & Aharon, 2019). Moreover, the variations in the premium are due to not controlling for a firm's quality, which when accounted for reveals a stable and significant size effect Asness, Frazzini, Israel, Moskowitz, & Pedersen (2018), and its strong positive impact only at the bottom of the business cycles, with its perceived disappearance linked to less frequent economic troughs (Ahn, Min, & Yoon, 2019).

2.2. The Value Factor

Building on the role of the size factor, Fama & French (1993) introduced the value factor as another critical dimension of their model. This factor captures the performance difference between value and growth stocks. By integrating additional factors into Merton's model, Fama & French (1993) demonstrated that value stocks provide a risk premium over growth stocks, which could not be explained by the traditional CAPM alone. Qadan & Jacob (2022) point out that the value-to-growth premium reacts positively to investors' economic sentiment and risk appetite, with optimism predicting positive premiums and vice versa. This effect is more significant for small firms and varies non-linearly with data distribution. Park, Jung, & Fang (2023) identified that the recent outperformance of growth firms has caused doubt in the value strategy, attributing this to time-varying risk. In contrast, Park, Jung, & Fang (2022) showed that growth firms are being outperformed by the value firms due to higher risk and faster profit growth. The volatility feedback effect benefits growth firms during volatile periods like the COVID-19 pandemic, while the risk premium effect results in higher long-term returns for value firms. Rozeff & Zaman (1998) documented that after low stock returns, insider buying increases as stocks move from growth to value categories, which shows insider transactions are not random. This suggests insiders exploit misvaluation with value stocks often priced below and growth stocks above their fundamental values. Adding to this, Piotroski & Roulstone (2005) concluded that insiders who act as contrarians and possess more information can take advantage of the value-to-growth premium. Insider trades have an adverse relationship with current returns and a favourable relationship with book-to-market ratios and future earnings performance. This indicates insiders buy undervalued value stocks and sell overvalued growth stocks. These studies collectively highlight how insiders leverage their informational advantages to capture the value-to-growth premium. PETKOVA & ZHANG (2005) that the value premium can be partially explained by time-varying risk, suggesting that changes in risk levels may justify the higher returns associated with value firms. However, Houge & Lughran (2006) challenge this notion by reporting no consistent evidence that value firms provide higher returns than growth firms. Vassalou & Xing (2004) imply that default risk is linked to size and book-to-market effects, but it is not the only possible explanation for equity returns in the Fama-French model.

2.3. The Momentum Factor

Building on this, Carhart (1997) introduced the momentum factor. By including an additional factor, the model is enhanced, which reflects the persistence of past stock performance over the short run. The momentum factor captures this phenomenon by enhancing the explanatory power of the asset pricing model. Jegadeesh & Titman (1993) examined the momentum strategy by creating portfolios that go long on prior outperformers and short on prior underperforming stocks, resulting in statistically significant positive returns over the subsequent periods. Momentum profits within the Indian ecosystem are strongly influenced by factors such as price-to-earnings ratio, price-to-book ratio, and net foreign institutional inflows (Mohapatra & Misra, 2020). According to Ansari & Khan (2012), investor behaviour, such as idiosyncratic volatility and cognitive biases, is responsible for the momentum effect in the Indian stock market. Supporting this, Barik & Balakrishnan (2022) provide evidence by demonstrating a positive relationship between stock momentum returns and idiosyncratic volatility. Furthermore, Ansari & Khan (2012) conclude that the size and value factors in the three-factor model are not adequate to explain the momentum effect, while Boussaidi & Dridi (2020) demonstrate that the five-factor model also fails to account for it. The findings by Hur & Singh (2016) argue that underreaction to firm-specific information significantly contributes to momentum, particularly due to the low visibility of certain stocks. Boussaidi & Dridi (2020) suggest that momentum in the Tunisian stock market is primarily driven by the market's slow adjustment to unexpected earnings, which supports the underreaction hypothesis. Jiang & Zhu (2017) further corroborate this by demonstrating that short-term underreaction to information shocks, especially overnight jumps which leads to significant momentum profits in the US equity market. These studies collectively demonstrate that momentum is driven by the market's slow adjustment to new information, highlighting underreaction as a key factor. The literature reveals distinct behavioural tendencies among investors regarding momentum. Chhimwal & Bapat (2021) and Grinblatt (2000) identify that foreign and institutional investors exhibit momentum behaviour, whereas domestic retail investors are contrarians, particularly in past losing firms. Sadhwani & Bhayo (2021) claim that the disposition effect drives momentum in the US stock market, while Merkle & Sextroh (2021) show financial professionals perceive momentum stocks as less risky with higher return expectations, which is challenging to the traditional risk-return trade-off. Balakrishnan (2016) finds that in the Indian stock market, the momentum effect is profitable primarily for small size-winner portfolios, and asset pricing models partly explain returns on size-value and size-momentum portfolios. Alhenawi (2015) reports that in US markets, the size effect has been absorbed by momentum and becomes stronger in larger firms in booming markets, which indicates a significant interaction between size and momentum driven by economic growth. similarly, Chun (2021) shows that the Korean stock market dynamic factor model with financial and macroeconomic variables significantly predicts equity risk premiums, which improves momentum return forecasts. Durand et al. (2011) find that while Value and size factors interact significantly with VIX, the momentum factor also significantly explains the asset returns, reflecting a "flight to quality" during increased volatility.

2.4. Market Risk Premium and Volatility

Merton (1980) connects the premium of market risk over market portfolio variance by suggesting that the premium should be proportional to the market variance. It was also observed that the variance of market returns is notably high. From this, Merton concludes that the premium for market risk is significant, reflecting the substantial variability in market returns. This relationship implies that higher market volatility demands a higher risk premium for investors. Consequently, understanding market variance is crucial for estimating expected returns. French, Schwert, & Stambaugh (1987) build on Merton's (1980) framework by describing the composition of observed market variance as comprising both expected and unexpected components. In line with Merton's argument that greater variance necessitates a higher premium, they find a positive relationship between changes in both expected and unexpected volatility and the expected market risk premium. Their empirical results support these theoretical expectations, showing that higher expected volatility correlates with a higher market risk premium. This underscores the crucial role of market variance in estimating expected returns. Hitz, Mustafi, & Zimmermann (2022) examine the pricing of volatility risk in the stock market of the USA using both macroeconomic and fundamental asset pricing models with various volatility measures and portfolio sorts. They discover that the VIX volatility factor consistently shows a strong and significant pricing effect on equity returns. The volatility risk premium is negative because increases in volatility are associated with declines in equity prices across different models and specifications, which is like (Bakshi & Kapadia, 2003). The findings of Qadan, Kliger, & Chen (2019) align with those of Hitz et al. (2022), as both studies emphasize the significant impact of volatility on equity returns. The influence of VIX on the association with idiosyncratic volatility and stock returns was examined by Qadan et al. (2019). The researchers found that a rise in VIX correlates with lower future returns for high idiosyncratic volatility stocks, while a decrease in VIX correlates with higher future returns. The authors confirm that high idiosyncratic volatility stocks generally have lower returns, as evidenced by residuals obtained from the Fama-French model. The negative relationship is more pronounced during periods of high market volatility. The study also reveals that stocks with elevated idiosyncratic volatility tend to exhibit lower future returns. Ansari & Khan (2012) report that higher idiosyncratic volatility is associated with elevated momentum profits. This indicates that idiosyncratic risk might influence asset pricing due to underreaction to firm-specific information. Additionally, Chandra & Thenmozhi (2015a) found a statistically significant inverse association linking stock market returns to volatility. The study conducted by the authors focused on the asymmetry in the relationship between the Volatility Index of India with stock market returns and risk management. The findings indicate that an abrupt increase in market volatility is likely connected to unanticipated declines in equity returns. According to Giot (2005), high VIX levels reflect oversold market conditions, often followed by favorable future returns. Sarwar (2012) supported this view and noted that high VIX values indicate oversold markets and positive return expectations, with the VIX serving as a fear gauge in both U.S. and emerging markets like China, Brazil, and India. Kim & In (2007) explored the association between changes in share prices and bond yields within the G7 nations. They found a broader trend of an adverse association between stock prices and bond yields, except in Japan. The authors explained that when investors expect higher stock returns with lower risk, they shift to stocks, reducing bond demand and increasing bond yields.

2.5. Recent Advances in Behavioural and Forward-Looking Indicators in Emerging Markets

Recent studies deepen the understanding of how behavioural and forward-looking indicators affect asset pricing and portfolio outcomes in emerging markets. Khan and Chahal (2025) demonstrate that social-media-based Optimism and Pessimism indices exert asymmetric quantile-on-quantile effects on sectoral returns in India, highlighting online sentiment's role in driving disaggregate market dynamics. Pham et al. (2025) develop an irrationality-focused sentiment index capturing heuristic, overconfidence, loss aversion, and herding biases, showing via TVP-VAR with stochastic volatility that these biases predict misvaluation in both U.S. and Chinese markets, suggesting similar mechanisms may operate among Indian retail investors. Božović (2024) uses VIX-based scaling to outperform realized-volatility strategies across equity factors and anomaly portfolios net of transaction costs, though without connecting findings to India's market structure. Nain et al. (2025) reveal through structural equation modeling that information seeking, anchoring, herding, overconfidence, and loss aversion significantly shape Indian investors' decisions, underscoring persistent market inefficiencies while omitting insights from cognitive neuroscience or fintech innovations. Meng et al. (2024) provide a scientometric overview of machine learning–driven asset pricing research through 2023, charting global trends without detailing relevance for India's digital finance ecosystem.

2.6. Research Gap

The gap in the existing literature is the limited understanding of the dynamic relationships and causality between investor fear (as measured by the India VIX) and equity risk factors (size, value, momentum, and market risk premium). Although prior studies, such as Durand et al. (2011), have explored similar interactions, they are outdated and primarily focused on the US market. Also, the study does not provide a comprehensive analysis of these factors' mutual dependence or causality. Furthermore, the nature of how shocks in the India VIX influence equity risk factors over time and vice versa remains unexplored in the context of the Indian market. This research aims to fill this gap by analysing these dynamic interactions and their implications in the Indian market context.

3. Data and Methodology

This research comprises five variables collected as daily data over a span of 16 years from 2008-2024. This results in 3,977 daily observations for each variable. This study utilizes daily data on the market risk premium (MRP), size factor (SMB), value factor (HML), momentum factor (MOM), and India VIX (IND_VIX). The survivorship-bias adjusted data for the MRP, SMB, HML, and MOM have been sourced from the Data Library provided by IIM Ahmedabad (Agarwalla, Jacob, & Varma, 2013). Additionally, daily data on the India VIX have been obtained from the NSE website. This period includes the subprime crisis and the COVID-19 pandemic, two significant events that profoundly impacted financial markets. We employed Granger Causality Tests to investigate whether changes in the India VIX Granger cause changes in the risk premia (MRP, SMB, HML, and MOM) and vice versa. Vector Autoregression (VAR) was used to analyse the dynamic relationship between the India VIX and the equity factors, allowing for an examination of how current and past values of the India VIX and equity factors influence each other. Impulse Response Functions (IRF) were utilized to visualize the effect of a one standard deviation innovation in the India VIX on the risk premia over time, illustrating how these factors respond to shocks in the India VIX. Variance Decomposition was applied to determine the proportion of variance in each equity factor that can be explained by its own past values and by innovations in the VIX and other factors.

Table 1: Variable Descriptions, Identifiers and Sources

Variable Description	Variable Identifiers	Source
Market risk premium	MRP	Data Library, IIM Ahmedabad
Size factor	SMB	Data Library, IIM Ahmedabad
Value factor	HML	Data Library, IIM Ahmedabad
Momentum factor	MOM	Data Library, IIM Ahmedabad
Volatility Index for India	INDIA_VIX	National Stock Exchange (NSE)

4. Results and Discussion

The descriptive statistics, presented in Table 2, provided for the five variables that is MRP, SMB, HML, MOM, and INDIA_VIX offer a comprehensive view of their distributions and characteristics. MRP has a mean close to zero, indicating a low average return. It shows substantial variation as reflected by its standard deviation of 1.170283. Its slightly negative skewness (-0.161254) and high kurtosis (18.99417) suggest occasional extreme values, leading to a leptokurtic distribution. SMB with a negative mean of -0.003218 indicates that small-cap stocks generally underperform large-cap stocks. It is left-skewed (-0.507573) and leptokurtic (6.389043), which reflects more frequent extreme negative values. HML has a positive mean (0.033865), signifying that value stocks tend to outperform growth stocks on average. Its skewness (0.08246) is minimal, indicating near-symmetry, but it remains leptokurtic (5.467158) and shows a propensity for occasional extreme values. MOM, with a positive mean of 0.049247, suggests that stocks with higher past returns continue to perform well. It is moderately left-skewed (-0.390751) and highly leptokurtic (7.551104), indicating frequent large negative returns. INDIA_VIX has a notably high mean (20.53043), reflecting significant market fluctuations. Its right-skewed distribution (2.266623) and extreme leptokurtosis (9.792755) suggest frequent large increases in volatility. All variables display a high Jarque-Bera statistic and a probability of 0.000000 rejecting the null hypothesis of normality. This indicates that none of these distributions is normal, as evidenced by their significant skewness and kurtosis. The large sum of squared deviations for each variable underscores the substantial variability within the data. These statistics provide a robust analysis of their respective distributions. They highlight the non-normality and the tendency towards extreme values in these financial metrics.

Table 2: Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P value	Sum Sq. Dev.	Observations
MRP	0.001248	0.076922	15.88686	-10.82415	1.170283	-0.161254	18.99417	42407.66	0.000000	5445.379	3977
SMB	-0.003218	0.054918	4.861049	-5.329015	0.793742	-0.507573	6.389043	2074.028	0.000000	2504.983	3977
HML	0.033865	0.036504	5.425108	-4.724853	0.886938	0.08246	5.467158	1013.152	0.000000	3127.755	3977
MOM	0.049247	0.088948	7.762833	-5.753208	0.938742	-0.390751	7.551104	3533.447	0.000000	3503.794	3977
INDIA_VIX	20.53043	17.72	85.13	10.135	9.308677	2.266623	9.792755	11051.39	0.000000	344526.3	3977

The correlation matrix in Table 3 provides insights into the relationships between five variables that show a weak negative correlation with SMB (-0.1693) and MOM (-0.2388), which suggests that as the MRP increases, small-cap stocks and momentum strategies tend to underperform. Conversely, MRP has a positive correlation with HML (0.3382), which indicates that value stocks tend to outperform growth stocks as the market risk premium rises. The very weak negative correlation between MRP and INDIA_VIX (-0.0463) indicates almost no relationship between the two. SMB displays a weak negative correlation with HML (-0.1523) and MRP (-0.1693), implying that small-cap stocks tend to underperform relative to large-cap stocks when the market risk premium is high or when value stocks are performing well. The minimal positive correlation between SMB and MOM (0.0392) suggests a slight relationship between small-cap performance and momentum strategies. The weak negative correlation between SMB and INDIA_VIX (-0.0450) shows a slight tendency for small-cap stocks to underperform during periods of higher market volatility. HML has a positive correlation with MRP (0.3382), suggesting that value stocks perform better when the MRP is high. Its negative correlations with SMB (-0.1523) and MOM (-0.1707) indicate that value stocks underperform when small-cap stocks or momentum strategies do well. The very weak negative correlation between HML and INDIA_VIX (-0.0144) suggests almost no relationship with market volatility. MOM has weak negative correlations with MRP (-0.2388) and HML (-0.1707), indicating that momentum strategies underperform when the market risk premium is high or when value stocks outperform. The weak positive correlation with SMB (0.0392) and the very weak negative correlation with INDIA_VIX (-0.0489) suggest minimal relationships with small-cap performance and market volatility. Lastly, INDIA_VIX shows very weak negative correlations with all variables, indicating almost no direct relationship between market volatility and the other financial metrics. This overall analysis highlights that the market risk premium, size, value, momentum factors, and market volatility are mostly independent, with only modest interdependencies.

Table 3: Correlation Matrix

.	MRP	SMB	HML	MOM	INDIA_VIX
MRP	1				
SMB	-0.1692729817	1			
HML	0.338246395	-0.1522973279	1		
MOM	-0.2388061441	0.03916641818	-0.1706973483	1	
INDIA_VIX	-0.04629434041	-0.04504186972	-0.01435759382	-0.04893958688	1

Table 4: Stationarity Test Results

Variables	ADF Test Statistic	p-value	ADF Conclusion	PP Test Statistic	p-value	PP Conclusion
MRP	-14.288	0.01	Stationary	-3935.9	0.01	Stationary
SMB	-15.266	0.01	Stationary	-3793.2	0.01	Stationary
HML	-14.657	0.01	Stationary	-3819.8	0.01	Stationary
MOM	-14.676	0.01	Stationary	-3182.2	0.01	Stationary
INDIA_VIX	-5.3407	0.01	Stationary	-72.665	0.01	Stationary

Table 4 shows the findings of the Augmented Dickey-Fuller (ADF) stationarity tests alongside the results of the Phillips-Perron (PP) stationarity tests. Stationarity is essential in time series analysis as it ensures consistent statistical properties over time and facilitates reliable model estimation and forecasting (Hamilton, 1994). Non-stationary data can lead to misleading statistical inferences and spurious regression results (Granger & Newbold, 1974). The primary methods to test stationarity in time series analysis are the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. These tests check for unit roots to determine if a time series is nonstationary (Dickey & Fuller, 1979; PHILLIPS & PERRON, 1988). The ADF test addresses autocorrelation by incorporating lagged differences of the variable, while the PP test corrects for autocorrelation and heteroscedasticity using non-parametric statistical methods. The results of both stationarity tests indicate that all variables exhibit stable statistical properties. The MRP shows test statistics with p-values of 0.01, confirming stability. Similarly, SMB, HML, MOM, and INDIA_VIX all show consistent results with p-values of 0.01, providing strong evidence against the null hypothesis of a unit root. Consequently, all variables are integrated of order zero, i.e., I(0), ensuring reliability for further analysis.

In Table 5, hypotheses with p-values less than 0.05 are marked as "Rejected" and those with p-values equal to or greater than 0.05 are marked as "Accepted". Significance levels are denoted as *** for significance at the 0.01 level and ** for significance at the 0.05 level.

To check if one time series can cause another, Granger causality tests are used. This method is based on the rationale that if variable X Granger-causes Y, then prior values of Y should enhance the prediction of future values of Y. This technique is crucial in economics and finance for visualizing the correlation between variables over time. It helps in understanding financial markets, economic indices, or any time series data. Granger causality tests have been applied in this study to examine how these financial indicators can predict one another. The Granger causality test results reveal significant interdependencies among the variables. INDIA_VIX Granger-causes MRP, SMB, and MOM, but not HML, indicating that market volatility can predict market risk premiums and momentum factors. Conversely, MRP Granger-causes INDIA_VIX, which suggests a feedback loop, while SMB, HML, and MOM do not have predictive power over INDIA_VIX. Within the market factors, SMB and MOM Granger-cause MRP and MRP Granger-causes both SMB and MOM, which demonstrates mutual predictive relationships. HML Granger-causes SMB and MOM Granger-causes HML, indicating unidirectional causality between these factors. However, there is no causality between SMB and HML or between SMB and MOM. Additionally, there is bidirectional causality between MOM and HML, highlighting the interconnectedness of these market factors in predicting each other’s movements.

The IRF (Figure 1) and Accumulated IRF (Figure 2) highlight the dynamic and cumulative effects of a VIX shock on MRP, SMB, HML, and MOM. For the MRP, an initial positive response is followed by a negative adjustment with the accumulated effect showing a sustained decline, indicating that heightened volatility reduces risk compensation over time. The SMB initially reacts positively, which suggests a short-term advantage for small-cap stocks, but this reverses over time, leading to underperformance relative to large-cap stocks. HML exhibits minimal short-term reactions and a mild negative accumulated impact, indicating that value stocks are only slightly disadvantaged by market uncertainty. MOM responds strongly and negatively to an INDIA_VIX shock with both immediate and long-term effects showing a significant and persistent decline. This reflects its vulnerability to price reversals and increased risk aversion during periods of heightened volatility. Overall, the findings highlight that MOM and MRP are most sensitive to volatility shocks, while SMB and HML experience more moderate impacts, which emphasizes the varying resilience of different investment styles to market uncertainty.

Table 5: Causality Tests

Section A:		
Null Hypothesis	F-Statistic	Decision
INDIA_VIX does not have a “Granger Causality” effect on MRP	7.44209***	Rejected
INDIA_VIX does not have a “Granger Causality” effect on SMB	6.50181***	Rejected
INDIA_VIX does not have “Granger Causality” effect on HML	0.50624	Accepted
INDIA_VIX does not have “Granger Causality” effect on MOM	5.73688***	Rejected
Section B:		
Null Hypothesis	F-Statistic	Decision
MRP does not have “Granger Causality” effect on INDIA_VIX	5.90974***	Rejected
SMB does not have a “Granger Causality” effect on INDIA_VIX	1.7945	Accepted
HML does not have a “Granger Causality” effect on INDIA_VIX	1.16474	Accepted
MOM does not have a “Granger Causality” effect on INDIA_VIX	1.39687	Accepted
Section C:		
Null Hypothesis	F-Statistic	Decision
SMB does not have a “Granger Causality” effect on MRP	4.46507***	Rejected
HML does not have a “Granger Causality” effect on MRP	0.89388	Accepted
MOM does not have a “Granger Causality” effect on MRP	2.56874**	Rejected
MRP does not have a “Granger Causality” effect on SMB	60.6384***	Rejected
MRP does not have a “Granger Causality” effect on HML	2.06653	Accepted
MRP does not have a “Granger Causality” effect on MOM	8.53691***	Rejected
HML does not have a “Granger Causality” effect on SMB	24.5162***	Rejected
MOM does not have a “Granger Causality” effect on SMB	15.6272***	Rejected
SMB does not have a “Granger Causality” effect on HML	2.0242	Accepted
SMB does not have a “Granger Causality” effect on MOM	0.95442	Accepted
MOM does not have a “Granger Causality” effect on HML	3.48843**	Rejected
HML does not have a “Granger Causality” effect on MOM	3.11253**	Rejected

Following the insights from the IRF, the variance decomposition provides a deeper quantitative analysis of how shocks to one variable spread across others within the model over time. As illustrated in Table 6, the variance decomposition results demonstrate that all variables are predominantly explained by their own shocks. For instance, MRP accounts for ~84.80% of its own variance by period 10, with minor contributions from HML (~9.04%) and SMB (~4.87%). Similarly, SMB is largely self-driven (~89.26%), with MRP (~6.48%) and HML (~3.15%) exerting limited influence. HML remains highly independent (~95.18%), with small contributions from SMB (~3.95%) and MRP (~0.41%). MOM follows a similar trend, with ~90.11% of its variance explained by its own shocks, while MRP (~5.15%) and HML (~2.59%) have marginal effects. Lastly, INDIA_VIX is largely self-driven (~78.95%), though MRP (~19.39%) plays a significant role, indicating some influence from market-wide risks. These results highlight the independent nature of each variable, while also revealing modest interactions, particularly between MRP, SMB, and HML, underscoring their interconnectedness in explaining financial dynamics.

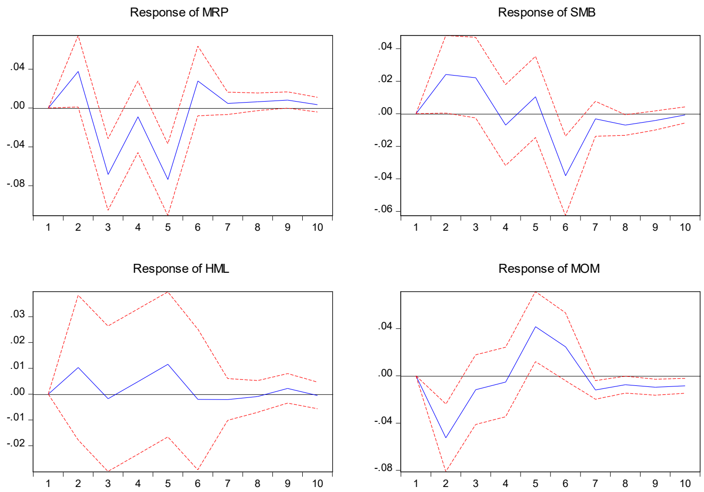

Fig. 1: IRF For the Fama-French and Carhart Risk Premia and the India VIX.

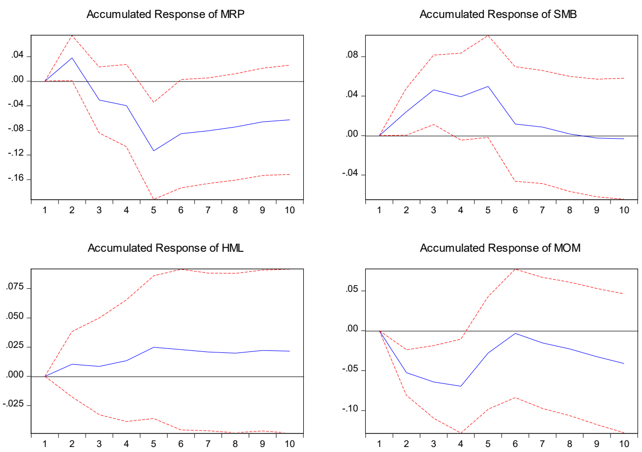

Fig. 2: Accumulated IRF for the Fama-French and Carhart Risk Premia and the India VIX.

5. Conclusion

This research endeavors to elucidate the dynamic interrelations between market volatility as captured by the India VIX and key asset pricing factors, including Market Risk Premium, value, size, and Momentum within the frameworks established by (Carhart, 1997; Fama & French, 1993; Merton, 1980). The study leverages sophisticated econometric tools such as Granger causality, Impulse Response Functions (IRF), and Variance Decomposition to dissect the temporal interactions of these variables.

5.1. Key Findings and Discussion

Our findings highlight a significant interconnectedness of market volatility (INDIA_VIX) with equity risk factors, guiding investors and portfolio managers in adjusting strategies during volatile periods. The strong influence of INDIA_VIX on MRP and MOM aligns with findings by Chandra & Thenmozhi (2015), which suggests that rising volatility may signal changes in market risk premiums and momentum profits, helping investors anticipate shifts in asset returns. Additionally, the bidirectional causality between SMB and MRP emphasizes the need to consider size-based factors when managing portfolios in varying market conditions, consistent with findings from (Durand et al., 2011). Building on the insights from the IRF, the variance decomposition results confirm the interconnectedness between market volatility and equity risk factors. While all variables are predominantly influenced by their own shocks and modest interactions indicate that market-wide volatility plays a critical role in shaping equity returns. These findings are consistent with Durand et al. (2011), who observed significant interactions between size, value, and volatility, and Qadan et al. (2019), who highlighted the impact of VIX on equity returns. Furthermore, studies like Chandra & Thenmozhi (2015) emphasize the influence of volatility on risk premiums, which aligns with the observed sensitivity of momentum and market risk premium factors to volatility shocks. These results underscore the importance of understanding volatility in managing risk and optimizing portfolio strategies.

5.2. Practical Implications

When the India VIX rises above its twenty-day moving average by 25%, investors should reduce high-beta large-cap exposure by 10–15% and reallocate low-volatility value stocks or short-term government bond ETFs to cushion drawdowns. Portfolio managers can implement dynamic stop-loss triggers: if the cumulative IRF indicates a 2% drop in market risk premium within three trading days of a VIX spike, equity allocations should be trimmed by 5%. Policymakers can tie market-wide circuit breakers to VIX thresholds, halting trading for 30 minutes when VIX exceeds 35, to prevent panic selling, and offer temporary margin relief on derivatives when VIX remains above its 75th percentile for more than five consecutive sessions.

5.3. Limitations

While this study provides valuable insights into market volatility-risk factor dynamics in India, certain limitations warrant consideration for future research. The reliance on daily data, though providing a robust sample size, may introduce microstructure noise and bid-ask bounce effects that could influence short-term relationships. Additionally, our focus on traditional Fama-French factors and VIX excludes potentially important variables such as liquidity risk measures, which have proven significant during Indian market crises, and key macroeconomic factors, including inflation, interest rates, and foreign institutional flows that substantially influence Indian equity returns.

5.4. Concluding remarks

In sum, this research substantiates the intricate interplay between market volatility and critical financial variables, offering a granular perspective on the mechanisms through which market sentiment and economic crises influence asset pricing and investment strategies. By integrating the behavioral nuances of market participants during periods of uncertainty, the study contributes robust empirical evidence to the financial economics literature, providing a comprehensive framework for predicting and managing the financial market's reaction to economic shocks. This deepened understanding is pivotal for both theoretical advancements in financial economics and practical applications in financial management and policy formulation.

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References

[1] Adelino, J., & Kim, S. (1996). SMALL FIRM AND STOCK RETURN SEASONALITY: (NEW) EVIDENCE FROM THE LISBON STOCK EXCHANGE. *Global Business and Finance Review*, *1*(2), 55–66. Retrieved from https://scholar.kyobobook.co.kr/file/view?downOrView=pdf&schlrCmdtcode=4010023852315&artlNum=10122160&artlName=SMALL%20FIRM%20AND%20STOCK%20RETURN%20SEASONALITY%3A%20(NEW)%20EVIDENCE%20FROM%20THE%20LISBON%20STOCK%20EXCHANGE.

[2] Agarwalla, S. K., Jacob, J., & Varma, J. R. (2013). Four Factor Model in Indian Equities Market. *SSRN Electronic Journal*, 1–21. https://doi.org/10.2139/ssrn.2334482.

[3] Ahn, D.-H., Min, B.-K., & Yoon, B. (2019). Why has the size effect disappeared? *Journal of Banking & Finance*, *102*, 256–276. https://doi.org/10.1016/j.jbankfin.2019.02.005.

[4] Alhenawi, Y. (2015). On the interaction between momentum effect and size effect. *Review of Financial Economics*, *26*, 36–46. https://doi.org/10.1016/j.rfe.2015.03.005.

[5] Ansari, V. A., & Khan, S. (2012). Momentum anomaly: evidence from India. *Managerial Finance*, *38*(2), 206–223. https://doi.org/10.1108/03074351211193730.

[6] Asness, C., Frazzini, A., Israel, R., Moskowitz, T. J., & Pedersen, L. H. (2018). Size matters, if you control your junk. *Journal of Financial Economics*, *129*(3), 479–509. https://doi.org/10.1016/j.jfineco.2018.05.006.

[7] Bakshi, G., & Kapadia, N. (2003). Delta-Hedged Gains and the Negative Market Volatility Risk Premium. *Review of Financial Studies*, *16*(2), 527–566. https://doi.org/10.1093/rfs/hhg002.

[8] Balakrishnan, A. (2016). Size, value, and momentum effects in stock returns: Evidence from India. *Vision*, *20*(1), 1–8. https://doi.org/10.1177/0972262916628929.

[9] Barik, N., & Balakrishnan, A. (2022). Are momentum profits influenced by idiosyncratic volatility? Evidence from India. *IIMB Management Review*, *34*(1), 44–53. https://doi.org/10.1016/j.iimb.2022.03.003.

[10] Boussaidi, R., & Dridi, G. (2020). The momentum effect in the Tunisian stock market: Risk hypothesis vs. underreaction hypothesis. *Borsa Istanbul Review*, *20*(2), 178–195. https://doi.org/10.1016/j.bir.2020.01.002.

[11] Božović, M. (2024). VIX-managed portfolios. International Review of Financial Analysis, 95, 103353. https://doi.org/10.1016/j.irfa.2024.103353.

[12] Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x.

[13] Chandra, A., & Thenmozhi, M. (2015a). On asymmetric relationship of India volatility index (India VIX) with stock market return and risk management. *DECISION*, *42*(1), 33–55. https://doi.org/10.1007/s40622-014-0070-0.

[14] Chandra, A., & Thenmozhi, M. (2015b). On asymmetric relationship of India volatility index (India VIX) with stock market return and risk management. *DECISION*, *42*(1), 33–55. https://doi.org/10.1007/s40622-014-0070-0.

[15] Chhimwal, B., & Bapat, V. (2021). Comparative Study of Momentum and Contrarian Behavior of Different Investors: Evidence from the Indian Market. *Asia-Pacific Financial Markets*, *28*(1), 19–53. https://doi.org/10.1007/s10690-020-09315-3.

[16] Chun, S. (2021). Forecasting the Equity Risk Premium in the Korean Stock Market: A Factor Analysis Approach. *Global Business and Finance Review*, *26*(4), 77–89. https://doi.org/10.17549/gbfr.2021.26.4.77.

[17] Deb, S. G., & Mishra, B. (2019). A new insight into value premium and size premium. *IIMB Management Review*, *31*(4), 324–335. https://doi.org/10.1016/j.iimb.2019.07.004.

[18] Durand, R. B., Lim, D., & Zumwalt, J. K. (2011). Fear and the Fama-French Factors. *Financial Management*, *40*(2), 409–426. https://doi.org/10.1111/j.1755-053X.2011.01147.x.

[19] Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds*. In *Journal of Financial Economics* (Vol. 33). https://doi.org/10.1016/0304-405X(93)90023-5.

[20] French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, *19*(1), 3–29. https://doi.org/10.1016/0304-405X(87)90026-2.

[21] Giot, P. (2005). Relationships Between Implied Volatility Indexes and Stock Index Returns. *The Journal of Portfolio Management*, *31*(3), 92–100. https://doi.org/10.3905/jpm.2005.500363.

[22] Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111–120. https://doi.org/10.1016/0304-4076(74)90034-7.

[23] Grinblatt, M. (2000). The investment behavior and performance of various investor types: a study of Finland's unique data set. *Journal of Financial Economics*, *55*(1), 43–67. https://doi.org/10.1016/S0304-405X(99)00044-6.

[24] Hamilton, J. D. (1994). *Time Series Analysis*. Princeton University Press. https://doi.org/10.1515/9780691218632.

[25] Hitz, L., Mustafi, I. H., & Zimmermann, H. (2022). The pricing of volatility risk in the US equity market. *International Review of Financial Analysis*, *79*. https://doi.org/10.1016/j.irfa.2021.101951.

[26] Houge, T., & Lughran, T. (2006). Do Invesrtors Capture the Value Premium? *Financial Management*, *35*(2), 5–19. https://doi.org/10.1111/j.1755-053X.2006.tb00139.x.

[27] Hur, J., & Singh, V. (2016). Reexamining momentum profits: Underreaction or overreaction to firm-specific information? *Review of Quantitative Finance and Accounting*, *46*(2), 261–289. https://doi.org/10.1007/s11156-014-0469-x.

[28] Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. In *Source: The Journal of Finance* (Vol. 48). https://doi.org/10.2307/2328882.

[29] Jiang, G. J., & Zhu, K. X. (2017). Information Shocks and Short-Term Market Underreaction. *Journal of Financial Economics*, *124*(1), 43–64. https://doi.org/10.1016/j.jfineco.2016.06.006.

[30] Khan, H. A., & Chahal, R. J. K. (2025). Asymmetric impact of social media sentiments and stock market uncertainty on Indian sectoral returns: A quantile-on-quantile approach. North American Journal of Economics and Finance, 79, 102456. https://doi.org/10.1016/j.najef.2025.102456.

[31] Kim, S., & In, F. (2007). On the relationship between changes in stock prices and bond yields in the G7 countries: Wavelet analysis. *Journal of International Financial Markets, Institutions and Money*, *17*(2), 167–179. https://doi.org/10.1016/j.intfin.2005.10.004.

[32] Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13. https://doi.org/10.2307/1924119.

[33] Meng, C., Chen, C., Xu, H., & Li, T. (2024). Asset pricing and portfolio investment management using machine learning: Research trend analysis using scientometrics. Economics, 18, 20220108. https://doi.org/10.1515/econ-2022-0108.

[34] Merkle, C., & Sextroh, C. J. (2021). Value and momentum from investors' perspective: Evidence from professionals' risk-ratings. *Journal of Empirical Finance*, *62*, 159–178. https://doi.org/10.1016/j.jempfin.2021.03.004.

[35] Merton, R. C. (1980). ON ESTIMATING THE EXPECTED RETURN ON THE MARKET An Exploratory Investigation*. In *Journal of Financial Economics* (Vol. 8). North-Holland Publishing Company. https://doi.org/10.1016/0304-405X(80)90007-0.

[36] Mohapatra, S., & Misra, A. K. (2020). Momentum returns: A portfolio-based empirical study to establish evidence, factors and profitability in Indian stock market. *IIMB Management Review*, *32*(1), 75–84. https://doi.org/10.1016/j.iimb.2019.07.007.

[37] Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, *34*(4), 768. https://doi.org/10.2307/1910098.

[38] Nain, A., Borha, N. S., Ali, F., Sayal, A., Suri, P., Chauhan, S. S., & Ahmad, V. (2025). Decoding investor sentiments in the Indian stock market: A structural equation modelling approach. F1000Research, 13, 1378. https://doi.org/10.12688/f1000research.156635.2.

[39] Park, K., Jung, M., & Fang, Z. (2022). Which is Better: Value Strategy or Growth Strategy? *Global Business and Finance Review*, *27*(1), 83–94. https://doi.org/10.17549/gbfr.2022.27.1.83.

[40] Park, K., Jung, M., & Fang, Z. (2023). The value-growth premium in a time-varying risk return framework. *International Review of Economics and Finance*, *88*, 1500–1512. https://doi.org/10.1016/j.iref.2023.07.043.

[41] PETKOVA, R., & ZHANG, L. (2005). Is value riskier than growth? *Journal of Financial Economics*, *78*(1), 187–202. https://doi.org/10.1016/j.jfineco.2004.12.001.

[42] Pham, Q., Pham, H., Pham, T., & Tiwari, A. K. (2025). Revisiting the role of investor sentiment in the stock market. International Review of Economics and Finance, 100, 104089. https://doi.org/10.1016/j.iref.2025.104089.

[43] PHILLIPS, P. C. B., & PERRON, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346. https://doi.org/10.1093/biomet/75.2.335.

[44] Piotroski, J. D., & Roulstone, D. T. (2005). Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? *Journal of Accounting and Economics*, *39*(1), 55–81. https://doi.org/10.1016/j.jacceco.2004.01.003.

[45] Qadan, M., & Aharon, D. Y. (2019). Can investor sentiment predict the size premium? *International Review of Financial Analysis*, *63*, 10–26. https://doi.org/10.1016/j.irfa.2019.02.005.

[46] Qadan, M., & Jacob, M. (2022). The value premium and investors' appetite for risk. *International Review of Economics & Finance*, *82*, 194–219. https://doi.org/10.1016/j.iref.2022.06.014.

[47] Qadan, M., Kliger, D., & Chen, N. (2019). Idiosyncratic volatility, the VIX and stock returns. *North American Journal of Economics and Finance*, *47*, 431–441. https://doi.org/10.1016/j.najef.2018.06.003.

[48] ROLL, R. (1981). A Possible Explanation of the Small Firm Effect. *The Journal of Finance*, *36*(4), 879–888. https://doi.org/10.1111/j.1540-6261.1981.tb04890.x.

[49] Rozeff, M. S., & Zaman, M. A. (1998). Overreaction and Insider Trading: Evidence from Growth and Value Portfolios. *The Journal of Finance*, *53*(2), 701–716. https://doi.org/10.1111/0022-1082.275500.
[50] Sadhwani, R., & Bhayo, M. U. R. (2021). Momentum and disposition effect in the US stock market. *Cogent Economics and Finance*, *9*(1). https://doi.org/10.1080/23322039.2021.1999004.
[51] Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets? *Journal of Multinational Financial Management*, *22*(3), 55–65. https://doi.org/10.1016/j.mulfin.2012.01.003.
[52] Sharpe, W. F. (1964). CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK*. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x.
[53] Vassalou, M., & Xing, Y. (2004). Default Risk in Equity Returns. *Journal of Finance*, *59*(2), 831–868. https://doi.org/10.1111/j.1540-6261.2004.00650.x.
[54] Whaley, R. E. (2000). The Investor Fear Gauge. *The Journal of Portfolio Management*, *26*(3), 12–17. https://doi.org/10.3905/jpm.2000.319728.
[55] Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management*, *35*(3), 98–105. https://doi.org/10.3905/JPM.2009.35.3.098.