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Market Volatility vs. Economic Growth: The Role of Cognitive Bias

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Abstract: This study aims to investigate the interaction between market volatility, economic growth, and cognitive biases over the period from April 2006 to March 2024. Market volatility and economic growth are critical indicators that influence economic stability and investment behavior. Financial market volatility, defined by abrupt and erratic changes in asset values, can have a big impact on the expansion and stability of the economy. According to conventional economic theory, there should be an inverse relationship between market volatility and economic growth since high volatility can discourage investment and erode trust. Market participants' cognitive biases are a major aspect that complicates this connection. Due to our innate susceptibility to cognitive biases, including herd mentality, overconfidence, and loss aversion, humans can make poor decisions and increase market volatility. These prejudices frequently cause investors to behave erratically and irrationally, departing from reasonable expectations and causing inefficiencies in the market. Cognitive biases have the capacity to sustain feedback loops, which heighten market turbulence and may hinder economic expansion. Similarly, cognitive biases have the potential to cause investors to misread economic indicators or ignore important details, which would increase volatility. This study uses the generalized autoregressive conditional heteroskedasticity (GARCH) model on GDP growth data from the US, the UK, and India, alongside S&P 500, FTSE 100, and NIFTY 50 data sourced from Bloomberg, to examine evidence of these biases. The results show evidence of the predictive nature of market fluctuations on economic performance across the markets and highlight the substantial effects of cognitive biases on market volatility, disregarding economic fundamentals and growth, emphasizing the necessity of considering psychological factors in financial market analyses and developing strategies to mitigate their adverse effects.

Keywords: market volatility; economic growth; cognitive bias; investor sentiment

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1. Introduction

Market volatility is the natural fluctuation in the prices of an asset in the financial market. Fear or uncertainty due to negative news or a recession can lead to selling, which lowers prices. Understanding that volatility is a normal phenomenon of a healthy market is critical for investors, especially newbies. Contrary to popular belief, volatility is not always the trigger for doom. As a matter of fact, occasional volatility may indicate a robust and dynamic economy. As new businesses are established, innovation flourishes, and corporations make investments in expansion prospects, economic growth exacerbates market volatility. As investors evaluate the prospects of these initiatives, stock prices are subject to fluctuations due to this intrinsic dynamic. Although some companies could fail, others might emerge as the next great success story, eventually supporting the economy's expansion as a whole. It is not always evident, though, how volatility and economic growth are related. Sometimes, there is a correlation between rapid economic growth and higher market volatility.

Confirmation bias makes things even more complicated. It causes us to seek information confirming our beliefs, ignoring conflicting evidence (Huttunen et al. 2020). This can lead us to ignore negative news about our investments or overestimate the potential of companies that align with our biases. In addition, investment decisions can be influenced by loss aversion, the tendency to feel the pain of loss more strongly than the joy of victory (Wang et al. 2023). This emotional reaction can lead us to sell investments prematurely to avoid losses, even if the long-term outlook remains positive. Recognizing and mitigating these cognitive biases is essential for investors to make sound decisions in the face of market volatility.

Navigating a turbulent market requires a disciplined approach (Erixon and Johannesson 2015). Strategies include maintaining a long-term investment horizon, diversifying portfolios across asset classes, and managing emotions to make rational decisions. Diversifying portfolios across asset classes, industries, and geographies can help reduce risk and the impact of single events or market downturns (Shin et al. 2019). Techniques such as dollar-cost averaging, where investments are made at regular intervals regardless of market conditions, can help mitigate the effects of emotional decision-making. By implementing such strategies, investors can navigate the challenges of volatile markets and take advantage of growth opportunities. However, managing emotions, especially during times of increased volatility, is critical to rational decision-making.

Therefore, understanding the interplay between market volatility and economic growth, especially through the lens of cognitive biases, is crucial for both investors and policymakers. Some studies have found interactions between market volatility and economic growth where fluctuations in stock markets can predict economic growth, whereas, on the contrary, some studies have suggested no correlation between them (Babatunde 2013; Silva et al. 2017; Chang and Li 2024). In this study, we aim to investigate how cognitive biases, specifically herding, confirmation bias, and loss aversion, affect market volatility and its divergence from economic growth. The contribution of this study lies in its novel integration of these cognitive biases into the analysis of market volatility and economic growth using the generalized autoregressive conditional heteroskedasticity (GARCH) model. Although many studies focus on either cognitive biases or empirical modeling, those exploring how these biases manifest in market volatility and diverge from economic fundamentals are rarely found in existing literature. This study fills that gap by providing an interdisciplinary approach that combines behavioral finance with econometric modeling. This study aims to identify the evidence of these biases and seek insights into the relationship between market volatility and economic growth. By examining the role of cognitive biases, such as herding behavior, confirmation bias, and loss aversion, we can better grasp the psychological factors driving market dynamics. This study is organized as follows: the Literature Review Section provides an overview of existing research on cognitive biases in financial markets, summarizing the findings and the research gaps from the most relevant literature; the Methodology Section details the empirical and theoretical approaches used to analyze the data, including the application of the GARCH model; the Results and Discussion Section presents the findings, demonstrating the evidence of cognitive biases impacting market volatility and their relationship with economic growth; and, finally, the Conclusion Section summarizes the key insights and suggests areas for further investigation to enhance our understanding of behavioral finance in the context of market volatility and economic growth.

2. Literature Review

Understanding growth is vital, and studying the various factors that might influence growth is important and of great relevance in the current times when economies are facing new and unique challenges regularly. With globalization, emerging technologies, and the varied financial products introduced, economies are influenced by a myriad of factors. Stock markets are the true reflection of real economic growth, and the fluctuations in stock markets can help forecast economic growth. This can be illustrated by looking at how the growth of economies worldwide has been impacted by some events, like the 2008 international financial crisis (Chang and Li 2024).

Volatility is certainly related to economic growth both directly and indirectly. Volatility in stock markets hints at growth when the investors sort out their portfolio by excluding weak stocks and including viable ones, which leads to a stronger economy (Babatunde 2013). Hong Vo et al. (2019) examined the causal and dynamic relationship between derivatives and economic growth by employing a Granger causality test in the framework of a vector error correction model (VECM). Derivatives are the instruments used to mitigate the effects of volatilities and risks. In this study, authors could establish short-run relationships, with the derivatives market positively contributing to economic growth, but such effects faded away in the long run.

Ameziane and Benyacoub (2022) also tried to examine the direct and indirect effects of volatility on economic growth. The authors used the GARCH model and Dumitrescu and Hurlin the Granger non-causality test to establish the relationship between volatility and economic growth and concluded that volatility penalizes economic growth both directly and indirectly. Government policies and frameworks may intervene in such circumstances.

Volatilities in stock markets impact economic growth and vice versa (Babatunde 2013). Fluctuations in markets impact various capital markets, such as credit markets and foreign exchange, and such volatilities contribute toward high-quality capital formation and accelerate growth (Chang and Li 2024).

The efficient market hypothesis (EMH) proposes that stock markets are efficient in processing all available information, and in an efficient market, the prices fully reflect the available information, investors are not irrational, and any volatilities in stock prices can be explained with fundamentals (Spulbar et al. 2021). However, stock markets have evidenced chaos, and reconciling randomness is difficult. An explanation for this is given by Lo (2004), who proposed the adaptive market hypothesis (AMH), which is the evolutionary behavior of investors combined with the efficient market hypothesis. Accordingly, the informational efficiency of stock markets depends on the ability of investors to adapt to changing market conditions. The AMH theory supports the existence of mispricing in stock markets due to investor biases and risk perceptions (Dhankar and Shankar 2016).

Urquhart and McGroarty (2016) argued that market conditions have a strong influence on the psychology of the market participants and their information processing behavior, which, in turn, impacts the returns. To prove their argument, the authors used the variance ratio test to examine the predictability of returns and found that it fluctuates over time in every market, stressing the fact that the concept of an efficient market does not exist.

Cognitive biases like herding and loss aversion may lead to deviations from rational market behavior and economic growth. Psychological biases, especially overconfidence, loss aversion, and herding behaviors, significantly affect investment decisions among Indian investors. Akin and Akin (2024) investigated stock market volatility in the context of behavioral finance and found that loss aversion and sentiments negatively impact stock markets, whereas herding behavior and optimism have a positive influence.

In addition, socio-demographic factors like gender, income, and education level play a role in shaping investor behavior (Patel 2023). Individual investors' cognitive biases play a significant role in their investment decision-making behavior. Rationality has a significantly negative relationship with self-attribution bias and overconfidence bias (Mushinada and Veluri 2019). Cognitive biases like confirmation bias, loss aversion, and the illusion of control significantly influence investment decisions (Kiruthika and Ramya 2023). Investors exhibit momentum and contrarian biases in evaluating technical analysis signals (Zielonka et al. 2020).

The relevant literature in indexed peer-reviewed journals is scarce. Table 1 summarizes other relevant articles from the literature.

Table 1. Relevant articles from the literature.

SN	Title	Findings	Research Gap
1	Don't Fight the Tape! Technical Analysis Momentum and Contrarian Signals as Common Cognitive Biases. (Zielonka et al. 2020)	• Investors exhibit momentum and contrarian biases in evaluating technical analysis signals. • The disposition effect influences investors' beliefs in technical analysis signals.	• Lack of analysis on the reasons why investors continue to use TA despite its doubtful effectiveness. • Future research could explore the psychological and behavioral factors that drive investors to use technical analysis despite its doubtful effectiveness.
2	Cognitive Bias Factors Influencing Investors' Investment Decisions in Behavioral Finance Perception. (Kiruthika and Ramya 2023)	• Cognitive biases like confirmation bias, loss aversion, and the illusion of control significantly influence investment decisions.	• The study examined only five cognitive bias factors, leaving room to investigate other factors influencing investors' decision-making. • The sample size was relatively small, and increasing it could provide more robust results.
3	A Study on Influences of Psychological Biases on Investment Decisions of Indian Investors (Patel 2023)	• Psychological biases, especially overconfidence, loss aversion, and herding behaviors, significantly affect investment decisions among Indian investors. • Socio-demographic factors like gender, income, and education level play a role in shaping investor behavior.	• The sample size may not be representative of the entire Indian investor population. • The study addressed only three psychological biases and did not consider other factors that may influence investor behavior.
4	Elucidating Investors Rationality and Behavioral Biases in Indian Stock Market (Mushinada and Veluri 2019)	• Individual investors' cognitive biases play a significant role in their investment decision-making behavior. • Rationality has a significantly negative relationship with self-attribution bias and overconfidence bias. • Male investors exhibit higher levels of overconfidence bias than female investors.	• The study relies on a self-report questionnaire to collect subjective information from individual investors, which may be subject to social desirability bias and limit the generalizability of the findings.
5	Do Investors Exhibit Cognitive Biases: Evidence from Indian Equity (Sharma and Firoz 2020)	• Investors exhibit behavioral biases such as optimism bias, herding, mental accounting, and disposition effect. • These biases significantly affect their rational decision-making process.	• The study has a small sample size and an overemphasis on quantitative data. A qualitative study can supplement this study to provide insights into the underlying reasons for the observed behavioral biases and their impact on investment decision-making.

3. Materials and Methods

The primary objective of this study is to investigate the behavioral factors that contribute to market volatility and the divergence between market movements and the underlying economic fundamentals. This study combines theoretical analysis with empirical modeling techniques in order to identify evidence to support its propositions.

3.1. Data

Table 2 below describes the variables used in the study.

Table 2. Variables.

SN	Variable	Description (Dataset for the Period of April 2006 to March 2024)
1.	GDPUS	Monthly percentage GDP growth in the United States.
2.	SPX	Monthly closing price of the S&P 500 index.
3.	GDPGB	Monthly percentage GDP growth in the United Kingdom.
4	UKX	Monthly closing price of the FTSE 100 index.
5	GDPIN	Monthly percentage GDP growth in India.
6	NIFTY	Monthly closing price of the Nifty 50 index.
7	GDPUS_T	Min–max transformed GDPUS.
8	SPX_SR_T	Min–max transformed standardized residual of SPX based on eGARCH (2,1) and ARFIMA (3,0,1).
9	GDPGB_T	Min–max transformed GDPGB.
10	UKX_SR_T	Min–max transformed standardized residual of UKX based on eGARCH (2,1) and ARFIMA (3,0,1).
11	GDPIN_T	Min–max transformed GDPIN.
12	NIFTY_SR_T	Min–max transformed standardized residual of NIFTY based on eGARCH (2,1) and ARFIMA (3,0,1).

The study relied on data for the variables obtained from Bloomberg over the period from April 2006 to March 2024.

3.2. Methodology

The GARCH model was applied to the S&P 500 (SPX), FTSE 100 (UKX), and NIFY 50 (NIFTY) datasets. The desired results for model fit were obtained using the eGARCH specification (2,1), the exponential GARCH model with two lagged terms for the conditional variance and one lagged term for the conditional mean, and ARFIMA (3,0,1), the autoregressive fractional integrated moving average model, which includes three autoregressive terms, no differencing, and one moving average term. The model's output was presented in the form of plots, depicting the model fit (how well the model matched the actual data) and the standardized residuals (the differences between the actual data and the model's predictions). The standardized residuals were extracted from the model for SPX, UKX, and NIFTY, and min–max transformation was applied to obtain the min–max transformed standardized residuals SPX_SR_T, UKX_SR_T, and NIFTY_SR_T. Min–max transformation was also performed on GDP growth GDPUS, GDPGB, and GDPIN to obtain GDPUS_T, GDPGB_T, and GDPIN_T. The transformation was performed to aid the comparison between market volatility measured by the standardized residuals with GDP growth.

By comparing the volatility patterns observed across these datasets with the respective GDP growth, the study aimed to uncover insights into the interplay between market volatility and economic growth (Su et al. 2023). To achieve this, min–max transformed GDP growth (GDPUS_T, GDPGB_T, and GDPIN_T) was plotted against min–max transformed standardized residuals (SPX_SR_T, UKX_SR_T, and NIFTY_SR_T). The analysis sought to identify instances where market volatility diverged from the underlying economic fundamentals, as reflected in GDP growth, potentially due to the influence of the behavioral factors investigated using the propositions mentioned in Section 3.3.

The GARCH model was selected because it is widely used to model financial time-series data that exhibit volatility clustering, a common feature in market data. It allows us to capture time-varying volatility, which is crucial when studying the relationship between market volatility and economic growth. We did not use conditional standard deviation because the GARCH model's conditional variance is more appropriate for capturing the persistence of shocks and volatility over time. We also visually identified the propositions P1, P2, and P3 based on min–max transformed GDP growth and min–max transformed GARCH standardized residuals that do not require the use of conditional standard deviation.

The methodology combined theoretical underpinnings from psychology and behavioral economics with quantitative modeling techniques to provide a comprehensive understanding of the drivers of market volatility (Ni et al. 2015). By juxtaposing investor behavior with empirical data analysis, the study aimed to shed light on the complex dynamics shaping financial markets and highlight the importance of a disciplined, long-term investment approach that accounts for both economic realities and psychological biases.

3.3. Propositions

The phenomenon of herd mentality among investors during periods of extreme market volatility is a critical factor influencing market dynamics. Psychological concepts reveal that factors such as anxiety and the need for social conformity drive investors to follow the majority opinion rather than conduct independent research. This herding behavior exacerbates price swings and disassociates market dynamics from economic realities (Christoffersen and Stæhr 2019).

P1: In periods of high market volatility, investors exhibit herding behavior, leading to exaggerated market movements that may not align with the underlying economic fundamentals.

The impact of confirmation bias on investor decision-making plays a significant role in shaping market volatility. This cognitive bias occurs when individuals prioritize information that supports their preconceived notions while disregarding contradictory evidence. In the context of investment choices, confirmation bias can lead to investment decisions that fail to accurately reflect the overall state of the economy, thereby contributing to market volatility (Sharma and Firoz 2020).

P2: Confirmation bias influences investor decisions, causing them to react more strongly to news or events that confirm their existing beliefs, amplifying market volatility even when GDP growth remains stable.

The concept of loss aversion highlights another cognitive factor influencing investor behavior. The behavioral economics principle indicates that individuals exhibit a stronger tendency to avoid losses than to achieve equivalent gains. Loss aversion can precipitate overreaction to short-term market fluctuations, resulting in temporary surges in volatility driven by impulsive selling or buying behavior (Cascão et al. 2023).

P3: Overreaction to short-term market fluctuations due to loss aversion results in temporary spikes or dips in market volatility, even if these fluctuations do not significantly impact long-term economic growth (GDP).

4. Results

As explained in Section 3.2, min–max transformed monthly percentage GDP growth (GDPUS_T, GDPGB_T, and GDPIN_T) was compared to min–max transformed standardized residuals (SPX_SR_T, UKX_SR_T, and NIFTY_SR_T), which were extracted from the GARCH model with eGARCH model specification (2,1) and ARFIMA (3,0,1) for the S&P 500 (SPX), FTSE 100 (UKX), and NIFTY 50 (NIFTY) datasets. The descriptive statistics are shown in Table 3.

The mean values indicate moderate average growth across the economies, with GDPIN_T showing the highest average at 0.655. In contrast, the standardized residuals exhibit greater average volatility, reflecting the heightened fluctuations in stock indices compared to GDP growth. The standard deviations reveal low variability in GDP growth rates (approximately 0.09 to 0.11), whereas the standardized residuals demonstrate higher volatility (ranging from 0.12 to 0.15). Notably, the kurtosis values for GDP growth rates (ranging from 11.52 to 21.6) indicate a leptokurtic distribution, suggesting the presence of potential outliers, whereas the standardized residuals display more moderate kurtosis values, indicating a departure from normality. The skewness reveals a slight right skew for GDPUS_T and GDPGB_T, whereas GDPIN_T exhibits significant left skewness. These statistics highlight the stable nature of economic growth compared to the more volatile behavior of stock markets, underscoring the importance of investigating cognitive biases that may influence market dynamics.

Table 3. Descriptive statistics.

	GDPUS_T	SPX_SR_T	GDPGB_T	UKX_SR_T	GDPIN_T	NIFTY_SR_T
Mean	0.476962	0.509196	0.488426	0.601822	0.654952	0.669888
Standard Error	0.006324	0.010387	0.007315	0.010101	0.007112	0.007931
Median	0.482484	0.516874	0.502101	0.623942	0.667504	0.6651
Mode	0.496815	N/A *	0.506303	N/A *	0.692745	N/A *
Standard Deviation	0.09294	0.152653	0.10751	0.148457	0.104526	0.116556
Sample Variance	0.008638	0.023303	0.011558	0.02204	0.010926	0.013585
Kurtosis	21.5406	2.340556	11.52155	1.172003	21.60329	4.693334
Skewness	0.486687	−0.40639	0.042541	−0.67702	−3.18787	−0.72907
Range	1	1	1	1	1	1
Minimum	0	0	0	0	0	0
Maximum	1	1	1	1	1	1
Sum	103.0239	109.9864	105.5	129.9936	141.4696	144.6958
Count	216	216	216	216	216	216

* Mode for SPX_SR_T, UKX_SR_T, and NIFTY_SR_T cannot be calculated because of no repetitive values.

Since SPX_SR_T, UKX_SR_T, and NIFTY_SR_T are derived from the standardized residuals of the GARCH model applied to the S&P 500 (SPX), the FTSE 100 (UKX), and the NIFTY 50 (NIFTY), it is important to verify that the models are able to capture the volatility dynamics appropriately. Table 4 shows the GARCH model results for SPX, UKX, and NIFTY. The GARCH model fit vs. the standardized residuals is shown in Figure 1.

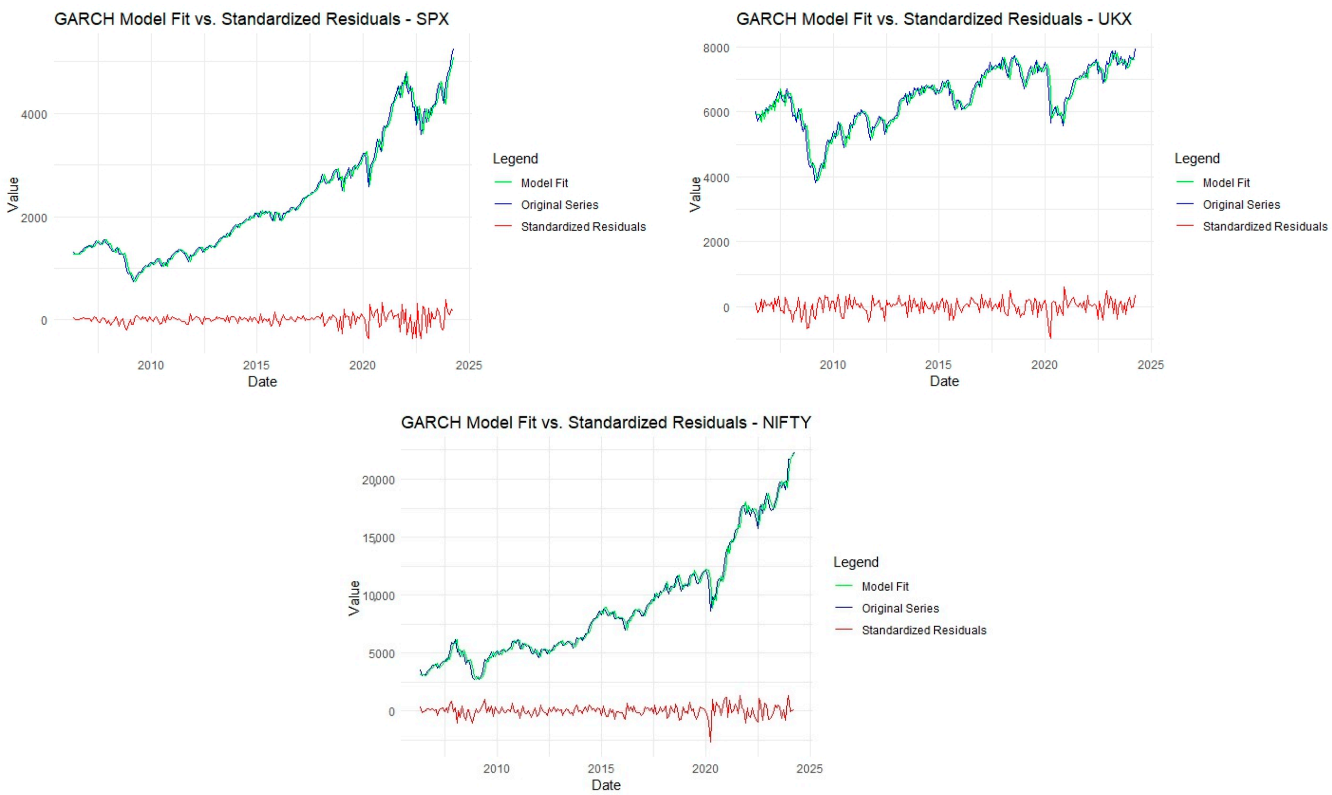

Figure 1. GARCH model fit vs. the standardized residuals of SPX, UKX, and NIFTY.

Table 4. GARCH model results.

	SPX				UKX				NIFTY			
	Estimate	**Std. Error**	***t*-Value**	***p*-Value**	**Estimate**	**Std. Error**	***t*-Value**	***p*-Value**	**Estimate**	**Std. Error**	***t*-Value**	***p*-Value**
mu	1269.74	4.89	259.64	0.00	5871.09	43.47	135.05	0.00	3170.36	103.79	30.54	0.00
ar1	0.02	0.04	0.36	0.72	−0.04	0.06	−0.69	0.49	0.01	0.00	2.17	0.03
ar2	0.96	0.02	62.27	0.00	0.94	0.02	48.30	0.00	0.91	0.01	93.82	0.00
ar3	0.03	0.05	0.69	0.49	0.07	0.06	1.10	0.27	0.11	0.01	14.09	0.00
ma1	1.00	0.00	496.34	0.00	1.00	0.00	68,823.23	0.00	0.96	0.01	66.00	0.00
omega	0.26	0.06	4.21	0.00	8.06	0.71	11.39	0.00	0.12	0.01	15.10	0.00
alpha1	−0.46	0.10	−4.71	0.00	−0.53	0.11	−4.96	0.00	−0.28	0.11	−2.65	0.01
alpha2	0.48	0.11	4.43	0.00	−0.16	0.12	−1.35	0.18	0.31	0.11	2.73	0.01
beta1	0.97	0.01	128.99	0.00	0.25	0.07	3.85	0.00	0.99	0.00	20,034.37	0.00
gamma1	0.12	0.15	0.85	0.40	−0.05	0.16	−0.29	0.77	0.60	0.16	3.63	0.00
gamma2	0.41	0.13	3.16	0.00	0.13	0.18	0.68	0.49	−0.45	0.16	−2.74	0.01

The GARCH model fit plots in Figure 1 for the SPX, UKX, and NIFTY indices illustrate the model's effectiveness in capturing the dynamics of each market. For SPX, the green line representing the GARCH model closely aligns with the blue line of the original series, indicating a strong fit. The standardized residuals, shown in red, fluctuate around zero, suggesting that the model successfully accounts for the volatility in returns. The absence of significant patterns in the residuals reinforces the adequacy of the model in reflecting market behavior, particularly during periods of heightened volatility.

Similarly, the UKX plot demonstrates a robust model fit, with the GARCH model effectively tracking the original series. The residuals remain consistently centered around zero, further validating the model's performance. In the case of NIFTY, the plot shows a strong alignment between the GARCH fit and the original series, especially during periods of market fluctuations. The standardized residuals again indicate that the model adequately captures the volatility dynamics, with no discernible patterns. These results confirm the suitability of the GARCH model for analyzing the volatility of these indices, thereby providing valuable insights into market behavior and the influence of cognitive biases on economic growth.

The GARCH model results for the SPX, UKX, and NIFTY indices underscore the model's suitability in capturing the complexities of financial market behavior. The parameters exhibit significant estimates, particularly for the autoregressive terms, with ar2 demonstrating a strong relationship across all indices, indicating the clear persistence of past values in influencing current returns. The moving average parameter (ma1) being consistently set at 1 further supports the model's robustness, suggesting an effective capture of the impact of past shocks on current volatility. Additionally, the omega parameter signifies a positive baseline level of volatility, whereas the GARCH parameters (alpha1 and beta1) reveal a persistent volatility structure, particularly evident in NIFTY, with a beta1 close to 1. This highlights the model's capacity to account for the inherent volatility dynamics in financial markets.

Therefore, the use of standardized residuals derived from this GARCH model is justified for further analysis. These standardized residuals provide a normalized measure of volatility, allowing for a clearer comparison between the fluctuations in market returns and the underlying economic growth indicator. By transforming the residuals, we eliminate any scale effects, enabling the examination of cognitive biases such as herding, confirmation bias, and loss aversion in the context of market volatility. This methodological approach enhances the validity of the analysis, as the standardized residuals accurately reflect the deviations from expected market behavior, providing critical insights into the interplay between cognitive biases and market dynamics. The GARCH model results validate its application, reinforcing the rationale for utilizing standardized residuals in the investigation of market volatility and investor behavior.

The diagnostic results shown in Table 5 for the GARCH model applied to the SPX, UKX, and NIFTY indices also demonstrate the model's robustness and suitability in capturing the volatility dynamics of these markets. The weighted Ljung–Box test results indicate no significant autocorrelation in the standardized residuals across all lags for each index, as evidenced by p-values well above the conventional significance level of 0.05. This lack of serial correlation suggests that the model has adequately captured the relationships within the data, validating its fit. Also, the weighted ARCH LM tests show no significant evidence of heteroskedasticity, indicating that the model effectively accounts for volatility clustering, a common phenomenon in financial time series. The standardized residuals from the model provide a normalized measure of volatility, facilitating the analysis of cognitive biases and their impact on market behavior. Their distribution around zero without significant patterns provides a reliable basis for further analysis.

Table 5. Model diagnostics.

		SPX		UKX		NIFTY	
Test	**Lag**	**Statistic**	***p*-Value**	**Statistic**	***p*-Value**	**Statistic**	***p*-Value**
Weighted Ljung-Box Test	Lag[1]	0.9209	0.3372	0.439	0.5076	0.6754	0.4112
	Lag[2*(p+q)+(p+q)-1][11]	5.6977	0.6831	3.518	1.0000	3.2310	1.0000
	Lag[4*(p+q)+(p+q)-1][19]	11.4383	0.2562	5.774	0.9787	9.7351	0.5129
Weighted ARCH LM Tests	ARCH Lag[4]	1.388	0.2388	0.3023	0.5824	0.3629	0.5469
	ARCH Lag[6]	2.254	0.4373	2.8136	0.3365	0.4850	0.8962
	ARCH Lag[8]	2.757	0.5899	4.0131	0.3735	3.2171	0.5036

The Granger causality test results, shown in Table 6, indicate that volatility Granger-causes GDP growth in the SPX, UKX, and NIFTY indices. However, GDP growth does not Granger-cause volatility in any of the indices, highlighting the predictive nature of market fluctuations on economic performance across these markets.

Table 6. Granger causality test.

Series	Causality Direction	F-Test	*p*-Value
SPX	Volatility does Granger-cause GDP_Growth	4.5545	0.01105
	GDP_Growth does not Granger-cause Volatility	0.0153	0.9848
UKX	Volatility does Granger-cause GDP_Growth	11.3880	1.53×10^{-5}
	GDP_Growth does not Granger-cause Volatility	1.0588	0.3478
NIFTY	Volatility does Granger-cause GDP_Growth	9.9916	5.777×10^{-5}
	GDP_Growth does not Granger-cause Volatility	0.2028	0.8165

5. Discussion

5.1. Market Volatility vs. Economic Growth

The following plots in Figures 2–4 for the S&P 500 (US), the FTSE 100 (UK), and the NIFTY 50 (India) depict the relationship between market volatility and GDP growth over time. The orange line represents the min–max transformed GARCH-standardized residuals (market volatility), and the blue line shows the min–max transformed GDP growth for each country. Key events are marked on the plots, highlighting the propositions (P1, P2, or P3) based on the events and details mentioned in Table 7.

To interpret this plot, we analyzed the patterns and deviations between the blue line of the min–max transformed GDP growth and the orange line of the min–max transformed GARCH-standardized residuals of the S&P 500, the FTSE 100, and the NIFTY 50. When the blue line exhibits stability or steady growth but the residual lines show significant fluctuations or volatility, it suggests a potential disconnect between market behavior and underlying economic fundamentals. The propositions were identified based on major global events, and, subsequently, the plot was interpreted. Table 7 summarizes the analysis.

The analysis of global market reactions to major geopolitical and economic events highlights significant differences between developed economies (the US and the UK) and a developing economy (India). As seen in the table, the propositions (P1, P2, and P3) vary across regions, indicating that investor behavior and market responses are shaped by distinct factors such as regional economic conditions, political stability, and investor sentiment. These differences provide valuable insights into how markets react to uncertainty and external shocks, as well as the influence of spillover effects across global markets.

Table 7. Summary of analysis.

Month (Identified from the Plot)	Event	Price Change (%)/Proposition (US—S&P 500)	Price Change (%)/Proposition (UK—FTSE 100)	Price Change (%)/Proposition (INDIA—NIFTY 50)	Explanation
October 2008	2008 Global Financial Crisis	−16.94%/P3	−10.71%/P3	−26.41%/P3	Loss aversion (P3) is evident across all regions, as investors overreacted to the financial crisis, triggering significant price drops. Despite the sharp declines in market prices, GDP growth was already on a downturn. Market volatility amplified the fear of economic downturn beyond the fundamentals.
December 2008	2008 Mumbai Attacks (India)	0.78%/P1	3.75%/P1	7.41%/P1	The herding behavior (P1) after the Mumbai attacks shows that despite the attacks being localized to India, all three regions exhibited a collective market reaction. The sharp price changes reflect heightened market volatility not aligned with GDP fundamentals but rather driven by fear and geopolitical risks.
May 2009	2009 Indian General Elections	5.3%/P3	4.11%/P3	28.07%/P1	Herding behavior (P1) in India led to an exaggerated price rise as investors speculated on political outcomes. In the US and the UK, despite a positive price change, the reaction reflects loss aversion (P3), with markets cautiously recovering, even though GDP growth remained stable post-elections.
October 2011	2011 Eurozone Debt Crisis	10.77%/P1	8.11%/P2	7.76%/ P1	Despite ongoing concerns about the Eurozone, markets reacted positively in October 2011 due to optimism surrounding bailout agreements and coordinated policy actions to stabilize the region. Herding behavior (P1) in the US and India drove market gains, whereas confirmation bias (P2) in the UK reflected relief from policy interventions.
May 2014	2014 Modi Government in India	2.1%/P2	0.95%/P2	7.97%/P2	Across all three markets, confirmation bias (P2) prevailed, as investors reacted optimistically to the anticipated pro-business policies of the new Indian government. Despite relatively stable GDP growth, the market movements were driven more by sentiment and expectations than by economic fundamentals.
October 2015	2015 Paris Climate Agreement	8.3%/P2	4.94%/P2	1.47%/P2	In all regions, confirmation bias (P2) drove market volatility, as investors speculated on the long-term impact of climate change policies. Despite this significant policy event, GDP growth remained stable, and the market reaction was based on expectations rather than immediate economic changes.
July 2016	2016 Brexit Vote (UK)	3.56%/P2	3.38%/P2	4.23%/P2	The Brexit vote caused volatility across global markets, driven by confirmation bias (P2), as investors reacted to the uncertainty surrounding the UK's departure from the EU. Despite GDP growth not being immediately affected, the markets anticipated long-term economic disruptions, leading to increased volatility.
November 2016	2016 US Presidential Election (Trump)	3.48%/P2	−2.45%/P3	−4.65%/P3	In the US, confirmation bias (P2) led to a positive market reaction, as investors speculated on Trump's pro-business policies. However, in the UK and India, loss aversion (P3) drove volatility, as investors reacted negatively to the political uncertainty and potential global economic implications.
August 2019	2019 India Revokes Article 370	−1.81%/P3	−5%/P3	−0.85%/4.09% (September) P3/P1	Loss aversion (P3) prevailed in the US, the UK, and India in August, as investors overreacted to the political risks posed by Article 370. However, in India, herding behavior (P1) took over in September, leading to a market rebound as investors speculated on the longer-term effects of the decision on the economy.
March 2020	COVID-19 Pandemic (2020)	−12.51%/ P1 & P3	−13.81%/ P1 & P3	−23.25%/ P1 & P3	The COVID-19 pandemic led to sharp declines in all markets driven by herding behavior (P1) and loss aversion (P3), as investors globally panicked. The immediate price drops were much larger than warranted by GDP declines, indicating an exaggerated reaction to the uncertainty posed by the pandemic.
March 2022	Russia–Ukraine War (2022)	3.58%/P1	0.77%/P3	3.99%/P1	Herding behavior (P1) is observed in the US and India, as investors reacted strongly to the geopolitical uncertainty caused by the war. In the UK, loss aversion (P3) is evident, as investors were more risk-averse, reflecting concerns about energy prices and the broader economic impact of the conflict.
September 2022	2022 Inflation and Energy Crisis	−9.34%/P3	−5.36%/P3	−3.74%/P3	Across all three regions, loss aversion (P3) dominates as investors overreact to rising inflation and energy crises, driving significant price declines. Despite the short-term market volatility, the long-term GDP impact remained limited, indicating an exaggerated market reaction to these events.
April 2023	2023 India Overtakes China's Population	1.46%/P3	3.13%/P3	4.06%/P2	In the US and the UK, loss aversion (P3) caused moderate market volatility, as investors speculated on the global economic implications of India's population growth. In India, confirmation bias (P2) drove the market reaction, as investors viewed the demographic shift positively, anticipating long-term economic benefits.

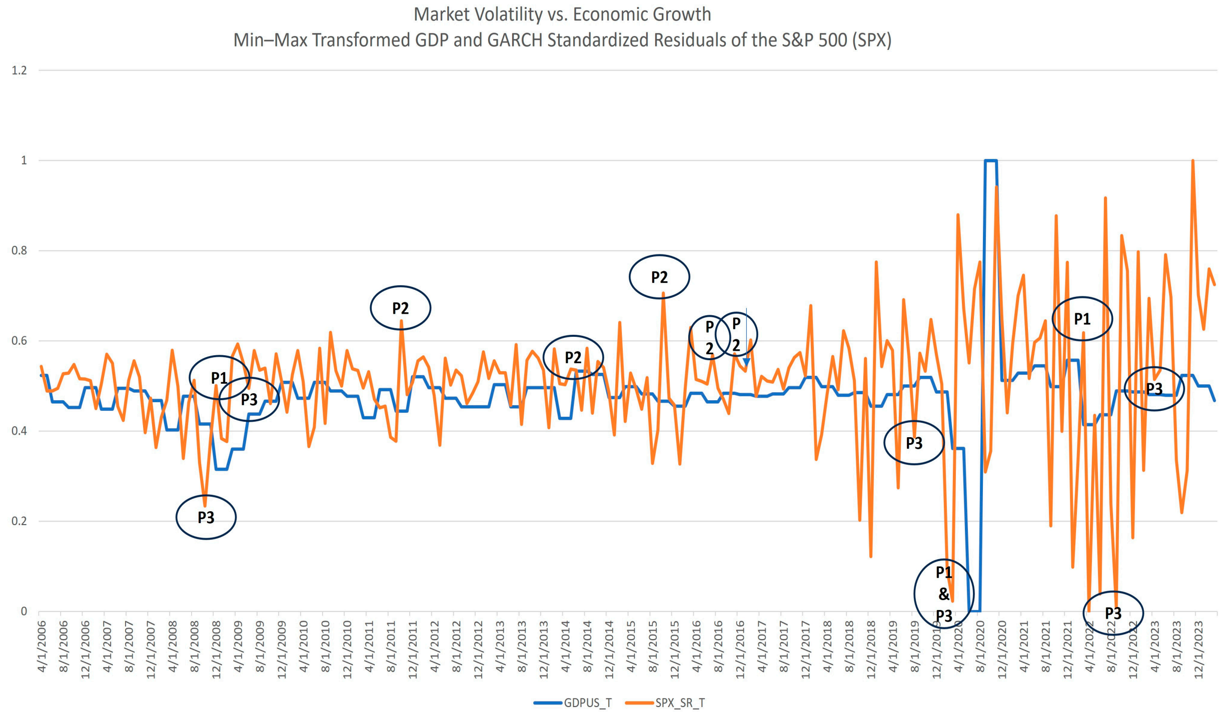

Figure 2. Market volatility vs. economic growth (US).

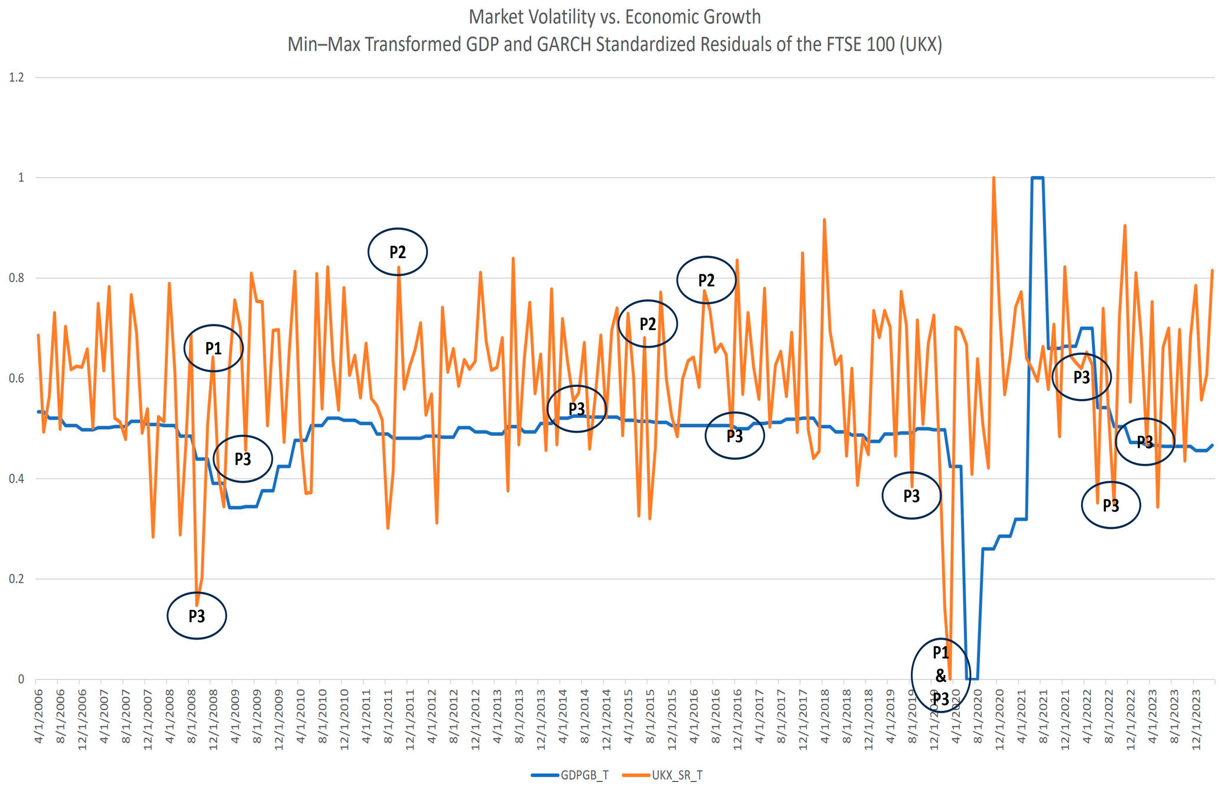

Figure 3. Market volatility vs. economic growth (UK).

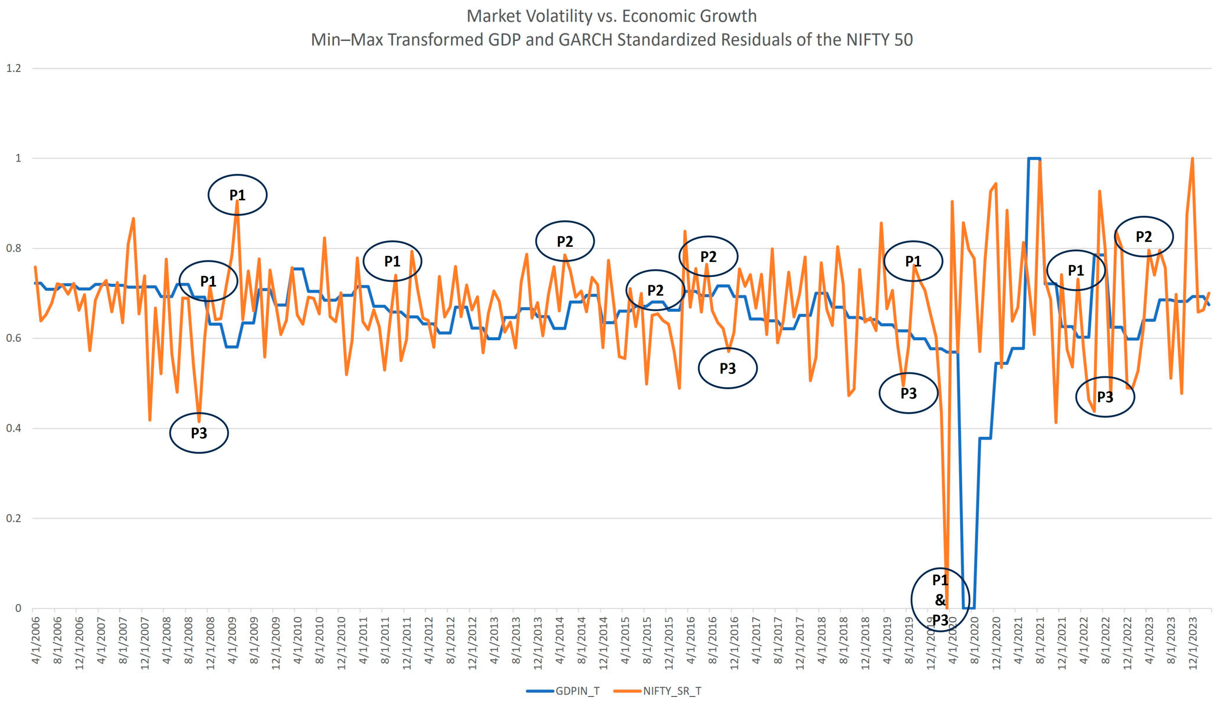

Figure 4. Market volatility vs. economic growth (India).

One clear pattern is that during major global crises, such as the 2008 global financial crisis and the COVID-19 pandemic, loss aversion (P3) dominated across all regions. In these instances, investors in both developed and developing economies overreacted to short-term fluctuations, leading to sharp declines in market prices. For example, during the 2008 crisis, market prices in the US, the UK, and India dropped by 16.94%, 10.71%, and 26.41%, respectively. This behavior shows that in times of global uncertainty, the spillover effect manifests as a global flight to safety, where markets collectively panic, amplifying volatility far beyond what GDP figures alone would suggest.

However, regional differences are evident in how markets react to more localized political or economic events. For instance, during the 2009 Indian general elections, herding behavior (P1) drove an exaggerated 28.07% rise in the NIFTY 50, whereas markets in the US and the UK exhibited more tempered reactions driven by loss aversion (P3), reflecting cautious optimism. Similarly, in the case of the 2014 Modi government in India, confirmation bias (P2) played a significant role across all markets, as investors anticipated pro-business reforms. This optimism was largely driven by expectations rather than immediate economic changes, demonstrating how sentiment can significantly impact market movements in both developed and developing economies.

In contrast, global events like the 2011 Eurozone debt crisis and the 2016 Brexit vote produced more varied market responses, depending on regional proximity and perceived risk. During the Eurozone debt crisis, the US and Indian markets exhibited herding behavior (P1), as investors responded to fears of contagion. In the UK, however, confirmation bias (P2) was more prominent, as investors anticipated a negative impact on the UK economy, despite stable GDP growth. Similarly, the Brexit vote caused volatility across global markets, driven by confirmation bias (P2), as investors in all regions reacted to the uncertainty surrounding the UK's departure from the EU. This event highlights how the spillover effect can cause markets to react differently depending on their perceived exposure to the event.

It is also important to note that during events such as the 2016 US presidential election and the Russia–Ukraine war in 2022, the reactions were region-specific. In the US, confirmation bias (P2) led to positive market movements, as investors speculated on pro-business policies under Trump. In contrast, markets in the UK and India exhibited loss aversion (P3), as investors reacted negatively to political uncertainty and its potential global implications.

Similarly, during the Russia–Ukraine war, herding behavior (P1) drove market movements in the US and India, whereas in the UK, loss aversion (P3) reflected concerns about energy prices and broader economic risks.

The analysis reveals that although global events often produce interconnected market responses, the specific investor behavior—whether driven by herding, confirmation bias, or loss aversion—varies between developed and developing economies. These regional differences are shaped by local economic conditions, the political context, and investor sentiment. Also, the spillover effect is not uniform but rather reflects the way global events influence markets based on their regional proximity and the perceived risks.

The Granger causality test results further deepen our understanding of the relationship between market volatility and GDP growth, particularly within the context of developed and developing economies. The finding that volatility Granger-causes GDP growth across all three indices—SPX, UKX, and NIFTY—supports the notion that fluctuations in financial markets act as leading indicators of economic performance. This is especially important when considering the differing investor behaviors identified in the table. For example, during events like the 2008 global financial crisis and the 2020 COVID-19 pandemic, herding behavior (P1) and loss aversion (P3) amplified market volatility, which, in turn, significantly influenced economic outcomes. The fact that GDP growth does not Granger-cause volatility reinforces the idea that economic performance is more reactive to market dynamics than vice versa. In developed markets like the US and the UK, this suggests that investor sentiment and cognitive biases—such as confirmation bias (P2) during the 2016 Brexit vote and the 2016 US presidential election—play a key role in shaping economic expectations. Similarly, in India, where herding behavior (P1) often drives market movements during political transitions, the Granger causality test underlines the importance of monitoring volatility as a predictive tool for economic planning. These results emphasize the need for both policymakers and investors to consider market volatility not just as a reflection of current economic conditions but as a potential predictor of future economic growth influenced by the underlying behavioral dynamics of the market.

5.2. Summary and Discussion

The analysis of market volatility and economic growth through the GARCH models and the interpretation of the graphical representations strongly support the three propositions proposed in this study.

P1 (herding behavior): The GARCH model results and the market volatility vs. economic growth plot clearly demonstrate instances where market movements deviated significantly from the underlying economic fundamentals. This divergence can be explained by the presence of herding behavior among investors, as indicated in P1. During periods of high uncertainty or market turbulence, investors tend to follow the crowd rather than make independent decisions based on rational analysis, leading to exaggerated market swings (McFadden and Lusk 2015).

P2 (confirmation bias): The analysis also supports the proposition that confirmation bias plays a role in amplifying market volatility. Investors tend to prioritize information that aligns with their existing beliefs, ignoring contradictory evidence or economic data. This selective perception can cause investors to overreact to news or events that confirm their biases, leading to market movements that are disconnected from the underlying economic fundamentals.

P3 (loss aversion): The plot and the interpretation table provide evidence of temporary spikes or dips in market volatility, even when long-term economic growth remained relatively stable. These short-term fluctuations can be attributed to loss aversion, as indicated in P3. Investors' tendency to avoid losses can lead to impulsive selling or buying behavior, resulting in heightened market volatility that is not necessarily reflective of the overall economic conditions.

Therefore, our analysis supports all three propositions, P1, P2, and P3, highlighting the significant impact of cognitive biases and behavioral factors on market volatility and its relationship with economic growth. These findings underscore the importance of considering psychological aspects in investment decision-making and developing strategies to mitigate the influence of cognitive biases on market dynamics.

6. Conclusions

This study has implications for investors, policymakers, economic analysts, and regulators. Investors need to be aware of the significant impact of behavioral biases such as herding behavior, confirmation bias, and loss aversion on their investment decisions. Recognizing these psychological factors can help investors develop strategies, such as diversification, risk management techniques, and a long-term investment approach, aligned with economic fundamentals rather than short-term market sentiments. This will help investors mitigate the influence of cognitive biases.

Policymakers should consider the role of behavioral biases in market volatility and implement measures to promote market stability, such as investor education programs and clear communication about economic policies and data. Regulations and interventions should aim to address the impact of cognitive biases on investor behavior, potentially including circuit breakers, trade halts, and measures to encourage rational decision-making.

Economic analysts should incorporate insights from behavioral finance and historical market data into their forecasting models and analyses to better predict and understand the complex interplay between market behavior and economic fundamentals. By considering the psychological factors that influence market dynamics, analysts can provide more accurate investment advice and economic forecasts, contributing to a more resilient financial ecosystem.

Regulators can draw insights from the findings of the study to develop effective investor protection measures, such as educational initiatives and transparency measures, that address cognitive biases and promote informed decision-making. Understanding the impact of behavioral biases on market stability, regulators can implement targeted policies and surveillance protocols to identify and mitigate potential market disruptions caused by irrational investor behavior.

The role of other potential psychological factors and individual characteristics that could influence investment decisions and market behavior should be investigated further. The generalizability of the results should be examined by replicating the study in different market contexts.

This study aimed to investigate the behavioral factors that contribute to market volatility and the divergence between market movements and the underlying economic fundamentals. By combining theoretical analysis and empirical modeling techniques, the study has achieved its objectives and provided valuable insights into the complex interplay between investor behavior, market dynamics, and economic growth.

The analysis strongly supports the proposed propositions, highlighting the significant impact of cognitive biases and behavioral factors on market volatility. Herding behavior (P1) was found to lead to exaggerated market swings, with investors following the crowd rather than making rational decisions based on economic fundamentals. Confirmation bias (P2) caused investors to overreact to information that aligned with their existing beliefs, amplifying market movements even in the face of stable economic conditions. Additionally, loss aversion (P3) prompted impulsive selling or buying behavior, resulting in temporary volatility spikes or dips that did not reflect long-term economic trends.

The GARCH models effectively captured the time-varying nature of volatility in financial time series. Moreover, the graphical representations and interpretation tables provided visual evidence of instances where market behavior deviated from underlying economic fundamentals. These findings underscore the importance of considering psychological aspects in investment decision-making and developing strategies to mitigate the influence of cognitive biases on market dynamics.

The study is constrained by a limited scope of variables, focusing primarily on herding behavior, confirmation bias, and loss aversion while ignoring other psychological biases such as overconfidence and anchoring bias. Also, the analysis did not account for demographic attributes that could influence market behavior, potentially limiting the understanding of overall investor psychology. The geographical focus on three countries—the US, the UK, and India—may lead to biased results, especially since India is classified as a developing economy. Future studies may benefit from including a broader range of developing or Asian countries to enhance comparability and generalizability. The time frame of April 2006 to March 2024 may limit the applicability of the results to different economic cycles. Finally, the reliance on historical data and specific model specifications, while robust, introduces potential limitations in capturing all the dynamics of market behavior. These factors present avenues for further exploration to enrich the understanding of cognitive biases and their implications in financial markets.

Future research directions:

1. Exploring the role of other potential psychological factors and individual characteristics that could influence investment decisions and market behavior, such as overconfidence, anchoring bias, or risk perception.
2. Investigating the impact of investor demographics, education levels, and cultural factors on the prevalence and manifestation of cognitive biases in different market contexts.
3. Conducting field studies and longitudinal analyses to examine the relationship between risk tolerance, herding behavior, and market outcomes in real-world investment scenarios.
4. Expanding the research scope to include a broader range of financial instruments, asset classes, and market environments to assess the generalizability of the findings.
5. Incorporating qualitative data and analysis techniques to provide deeper insights into the underlying reasons for observed behavioral biases and their impact on investment decision-making processes.

By addressing these research gaps and leveraging interdisciplinary approaches, future studies can contribute to a more comprehensive understanding of the complex dynamics shaping financial markets. Ultimately, this knowledge can inform the development of effective strategies and policies aimed at fostering market stability, investor protection, and the alignment of investment decisions with economic realities.

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