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The Knowledge Structure, Emerging Trends, and Future Directions of Stock Market Volatility Research: A Bibliometric Review

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Abstract: This bibliometric review examines the evolution of stock market volatility (SMV) research by analyzing 1,949 publications indexed in Scopus between 1980 and 2025. The study provides valuable insights into major research trends, influential contributions, and emerging themes, while highlighting potential directions for future research in the field. The research aimed to identify influential elements within the literature and perform a comprehensive analysis. The study investigated two direct research streams through a systematic review approach and conducted a network analysis of keywords and documents supported by content analysis. The findings suggested several areas for future research, including Islamic stock markets, structural breaks, cryptocurrency, economic policy uncertainty, and futures. Notably, hybrid models like ANN-GARCH, Wavelet-GARCH, and Copula-GARCH were found to have received limited attention, limited work is available on emotional and behavioural dimensions in the context of stock market volatility, which needs to be addressed through sentiment-driven modelling using NLP and social media indicators. Moreover, few studies are available related to comparative analysis across market segments & require panel Data-based Studies. The study covered various aspects of stock market volatility, encompassing models, applications, and empirical properties. The study comprehensively covers models, applications, and empirical properties of stock market volatility. Additionally, the study offered practical implications and recommendations for regulators (to make informed decisions regarding policy development and implementation) and portfolio managers (understanding of influential elements in stock market volatility). Overall, this bibliometric review

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contributes valuable insights to the field, providing a comprehensive knowledge of stock market volatility and paving the way for further research.

Keywords: bibliometric analysis; biblioshiny; literature review; stock market volatility; VosViewer; volatility spillovers.

JEL classification: G10; C55.

1. INTRODUCTION

Volatility, a pivotal characteristic of capital markets, remains a pressing concern in the realm of financial economics research (Ahmed, 2021; Apostolakis *et al.*, 2021). Volatility, characterised by the extent of variation in financial time-series data, serves as a crucial metric for assessing the risk associated with the unpredictability of underlying asset returns. Following the profound impact of the international financial crisis, global stock markets experienced unprecedented and tumultuous fluctuations (Bhowmik and Wang, 2020). It has created challenges for the stock market's functioning and raises risk and uncertainty. Therefore, the precise measurement of stock index return volatility is crucial for lowering this uncertainty. In the 1960s, Eugene Fama introduced the efficient market hypothesis (EMH), which posits that financial markets are informationally efficient. According to this theory, current prices fully reflect all relevant and available Information regarding the intrinsic value of underlying securities. However, viewpoints among investors and academics regarding the actual efficiency of markets diverge, as evidenced by the strong, semi-strong, and weak versions of the EMH. Empirical testing of market efficiency hypotheses has been conducted in both developed and developing countries, yielding diverse outcomes.

The existing literature on Stock Market Volatility (SMV) highlights that, in addition to market efficiency, volatility profoundly affects investment yields (Mamtha and Srinivasan, 2016). Stock prices have proven to be "too volatile" to be explained by efficient market hypotheses, and therefore, volatility has emerged as a distinct and increasingly surprising fact (Campbell and Shiller, 1988). Financial market volatility plays a crucial role in determining the risk of financial assets (Ji *et al.*, 2022) and is a significant determinant in the pricing of financial derivatives and asset allocation (Zhu and Ling, 2015), as well as in portfolio management. However, predicting volatility is difficult because it is an unknown latent variable with intricate properties such as heavy tails and non-stationarity. Despite the accessibility of numerous techniques to estimate volatility, not all perform significantly in all markets (Matar *et al.*, 2013). Many univariate, multivariate, and hybrid models have been used to model and quantify SMV (Kashyap, 2023). Recently, numerous forecasting methodologies have improved the forecasting accuracy of SMV by fully utilising the forecasted data from a large number of possible determinants (Li *et al.*, 2021). In recent years, Stock Market Volatility (SMV) has become a high-profile area of research due to increased global uncertainties, advancements in trading technology, and changing geopolitical and macroeconomic conditions (Xu *et al.*, 2024) . The COVID-19 pandemic aftermath, coupled with the Russia–Ukraine war, long-term inflation, and central bank interest rate increases globally, has heightened the degree of uncertainty in global equity markets (Papadamou *et al.*, 2023; Insaidoo *et al.*, 2024). All these have reflected the urgency for sophisticated volatility forecasting models that can handle real-time data and respond to structural shifts in market

behaviour. Artificial intelligence (AI), machine learning (ML), and deep learning (DL) models are gaining popularity for modelling and forecasting volatility more accurately (Salisu *et al.*, 2023; Saraf and Kayal, 2023; Chatziantoniou *et al.*, 2025). The models are capable of processing high-frequency data and extracting sophisticated nonlinear patterns lost by conventional econometric models. In addition, the complementarity of large datasets, including social media sentiment, news analysis, and Google Trends, has been effective in improving volatility prediction. A second new thread of literature concerns spillover effects and volatility transmissions between markets, particularly under financial crises, geopolitical conflicts, and times of international economic integration (Naeem, 2024; Chatziantoniou *et al.*, 2025). Analysts are now studying volatility in terms of networks and contagion with a view to deepening systemic risk. In addition, the inclusion of ESG factors, green finance metrics, and crypto market dynamics in SMV research is creating new research opportunities (Yang, 2025; Zhang *et al.*, 2025). As the financial system grows more interdependent, the proper modelling and forecasting of SMV continues to be a bedrock of well-informed investment decision-making, policymaking, and risk assessment.

1.1. Volatility modelling, measurement, and theoretical background

Volatility is a fundamental metric for capturing the extent of fluctuations in security or asset prices, providing insight into their dynamic nature. This key measure is derived through the calculation of the standard deviation of price returns, offering a quantitative representation of the magnitude of price changes (Hou *et al.*, 2024). The definition of the price return r (N, Δ_t) at a time scale of Δ_n is derived from.

$$P(N) = e^{r\,(N,\Delta_t)} P(N - \Delta_t) \quad (1)$$

where P(N) is the price level of the asset.

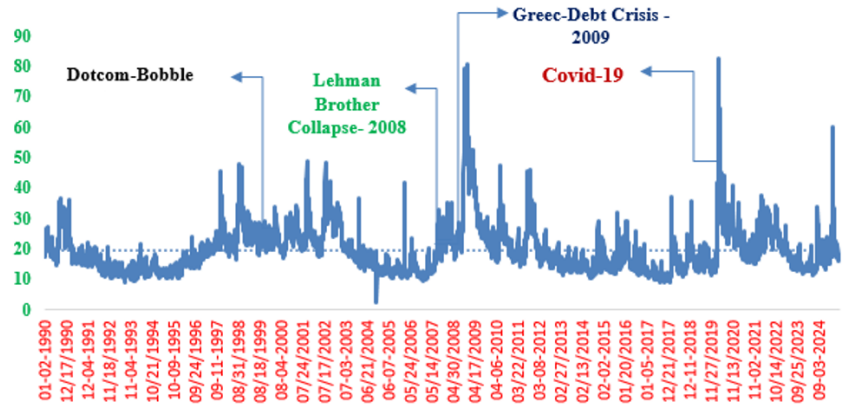
Hence:

$$r\,(N, \Delta_t) = \ln\left(\frac{P_N}{P(N-\Delta_t)}\right) \quad (2)$$

It can be calculated by applying traditional and emerging methods, and a wealth of financial economics literature on volatility forecasting has recently been developed. The influential ARCH model was given by (Engle, 1982), followed by the GARCH model (Bollerslev, 1986). Subsequently, a multitude of researchers have identified and developed various analytical volatility models, including EGARCH, GJRGARCH, QGARCH, SWARCH, M-GARCH, DCC-GARCH, BEKK-GARCH, ANN-GARCH, and others. These models have been devised to address the evolving challenges encountered in stock markets, such as volatility persistence, leverage effect, spillover effect, structural breaks, and the impact of macroeconomic variables.

Knowledge of the changing facets of volatility is essential for asset valuation, estimation, and risk management. For illustrative purposes, Figure no. 1 depicts the Chicago Board Options Exchange's (CBOE) Volatility Index's (VIX) yearly data based on the S&P 500 index from 1990 to 2025. A perceptive analysis of the data reveals intriguing insights about volatility returns in the United States. In 2018, the highest positive return of +130.25 per cent

was observed, while the lowest negative return of -45.80 per cent followed in 2019. These findings indicate the cyclical nature of volatility, with fluctuations occurring over time (Kashyap, 2023). Further, it also shows some other stylised facts about the stock market. It is affected by sudden changes or structural breaks due to several economic factors, like speculation, financial bubbles, and major catastrophic events like the early 1990s recession, the Dot-Com bubble, the 2008 Lehman collapse, the Greek debt crisis (2010), the European debt crisis (2011), and the COVID-19 pandemic (Simitis, 2016). It is due to the stock market's distinct characteristics, as depicted in Figure no. 1, that modelling volatility has become challenging. It seems that there is an inherent necessity to review volatility patterns. It also includes the movement of the data post-COVID.



Source: author's calculations

Figure no. 1 – CBOE Volatility Index (S&P returns: 1990-2025)

This paper reviews historical research developments in volatility, including interfaces in models and their extensions. It summarises and categorises the existing literature on SMV and can be used as a roadmap for future research (Raghuram *et al.*, 2010). As Winston Churchill once said, the farther back you look, the farther forward you can go. This study's analysis of previous literature on SMV since 1980 may be useful for estimating trends in the twenty-first century. It is believed to provide useful inputs for carrying out investigations in multiple emerging areas of stock markets and will aid the structure for subsequent studies (Tranfield *et al.*, 2003). This study has mapped the intellectual structure of SMV research based on the frequency of occurrence and co-occurrence of keywords and documents. This study also offers an overview of the forecasting models and their properties. SMV themes have further been reflected as crisis-specific and market-specific spillovers. Therefore, the current work, building on the previous research, provides a comprehensive bibliometric record of scientific contributions to the field of SMV to elicit a response to the ensuing questions:

1. How has the literature on stock market volatility (SMV) evolved, and what are the projected areas for future research advancements?
2. What are the key findings and trends identified through bibliometric and content analysis approaches?

3. How do methodological practices and contexts affect our understanding of stock market volatility?

4. What are the implications of the COVID-19 pandemic on stock market volatility and its differences between emerging and developed economies?

5. What are the dominant themes and niche areas in studying stock market volatility?

The remainder of this research is presented as follows: Section 2 demonstrates the methodology, encompassing data collection and examination scheme; Section 3 depicts the bibliometric and content analysis; Section 4 gives the discussion, and lastly, Section 5 provides implications and limitations of the study.

2. RESEARCH METHODOLOGY

This research applied a two-tiered investigative methodology, incorporating bibliometric analysis (Bhowmik and Wang, 2020) and content analysis (Kashyap, 2023; Insaidoo *et al.*, 2024). As a method for conducting systematic reviews, the bibliography framework of highlighting keywords, modelling, and synthesising the literature has been proposed. Researchers in the past have attempted to review the literature on SMV, but the conventional and customary literature assessments were constrained by the ability of investigators to manually handle data, resulting in a limited number of documents that could be reviewed (Ineichen, 2000; Hussain *et al.*, 2019; Seth and Sidhu, 2020; Kashyap, 2023). To statistically measure the vast, transparent, and reliable volume of Information, bibliometrics may be able to offer a systematised, fine, and regenerable investigative technique. However, the informational content of text-based records can be analysed using a series of organised, rule-based approaches known as "content analysis." In the social sciences, content analysis is a frequently employed technique that evaluates text data by condensing it into more easily understood clusters of facts (Kim and So, 2022). Figure no. 2 describes the entire research design and the procedures utilised for sampling, data collection, evaluation, and conclusion.

2.1. Sampling procedure

The study incorporates literature published from 1980 to 2025, dealing with SMV characteristics and patterns. The method of searching has been designed in such a manner as to ensure coverage of a broad spectrum of records. Documents have been sought, filtered, and assembled from the Scopus database (Khiste and Paithankar, 2017). This forum has been preferred for current academic work because it contains extensive peer-reviewed studies closely linked to the subjects of study (Anglada-Tort and Sanfilippo, 2019). For this article, we have taken the Scopus database for the literature review with the following strings; "Stock-Market" AND "volatility,"*TITLE("Stock-Market" AND "volatility") AND PUBYEAR > 1979 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,"cp") OR LIMIT-TO (DOCTYPE,"ch") OR LIMIT-TO (DOCTYPE,"re")) AND (LIMIT-TO (LANGUAGE,"English")))*. Additional filters were added to make the study concise and focused, such as publication stage (Final or AIP (Article in Press), Document type (Article (AR), Review (RE), Conference Paper (CP), Book Chapter (CH), or Book (BK)), source type (journal), and finally, language (to English). We defined academic produce broadly to include books, book chapters, and conference proceedings, even though Lisée *et al.* (2008) demonstrated that published scientific articles constitute the primary research source for

bibliometric investigations. Authors like Glänzel *et al.* (2006) showed that adding conference records to bibliometric research results in a more thorough and accurate representation of a certain discipline's scientific productivity and can measure the potential to invent and present novel notions. Furthermore, while citations for specific book chapters are lower, the intricacies of idea transmission would likely be lost without them. However, review publications that lack conceptual and empirical applications have been eliminated from the scope of this study. Furthermore, because of either honest scientific errors or scientific malfeasance, retracted documents that were defective or deceptive were not considered (Schneider, 2021). Finally, regarding the inclusion and exclusion criteria, various academic outputs, including journal articles, books, book chapters, and conference proceedings, whether published or available in the press, were evaluated for this review. Excluding non-English publications, 2176 documents have been embedded. Further, the review articles (19) which are excluded from the search strings have themes covering exchange rate volatility, oil price volatility, volatility spillover or contagion, SMV (specific to Granger causality), investment risk in securities, financial crisis effect and calendar anomalies are a few of them (Jones *et al.*, 2004; Guo and Savickas, 2006; Kamstra *et al.*, 2010; Brancaccio *et al.*, 2020; Zhong and Liu, 2021; Sreenu, 2022, 2023). Afterward, a thorough review was done, and it was observed that there are various review articles (17) published in the context of the individual country or regional blocks, such as in India, China, China, Pakistan, Southeast Asian countries, and European Unions, (Ahmed *et al.*, 2005; Chancharoenchai and Dibooglu, 2006; Harrison and Moore, 2012; Alikhanov, 2013; Zhang and Jaffry, 2015; Khan *et al.*, 2017; Singh, 2018). Further, review article (1) examined the SMV specifically to oil price and volatility spillover. Another study which are similar to our research work restricts its bibliometric analysis from the period of 2008 to 2019 (Bhowmik and Wang, 2020). Our research extended this work up to more than four decades, and apart from the bibliometric analysis, we considered content analysis to fill the research gap. Additionally, a manual elimination of 116 articles was done based on title, abstract and keywords specific to the other channels of volatility, say, import-export oil price volatility, commodity price volatility, exchange rate volatility, and some other macro-economic variables' volatility. The final sample of 1949 research articles has been taken for bibliometric and content analysis.

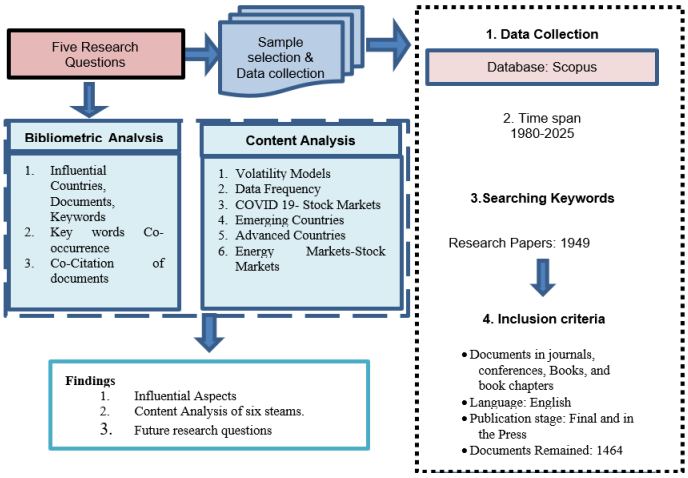


Figure no. 2 – Search parameters for document retrieval

2.2. Data analysis

There are two steps to the analysis of this research: bibliometric and content analysis. In the bibliometric stage, trends in publications and citations, as well as the co-occurrence of keywords and co-citation of documents, have been examined. To process the data statistically and visually, we used Biblioshiny and the VOS Viewer apps. In the second step of the project, we carried out a content analysis and were able to separate two independent research streams using subject keywords and a comprehensive review of abstracts.

3. BIBLIOMETRIC AND CONTENT ANALYSIS

3.1. Preliminary facts relating to data

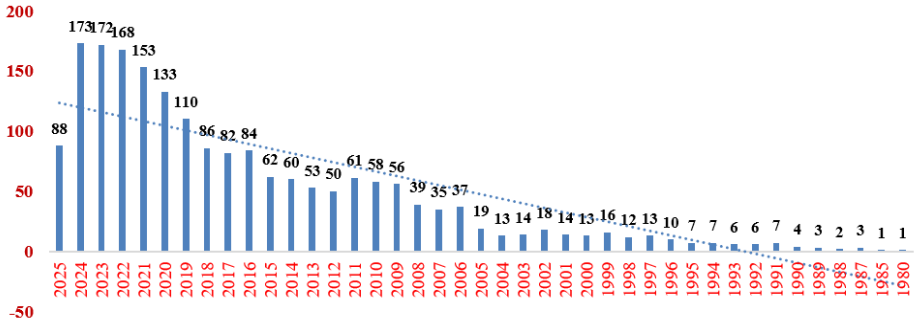
Table no. 1 presents a panoramic view of the database, wherein it can be seen that 3509 authors have made contributions in the field, applying 3562 non-identical keywords for classifying their work. Additionally, the mean citations per document equalled 26.91. The outcome stipulates that there are ample numbers of papers with huge citation counts, while a small number of papers have few citations. Moreover, the dataset included 328 single-authored studies on SMV. The average score of co-authors against each document is 2.61, indicating that SMV publications have been collectively explored.

Table no. 1 – Summary description of data

Description	Results	Description	Reseults
Main Information About Data		Authors	3509
Timespan	1980:2025	Authors of single-authored docs	284
Sources (Journals, Books, etc)	667	Authors Collaboration	
Documents	1949	Single-authored docs	328
Annual Growth Rate %	10.46	Co-Authors per Doc	2.61
Document Average Age	8.8	International co-authorships %	22.88
Average citations per doc	26.91	Document Types	
References	61860	Article	1684
Document Contents		book chapter	57
Keywords Plus (ID)	2442	conference paper	184
Author's Keywords (DE)	3562	Review	24

Source: authors' compilation

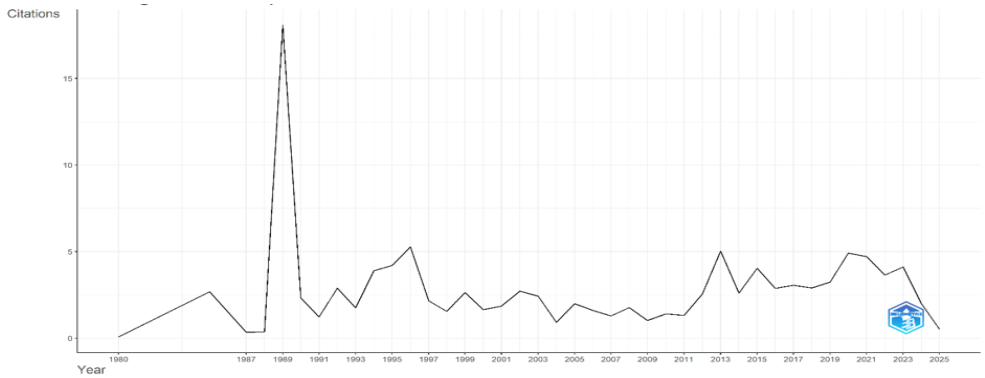
Figure no. 3 demonstrates the full order of publications in SMV during the time under consideration, from 1980 to 2025. The research concerns the notions of SMV and appeared in the year 1980 through the publication of a single document. Thereafter, 56 documents were issued during the year 2009, 104 documents in 2019, and 133 articles in 2020. As of December 15, 2022, 165 documents have been issued. Further, it depicts the annual growth rate of 12.93% and reveals that scholars are showing great interest in SMV. The annual Production has continuously increased as in the year 2024 it reached to 173 and is expected to continuously increase in the coming years as per the trend line.



Source: biblioshiny output

Figure no. 3 – Annual scientific production of SMV documents (1980-2025)

Figure no. 4 offers an appraisal of the citations, which permits the assessment of the superiority of the published documents. The only article published by Mankiw *et al.* (1985) has 110 citations. The article makes an unbiased reappraisal of SMV and offers impartial tests for small samples with no stationary hypotheses, avoiding the requirement to detrend. In 1989, only 3 articles were produced, and the mean number of citations per article was 582. Schwert (1989) has received 1710 citations so far. In the year 2013, 52 documents were produced, with the greatest number of 2401 citations, with an average of above 46 citations per article and 5 citations per year. The year 2015 witnessed 61 documents with 1840 citations and 30 citations on average per document. These findings disclose that research on SMV began several years ago, and 87 per cent of the publications have obtained citations.



Source: biblioshiny output

Figure no. 4 – Average article citations per year

3.2. Influential facets of the literature

We determined the influential countries, documents, and keywords in the SMV literature.

3.2.1. Influential countries

Table no. 2 portrays the prolific countries ascertained by the number of documents released. The studies on SMV are based in 60 different countries, with China having the most documents (484). However, surprisingly, the USA, which seems too small to see as compared to China in terms of publication counts, became the first-ranked country in total citations with 14637. On analysing the citations, it is established that the USA is producing quality work, as it gained the most citations. As a result, both developed nations like the United States and the United Kingdom and developing nations like India, China, and Malaysia have been trying to investigate SMV. It is evident from the table that other countries are also putting efforts in the same area to benefit domestic as well as Global stakeholders.

Table no. 2 – The leading publishing Nations in the SMV

Country	Documents	Citations	Country	Documents	Citations
China	484	10033	Jordan	16	198
United States	261	14637	Oman	16	532
India	223	3307	Czech Republic	15	615
United Kingdom	137	5617	Brazil	14	528
Australia	82	2484	Indonesia	14	118
Taiwan	80	1209	Netherlands	14	755
South Korea	79	2619	Poland	14	376
Turkey	73	1576	Bangladesh	13	195
Malaysia	69	1068	Egypt	13	205
France	63	2708	Ghana	12	102
Pakistan	61	1955	Iran	12	85
Tunisia	58	2053	Ireland	12	331
South Africa	55	825	Russian Federation	12	162
Germany	53	2487	Bahrain	11	69
Italy	47	1486	Denmark	11	276
Saudi Arabia	44	862	Qatar	10	181
Greece	43	1122	Sweden	10	100
Spain	39	1432	Switzerland	10	378
Canada	38	1494	Finland	9	350
Nigeria	35	431	Morocco	9	108
Viet Nam	35	772	Peru	8	52
Hong Kong	26	690	Slovakia	8	197
Japan	26	1145	Belgium	7	91
New Zealand	26	923	Kuwait	7	287
United Arab Emirates	26	640	Macao	7	283
Lebanon	25	988	Singapore	7	127
Portugal	23	746	Chile	6	45
Romania	23	178	Colombia	6	182
Thailand	22	184	Israel	6	448

Source: authors' compilation

3.2.2. Influential documents

Table no. 3 provides information about the top 10 documents that researchers most frequently cite. First is the local citation, depicting a document getting citations in each 1949-

node network, and second is the global citation, which speaks about the entire Scopus citations owing to the document. It is demonstrated that a noteworthy disparity prevails across the globally cited and locally cited documents. A leading document in global citations signifies that the paper has drawn the attention of the scholarly community from other domains as well. Schwert (1989) has the highest global citations (1,969) but the lowest Lc/Gc ratio of 6.70%, which implies wider influence outside the main research area. Conrad and Conrad and Loch (2015) and Paye (2012) have the highest Lc/Gc ratios of 22.62% and 22.06% respectively, reflecting strong contextual significance with lower global citation rates. Early classics by Engle *et al.* (2013), Bollerslev and Ole Mikkelsen (1996) and Hamilton (1996) retain high levels of international visibility, highlighting the impact their findings have had on econometrics and volatility modelling, although their reduced Lc/Gc ratios indicate they are today more referenced for theoretical foundation than recent empirical use. Later publications between 2012–2015 tend to have higher Lc/Gc ratios, indicating their methodological consistency with contemporary research directions.

Table no. 3 – The top 10 Most-cited Papers

Document	Year	Local Citations	Global citations	Lc/Gc Ratio (%)
(Schwert, 1989), j finance	1989	132	1969	6.70
(Engle *et al.*, 2013), rev econ stat	2013	104	760	13.68
(Paye, 2012), j financ econ	2012	75	340	22.06
(Koutmos and Booth, 1995) j int money financ	1995	62	450	13.78
(Liu and Zhang, 2015), finan res lett	2015	56	411	13.63
(Bollerslev *et al.*, 1988), j econom	1996	49	723	6.78
(Aggarwal *et al.*, 1999), j financ quant anal	1999	44	451	9.76
(Lee *et al.*, 2002), j bank finance	2002	40	487	8.21
(Conrad and Loch, 2015), j appl econom	2015	38	168	22.62
(Hamilton, 1996), j appl econom	1996	38	428	8.88

Source: authors' compilation

3.2.3. Influential keywords

The word cloud depicted in Figure no. 5 is a graphical representation of the frequency of occurrence of keywords in documents, as indicated by the size of the word in the graph. This may exhibit the significance of the keyword in scientific literature. When the authors' keywords were examined, it was discovered that the term "volatility" appeared the most (322 times), followed by words describing theoretical, methodological, contextual, and typical characteristics of volatility such as "GARCH" (224), "volatility spillover" (180), "realized volatility" (108), "volatility forecasting" (82), "emerging markets" (61), "EGARCH" (53), "COVID-19" (48), "long memory" (42) and others (50). Apart from these, psychological or behavioral variables like investor sentiments, variables depicting the structure of the data like "high-frequency data" and "idiosyncratic volatility," as most of the results lose reliability due to inappropriate collection of the data, and variables explaining some properties or effects of volatility like implied volatility, leverage effect, volatility persistence, etc. were noticed to be dominant. Internationally, numerous researchers have examined how investor sentiments influence stock markets. There is a strong relationship between investor sentiment and market

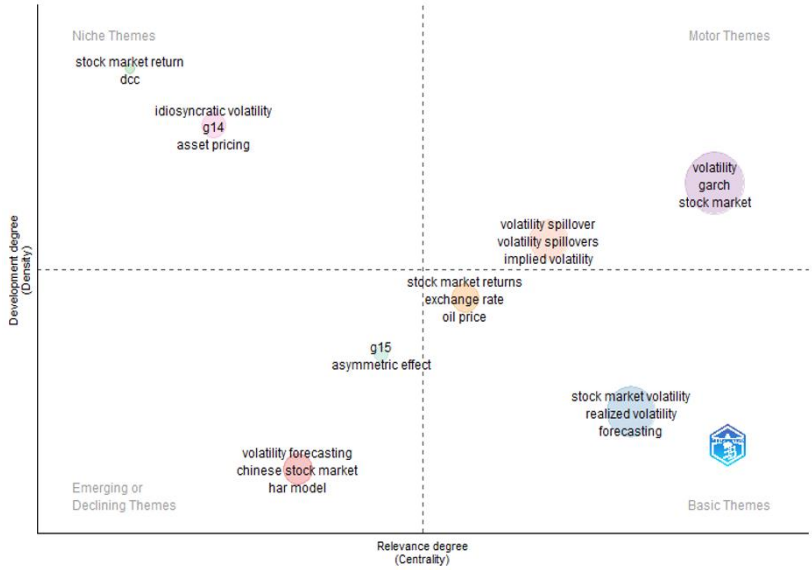
anomalies (Chen *et al.*, 2020; Ferreira *et al.*, 2021; Zhang *et al.*, 2021). It can be inferred from this word cloud that the existing literature on SMV has been exploring its various properties, effects, and mathematical and econometric models, which are of great significance to address the theme.

Source: biblioshiny output

Figure no. 5 – Word Cloud

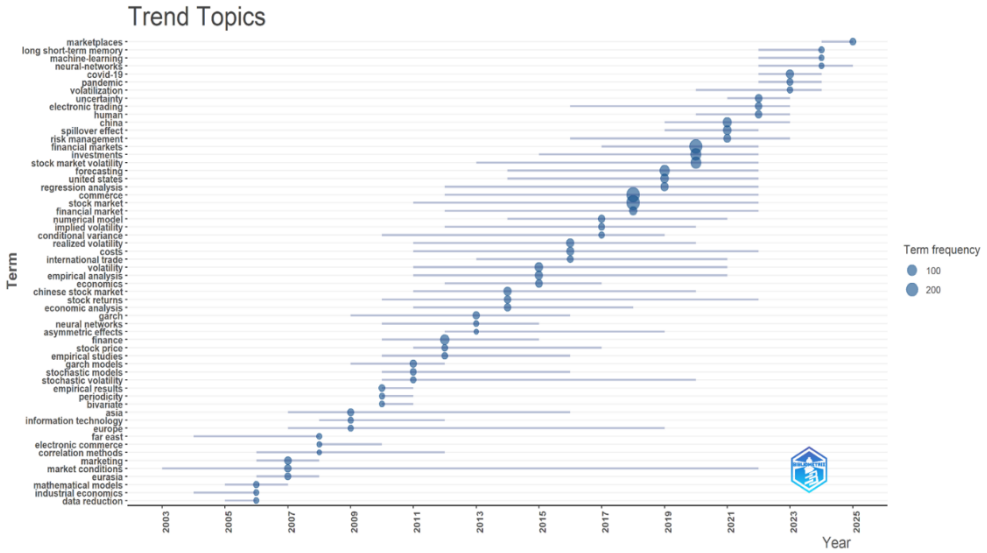
3.2.4. Influential themes

Figure no. 6 presents a thematic analysis that provides the potential for further developments in the domain. The themes of GARCH and spillover in Q1 (upper-right quadrant) are the leading themes. GARCH models have been extensively used to forecast volatility (Zhang and Zhang, 2022). The studies on volatility spillover have encompassed the evolving process of volatility spillover across the world (Charfeddine and Al Refai, 2019). Q2 (upper left) comprises idiosyncratic volatility and the DCC model, both of which are very high in density but low in centrality. Idiosyncratic volatility calculates the part of the variance in returns that a particular asset-pricing model fails to explain (Hoang Van *et al.*, 2020). The DCC-GARCH model is perceived as a powerful model since it accounts for time-varying volatility spillovers. Both the DCC-GARCH model and idiosyncratic volatility are extremely established, focused, and niche themes that need to form bonds with the leading theme of SMV. Q3 (lower left) shows asymmetric market interactions as the emerging theme, exhibiting how the oil market and stock markets have asymmetrical spillover effects and how bad volatility spillovers outweigh favourable volatility spillovers. Lastly, Q4 constitutes SMV, an underlying theme that is continuing with several experiments and explorations across the world. This theme is central and important for the research field.



Source: biblioshiny output

Figure no. 6 – Thematic map



Source: biblioshiny output

Figure no. 6.1 – Trending topics

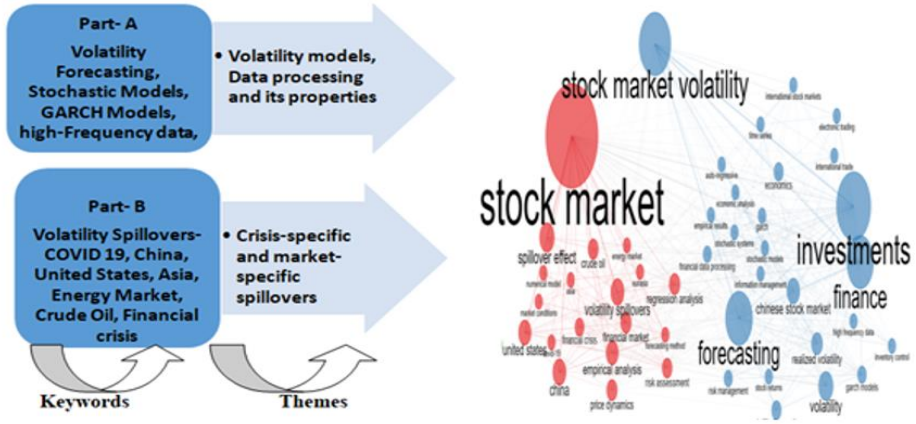
Figure no. 6.1 shows in these years how some topics became popular, along with the density of their popularity some of the trends started from 2004 to 2006 topics like industrial

economics, mathematical models and data reduction were in trend whereas from 2010 to 2015 topics like bivariate analysis, empirical studies, Stock Movement, Garch Models and Technological issues were in focus and from 2020 to 2025 Themes like machine learning, Neural- Networking, Spillover and Similar Themes are more frequently used and Focused. Over the past five years, stock market volatility has been increasingly influenced by global uncertainties, geopolitical tensions, and macroeconomic shocks such as the COVID-19 pandemic. Technological advancements and algorithmic trading have further amplified short-term market fluctuations. Additionally, investor sentiment shaped by social media, news flows, and behavioural biases has emerged as a critical driver of volatility trends.

3.3. Network analysis

3.3.1. Keywords co-occurrence network extended with content analysis

Co-occurrence Network, Categorisation, and Classification of Constructs on the basis of the keywords plus is the next analysis produced by Biblioshiny. It is a means to broadly comprehend the conceptual structure of this scientific work. Keyword co-occurrences in Figure no. 7 show that the whole literature on SMV revolves around two main categories identified in two parts.



Source: authors' compilation and biblioshiny output

Figure no. 7 – Themes based on the keywords

Part A: It displays the methodological practices implemented for the achievement of SMV. It covers Information about types of volatility models, data preprocessing, and properties of volatility models.

Volatility models and data pre-processing: The keywords "forecasting," "stochastic models," "financial data processing," "risk management," "conditional volatility," "GARCH models," "auto-regressive," and "high-frequency data" suggest that, given the econometric advances, SMV is predictable and that too with greater certainty (Pagan and Schwert, 1990).

Volatility modelling has been a rising area of investigation ever since the initiation of ARCH and stochastic volatility (SV) models. Table no. 4 exhibits Information about volatility models and authors who have used the respective volatility models to forecast volatility.

Table no. 4 – Volatility models and authors' information

S. No	Volatility Model	Model features	Author's Information
1.	Benchmark (GARCH)	The GARCH model posits that conditional volatility is a linear combination of prior volatility and errors, making it suitable for forecasting short-term volatility.	(Kiymaz and Berument, 2003; Hammoudeh and Li, 2008; Bouri, 2015; Boldanov *et al.*, 2016; Ewing and Malik, 2016)
2.	Integrated GARCH (IGARCH)	The IGARCH model (unit-root GARCH models) exhibits long memory in volatility, and the sum of the variance equation coefficients is close to unity.	(Horng *et al.*, 2012; Bentes, 2014)
3.	Fractionally Integrated GARCH (FIGARCH)	It is a non-linear model appropriate for capturing long-memory shocks.	(Zhang, 2014; Kyriakou *et al.*, 2021; Tripathy, 2022)
4.	Golsten, Jagannathan, and Runkle (GJR-GARCH) & Threshold GARCH (TGARCH) model	These models are used to analyse asymmetrical behaviour in volatility, and they add another residual term to the benchmark GARCH.	(Bakry *et al.*, 2022)
5.	GARCH-MIDAS	It is suitable to link the observations with macroeconomic variables and can be used to examine its impact on stock volatility.	(Bai *et al.*, 2021; Su and Liu, 2021; Song *et al.*, 2023)
6.	GARCH-in-Mean (GARCH-M), SWARCH	It permits the mean of the security returns to be a function of the conditional volatility. On the other hand, SWARCH is a regime-switching model designed to capture the high persistence of variance in returns.	(Natarajan *et al.*, 2014; Coffie, 2015)
7.	Exponential GARCH (EGARCH), AGARCH, QGARCH	It is suitable to capture the asymmetric behaviour of volatility, and it does not have the restriction that the coefficients be positive.	(Walid *et al.*, 2011)
8.	Multivariate GARCH	Their models are used to compute volatility at the same time for multiple securities.	(van Dieijen *et al.*, 2020; Yu *et al.*, 2020)
9.	Component GARCH(CGARCH)	It captures long-term effects by breaking the model down into long-run and short-run components.	(Chen *et al.*, 2015)
10.	Dynamic Conditional Correlation (DCC) model	It is a nonlinear model that has the versatility of standard GARCH models and can be approximated using univariate or two-step methods depending on the likelihood function.	(Gamba-Santamaria *et al.*, 2019; Luo and Wang, 2019; Tang and Aruga, 2021)

S. No	Volatility Model	Model features	Author's Information
11.	BEKK-GARCH	It is a benchmark GARCH model extension that allows interaction between conditional variances and covariance with limited parameters.	(Sarwar *et al.*, 2019; Zhang *et al.*, 2020; Ahmed and Huo, 2021)
12.	Hybrid models-ANN-GARCH, Neural Network GARCH, Fuzzy/SVM/ GARCH, COPULA, Wavelet	These are useful for capturing extreme values, structural breaks, and chaotic Information better than others.	(Chen *et al.*, 2022; Kashyap, 2023; Katoch and Peer, 2026)

Source: authors' compilation

Furthermore, the frequency of data also impacts the accuracy of the analysis of volatile time series. Table no. 5 provides Information about the frequencies of the data used to understand and estimate volatility. The majority of the existing volatility forecasting literature relied on a data set of equivalent frequencies that are easily accessible on a monthly, weekly, and daily basis. Since shock impacts are thought to be swift and short-lived, daily data is contended to be more revealing than weekly or monthly data (Madaleno and Pinho, 2014). However, with the availability of high-frequency data, researchers have found that these data are even more insightful on volatility, which has led to the development of the idea of realised volatility. High-frequency data has entered the literature on volatility modelling and forecasting quite rapidly (Andersen *et al.*, 2007) and has gained popularity in price forecasting as well as volatility models (Degiannakis *et al.*, 2018). It has been proved that extreme value models, structural break models, etc., fail to provide good volatility forecasts because of the low-frequency data being used (Bali and Weinbaum, 2007; Taylor, 2008).

Table no. 5 – Type of data and author information

S No.	Authors' Information	Type of data
1	(Ashwani and Sheera, 2018; Finta *et al.*, 2019)	High-frequency data
2	(Khalfaoui *et al.*, 2019; Belhassine and Karamti, 2021)	Daily data
3	(Abbas and Satti, 2019; Haritha and Rishad, 2020; Ma *et al.*, 2024)	Monthly data
4	(Wang and Moore, 2009; Cevik *et al.*, 2020; Kartsonakis-Mademlis and Dritsakis, 2020)	Weekly data

Source: authors' compilation

3.3.2. Properties of volatility model

Volatility Persistence Including Innovations: Empirical Evidence: The autocorrelation of absolute returns, known as persistent behaviour, is used to examine volatility clustering, and this level of persistence varies from market to market. The effects of shocks typically take a long time to return to the normal mean level, and the return series exhibits volatility persistence. It is influenced by innovations, public news, and trading volume (Hammoudeh and Li, 2008). Many scholars have also analysed the long-term persistence in SMV, proving that volatility exhibits long memory behaviour (Corsi, 2009;

Chkili and Hamdi, 2021; Lahmiri and Bekiros, 2021). During the COVID-19 pandemic, all markets exhibited a significant level of volatility persistence.

Volatility and Leverage Effect: Empirical Evidence: Volatility is frequently associated with asymmetric reactions (ups and downs), implying that negative Information generates more volatility than positive Information and increases financial leverage (Zhou *et al.*, 2012; Hussain *et al.*, 2019). The leverage effect describes how negative shocks increase conditional covariance, while positive shocks respond differently to conditional covariance. Many academicians have debated this asymmetric phenomenon, and it has been observed that global equity markets are usually assumed to be asymmetric with negatively correlated conditional variance returns (Dash and Mahakud, 2013; Bagchi, 2017). On the other hand, some scholars have given contradictory conclusions about the asymmetric phenomenon and are sceptical about whether negative conclusions generate more volatility than positive ones do (Chiang and Doong, 2001; Coffie, 2018; Kashyap, 2023). During the COVID pandemic, various researchers depicted the dominance of asymmetric phenomena in emerging market economies and proved that negative shocks generated more volatility than positive shocks (Bhattacharjee and De, 2022; Jindal and Kumar Gupta, 2022).

Structural breaks: It is a radical shift in the time series that affects the volatility model's persistence (Lamoureux and Lastrapes, 1990). The global stock markets have become more chaotic due to sudden changes in recent years, such as political or crisis news, or casualties like the COVID-19 pandemic. Scholars have utilised numerous methodological tools such as Chow tests, Iterated Cumulative Sum of Squares (ICSS), Bai & Perron (BP) tests, etc., to capture structural breaks (Kashyap, 2023). Various studies have concluded that if structural breaks are ignored, it may affect the volatility persistence and lead to forecasting errors (Ewing and Malik, 2016; Cevik *et al.*, 2020; Kartsonakis and Charitidis, 2020; Dabwor *et al.*, 2022). As a result, when analysing volatility and spillover effects, practitioners should consider structural breaks or run models that account for these changes.

Part B: It covers the dynamics of volatility spillovers in global financial markets. Spillover effects are influenced by crisis-specific and market-specific factors (Lien *et al.*, 2018). Li (2021) found that risk is transmitted by economically developed regions and received by economically undeveloped areas. Moreover, several studies discovered volatility spillovers to be crisis-sensitive during the coronavirus recession (Apostolakis *et al.*, 2021; Bahloul and Khemakhem, 2021; Li, 2021). Table no. 6 exhibits the summary table of crisis-specific and market-specific spillovers.

3.3.3. Crisis-specific (COVID-19) Spillovers on SMV

The connection between SMV and COVID-19 has garnered significant attention since the onset of the pandemic. Due to the pandemic's contagious effect, the whole globe changed drastically, and the stock markets were no exception. The conclusions are:

i) Spillover Effects between Thailand and Indian Stock Markets: There are significant spillovers from Thailand to Indian Stock Markets and vice versa, and further revealed the impact of negative shocks than positive shocks on these markets (Jindal and Kumar Gupta, 2022).

ii) Overconfidence Bias and Volatility Spillovers in Ghana: Overconfidence bias and volatility spillovers exist during the COVID-19 pandemic in Ghana.

(iii) Strengthened Connections across Continents: Cheng *et al.* (2022) observed that the pandemic period led to stronger connections among stock markets across different continents, highlighting the global nature of the crisis.

(iv) Unprecedented Volatility Spillovers across International Stock Market Indices: There is an unprecedented increase in volatility spillovers across international stock market indices in Brazil, China, Italy, India, Germany, Russia, Spain, the United Kingdom, and the United States of America (Basuony *et al.*, 2021).

(v) Currency Volatility and Stock Market Returns: Currency volatility has influenced the market returns of Brazil (BOVESPA), Chile (S&P CLX IPSA), India (SENSEX), Mexico (S&P BMV IPC), and Russia (MOEX) significantly, and significant volatility spillover between stock and currency markets was found in emerging economies.

The other studies depict a similar influence of COVID-19 on SMV (Lahmiri and Bekiros, 2021; Gupta *et al.*, 2022). These collective findings demonstrate the wide-ranging effects of the pandemic on stock market volatility, revealing important insights into the interconnectedness of global markets and the influence of various factors on investment dynamics during times of crisis.

3.3.4. Market-specific spillovers

Evidence from Emerging Countries

The intriguing research by Kambouroudis (2016) suggests that risk transmission in emerging markets is a recent phenomenon, rendering these markets susceptible to external shocks. These emerging markets have 25 developing nations, some of which fall under economic blocs such as BRICS, CIVETS, and MENA (Jeris *et al.*, 2022). The forthcoming information highlights the interconnectedness between the stock market and other markets within these emerging countries.

BRICS: BRICS is a block of five major countries (Brazil, Russia, India, China, and South Africa). The conclusions are:

(i) Long-term Dependencies and Energy Commodities: Long-term dependencies exist between energy commodities and the stock markets of the BRICS countries.

(ii) Volatility Spillovers during Major International Events: There is an increase in time-varying volatility spillovers in BRICS nations during major international happenings (Mensi *et al.*, 2021).

(iii) Heterogeneous Spillovers and Positive/Negative Shocks: Stock and oil market volatility exhibits heterogeneous spillovers, indicating positive and negative shocks (Salisu and Gupta, 2021).

(iv) Market-Specific Volatility and Persistence: Significant volatility spillovers are found in all markets and further, Chinese market is the most volatile, whereas the Brazilian market is the least volatile, and the Chinese market has the highest volatility persistence, followed by South Africa, Russia, India, and Brazil, respectively (Mukhodobwane *et al.*, 2020).

(v) Bi-Directional Volatility Spillover between Currency and Stock Markets: There is a bi-directional volatility spillover between currency and stock markets of India, China, and South Africa.

(vi) Risk Exporters and Risk Receivers: G7 is the exporter of risk, and BRICS is the receiver of risk (Zhang *et al.*, 2021).

(vii) Significant Spillover Effects and Volatility Shocks Persistence: There is evidence of significant spillover effects and persistence in volatility shocks in all BRICS stock markets. To sum up, it is concluded that most scholars have demonstrated the impact of stock market volatility in BRICS nations, and significant persistence and spillover effects have been observed.

North Africa (MENA), Middle East, and CIVETS: The findings are as follows:

(i) Influence of Macroeconomic Variables on SMV: The SMV is not fully influenced by spillovers and fluctuations in macroeconomic variables (Mechri *et al.*, 2021).

(ii) Impact of Political Events on SMV in MENA: Significant volatility spillovers are found, but political events have a greater impact on MENA's SMV than the financial crisis (Talbi *et al.*, 2022).

(iii) Economic Freedom Index and SMV: There is an association between the economic freedom index and SMV, and it proven that spillover effects can be lessened when economic freedom is linked with efficient regulations (Touny *et al.*, 2021).

(iv) Time-Varying Volatility Spillovers and Market Regimes: There are time-varying volatility spillovers in markets, and three regimes, as low, turmoil, and high volatility regimes, are found (Bahloul and Abid, 2014).

(v) Interlinkages of African and Middle East Stock Markets: The interlinkages of the African and Middle East region's stock markets are not uniform across all the region's countries.

vi) Volatility Spillovers between Chinese and African Stock Markets: There are significant volatility spillovers between the Chinese and African stock markets.

There are some other emerging nations (Thailand, Poland, Croatia, Hong Kong, South Korea, Malaysia, India, Philippines, and Singapore) where the scholars analyzed SMV and all markets depicted significant volatility persistence, spillover, and leverage effects (Spulbar *et al.*, 2020; Toe and Ouedraogo, 2022).

SMV in the Islamic stock market (ISM): Over the years, several studies have been conducted to analyse SMV in the Islamic market. Unfortunately, the ISM was not given much importance and was not considered a regular stock market. The conclusions are:

(i) Risk and Spillovers: There are investment risks in the Muscat securities market due to SMV spillovers in ISM (Alam *et al.*, 2020).

(ii) Political Uncertainty and Spillovers: The political uncertainty influenced the spillover effects (Li *et al.*, 2023).

(iii) Return-Volatility Relationship: There is a strong association between return and volatility spillovers of the global ISM as well as the conventional stock markets (Shahzad *et al.*, 2017).

(iv) Bonds and Volatility Spillovers: There is a significant dependence of bond returns on volatility spillovers in ISM (Naifar, 2016).

(v) Forex Market Spillovers: There are volatility spillovers from the ISM to the forex market of Turkey.

(vi) Oil Volatility and Market Returns: There is a negative spillover effect of the oil volatility on ISM returns (Karim and Masih, 2021).

(vii) Regional Volatility Dynamics: The volatilities depend upon their own short, mid, and long-term volatilities, which differ significantly between the Malaysian and global ISM indices. These themes collectively provide insights into the dynamics and implications of SMV in the Islamic stock market, emphasising the importance of considering the ISM as a regular and significant stock market.

3.3.5. SMV and advanced countries

This section covered the SMV and its interconnection in emerging as well as advanced economies. The conclusions are: (i) The bidirectional volatility spillovers and the structural breaks influenced the dynamic conditional correlations between Shanghai's and S&P trading return (Pan and Mishra, 2022); (ii) different markets (Hong Kong, and United States) have different reactions to the same events (Hou *et al.*, 2024); (iii) Share markets in USA, Germany, Hungary, India, and Canada depicted high positive volatility during the global financial crisis and also influence each other (Spulbar *et al.*, 2020); (iv) Economic policy uncertainty (EPU) connectedness significantly influences the partner country's SMV ; (v) There are crisis specific spillovers depicting shock transmission from the US to Latin America during the Lehman Brothers crisis, significant interactions between the European markets SMV during the Brexit crisis (Li, 2020), existence of financial contagion in US, Central and Eastern European stock markets (Horváth *et al.*, 2018).

3.3.6 SMV and Energy Markets

The scope and development of connections between stock markets and energy markets, including electricity, natural gas, coal, oil, and carbon, have also been reviewed in the study. The main conclusions are: (i) strong spillover relations exist between crude oil and stock markets (Wen *et al.*, 2019; Ashfaq *et al.*, 2020); (ii) Natural gas provides better hedging effectiveness to stock markets than crude oil (Jebabli *et al.*, 2022); (iii) spillovers became intense following the fall of Lehman Brothers (Wen *et al.*, 2020) and the COVID-19 pandemic (Hernandez *et al.*, 2022); (vi) There are reciprocal spillover effects between the coal market and the stock market for emerging energy companies (Lin *et al.*, 2019) (vii) The carbon and stock market correlation is strengthened by the financialization of the carbon market, policies governing carbon market performance, and investor behavior (Wen *et al.*, 2020).

Table no. 6 – Summary table crisis-specific and market-specific spillovers

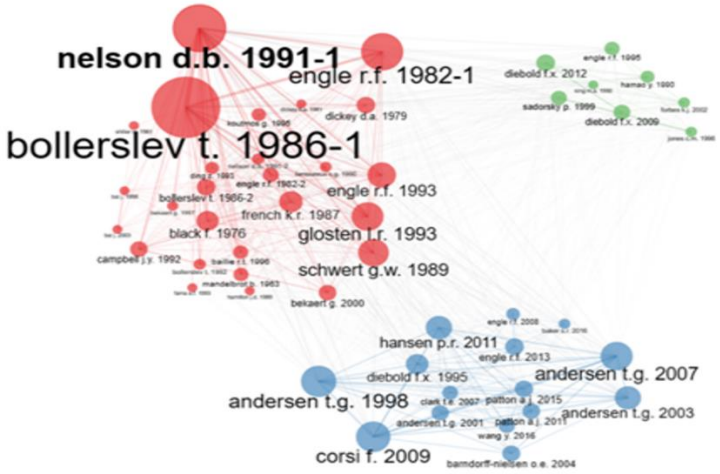
Spillover		Key Findings
Crisis-Specific Spillovers on SMV	COVID-19	Significant spillovers during the crisis, Existence of overconfidence bias, China is not the main carrier of volatility spillover, Connections across different continents became stronger, Significant volatility spillover between stock and currency markets was found.
Market-Specific Spillovers on SMV	BRICS	Long-term dependencies exist between energy commodities and the stock markets. Heterogeneous spillovers are found between the stock and oil markets, Bi-directional volatility spillover between currency and stock markets, G7 is the exporter of risk, and BRICS is the receiver of risk.

Spillover		Key Findings
	North Africa (MENA), Middle East, & CIVETS	No uniformity in African and Middle East regions, significant volatility spillovers between Chinese and African stock markets, Significant volatility spillovers between the Chinese and African stock markets.
	Islamic Stock Market (ISM)	Political uncertainty influenced the SMV spillovers. Strong association between return and volatility spillovers of the global ISM, Significant dependence of bond returns on SMV, Negative spillover effect of oil volatility on ISM returns.
	Advanced Countries	Different markets (China, Hong Kong, and the United States) have different reactions to the same events; Economic policy uncertainty (EPU) connectedness significantly influences the partner country's market spillover. Existence of financial contagion in the US, Central and Eastern European stock markets.
	Energy Markets	Strong spillover relations exist between crude oil and stock markets. Spillovers became intense after the crisis, such as the Lehman collapse and the pandemic.

Source: authors' compilation

3.4. Co-Citation network of documents

Figure no. 8 gives Information about the co-citation network of documents. It exhibits fresh papers of highly cited articles based on the citation indexes and offers a list of more significant "core" publications of former materials for a specific field (Small, 1973). In the red cluster, Bollerslev (1986) (GARCH-1986), Engle (1982) (ARCH-1982), Nelson (1991) (E-GARCH-1991), and Glosten *et al.* (1993) (GJR-GARCH-1993) models have been covered (Refer Table no. 4). In the blue cluster, Andersen *et al.* (2007) discovered the difference between the volatility jump component and continuous component and proved that the former is less persistent than the latter, yet an important predictor of future volatility. Andersen and Bollerslev (1998) proposed a realised volatility model, and relying on that, Andersen *et al.* (2007) gained the attention of many scholars. Later, others worked on realising volatility using high-frequency data, like Corsi (2009), Patton and Sheppard (2015). The green cluster gives Information about the authors who highlighted volatility spillovers between the markets (Engle, 1990; Hamao *et al.*, 1990; Sadorsky, 2009). The contributory work was done by Diebold and Yilmaz (2009), who analysed the volatility spillover across the markets, i.e., from one market to the other. They concluded that the markets have different behaviour in terms of the dynamics of return and volatility spillovers. Extending their previous work, Diebold and Yilmaz (2012) analysed the volatility spillovers across different assets, considering US stock, bond, currency, and commodity markets. The results showed significant volatility variations in all markets, limited cross-market volatility spillovers until the 2007 global financial crisis, and significant volatility spillovers after the crisis.



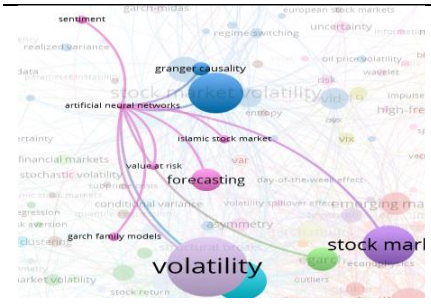
Source: biblioshiny output

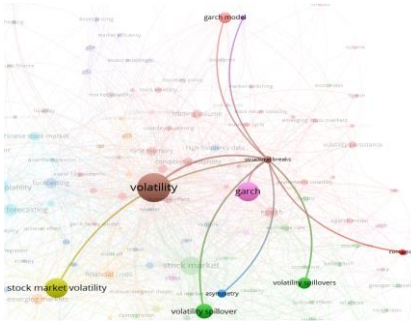
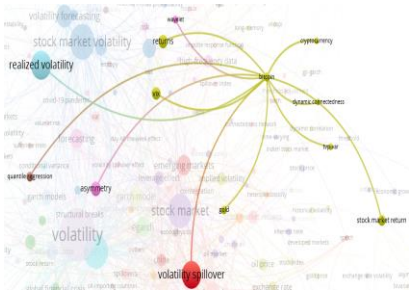
Figure no. 8 – Co-citation network of documents

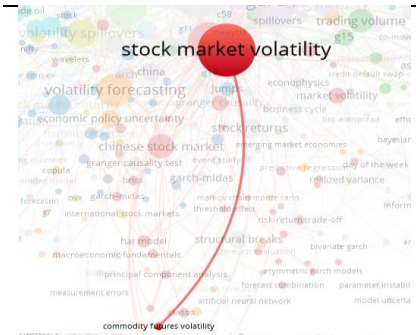
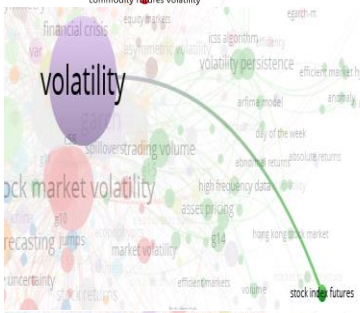
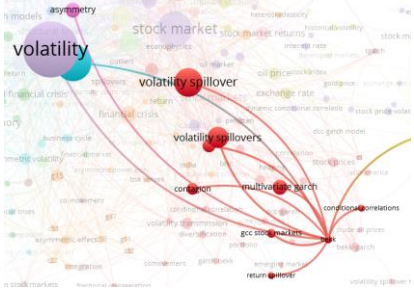
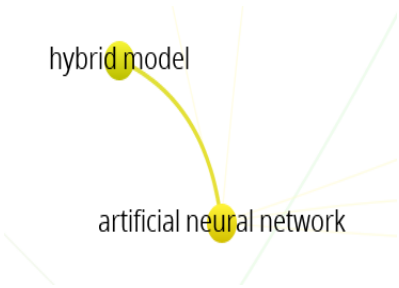
3.5. Future research gaps

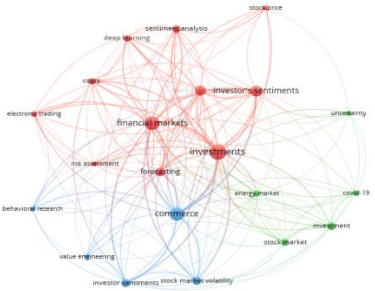
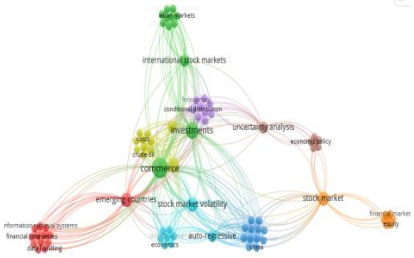
This section is significant as it highlights the research gaps, network gaps, and future research directions. The body of knowledge on SMV is growing quickly, but there are still crucial aspects that need to be addressed. Firstly, the bibliometric analysis helped us suggest various areas of research for additional investigation; subsequently, we developed the relevant research questions from future study agendas. We have used VOS viewer software, which is highly advised in this context since it assesses the importance of a particular subject in the literature by automatically counting the frequency of keywords in the sampled documents (José de Oliveira *et al.*, 2019). The potential research questions for upcoming studies are presented in Table no. 7.

Table no. 7 – Research Gaps & Future Research directions

Network Gaps	Keywords frequency in the identified network	Current State and Research Gap	Future Research Direction
	Volatility (280), Granger casualty Forecasting (21) GARCH (118). Sentimental analysis (24)	Few researchers have examined market-to-market effect (e.g. Islamic stock market and other markets) applying Granger causality. It has also been confirmed that hybrid volatility	a) What is the relationship between stock price movements and public sentiments? b) Does the Artificial Intelligence technique

Network Gaps	Keywords frequency in the identified network	Current State and Research Gap	Future Research Direction
	Islamic stock market (7), Hybrid models (3)	models are the emerging tools in measuring stock market volatility and sentiment analysis.	predict stock market volatility better than benchmark GARCH models?
	Volatility (280), GARCH (118) Volatility spillover (73) Asymmetry (61) Structural Breaks (15),	Though the majority of researchers have analysed volatility, structural breaks and spillover effects, few scholars have analysed volatility and spillovers simultaneously with structural breaks.	What are the emerging techniques to examine the volatility spillovers, and do they take into consideration the structural breaks?
	Volatility spillover (73) Quantile regression (8) Bitcoin (7) Wavelet (5) Cryptocurrenc y (3)	Concerning stock market volatility and cryptocurrency market, research is still at its infancy stage and that to apply quantile regression and wavelet techniques.	What are the spill-over effects from stock to the cryptocurrency market and vice versa?
	Stock market volatility (280) Economic policy uncertainty (15)	Few scholars have explored the relationship between economic policy uncertainty and stock market volatility.	a) How does stock market volatility react to economic policy uncertainty in different market conditions? b) What are the spillover effects from economic policy uncertainty to the stock market?

Network Gaps	Keywords frequency in the identified network	Current State and Research Gap	Future Research Direction
	Stock market volatility (280) commodity futures volatility (4)	Concerning stock market volatility and commodity futures market, research is still in its infancy, and the insights need to be explored.	Can commodity future volatility help in forecasting stock market volatility or vice versa?
	Stock market volatility (280) Stock index futures (4)	Few researchers have analysed the relationship between stock market volatility and stock index futures, and it needs to be explored.	Is there any risk transmission or risk spillover effect from stock market to stock index futures and vice versa?
	Volatility (282) volatility spillover (73) Multivariate GARCH (18) DCC (7) BEKK (5)	Few studies have examined volatility and its spillover effects by applying multivariate GARCH, DCC-GARCH and BEKK-GARCH models.	What are the emerging techniques to examine the volatility effects depicting marketwise, countrywide unidirectional, bidirectional, and multidirectional spill overs?
	Artificial Neural Network (5), Hybrid Model (3)	Few scholars have analysed SMV by applying a hybrid model approach. It has also been confirmed that hybrid volatility models (ANN-GARCH, Wavelet-GARCH, Copula GARCH	Do hybrid models take care of the non-linearity, structural breaks, chaotic Information of the data.

Network Gaps	Keywords frequency in the identified network	Current State and Research Gap	Future Research Direction
		etc) are emerging tools in measuring volatility spillovers.	
	Investors' Sentiments (13), Sentiment Analysis (11), Behavioural Research (5).	Only limited research is available in this area. Volatility studies often ignore the role of emotions and behavioural finance variables.	Develop sentiment-volatility models using NLP and social media indicators.
	Emerging Countries (4), Relationship Stock market Volatility (6), Developed Countries and Comparative Analysis (8).	Only Frew researchers have focused on Comparative analysis in the same Context.	Conduct comparative studies using panel data across market segments.

Source: Vosviewer output and authors' compilation

4. CONCLUSION

The landscape of stock market volatility (SMV) literature continues to evolve, presenting abundant opportunities for future research advancements. By employing a comprehensive bibliometric and content analysis approach, this study delved into the ongoing discourse surrounding SMV. The rigorous examination of 1,949 publications sourced from selected sources between 1980, and July 2025 shed light on the "how" and "what" of existing SMV research, encompassing methodological practices, contextualization within emerging and developed economies, and key properties like spillover effects. Notably, SMV has sustained the interest of researchers, particularly during the unprecedented circumstances of the global pandemic in 2020. Contributions to the SMV literature have emerged from scholars in both developed and developing countries, with notable prominence from China, the USA, and India. The study discovered that volatility exhibited higher levels in emerging markets compared to developed economies, and all markets exhibited significant volatility persistence during the COVID-19 period. Mixed conclusions regarding volatility and the leverage effect were observed in these countries simultaneously. Citation analysis highlighted the impact and significance of various publications, with Bollerslev's GARCH model (1986) and Engle's ARCH model (1982) identified as valuable "core" contributions. Thematic analysis revealed

GARCH and volatility spillover as dominant themes, while DCC-GARCH and the idiosyncratic volatility model emerged as niche areas. Content analysis exposed substantial persistence and spillover effects of SMV in emerging countries (e.g., BRICS, MENA) and advanced economies. The study identified emerging topics for further exploration in SMV research, emphasising the nascent stage of understanding the relationship between SMV and cryptocurrency, economic policy uncertainty, and derivatives such as commodity futures and stock index futures. Additionally, the utilisation of hybrid models represents a growing concern, warranting future investigation. In addition, behavioural and sentiment-based models of volatility are underdeveloped, particularly to the extent that they relate to social media and algorithmic trading's impact on investor responses. The use of machine learning and artificial intelligence in volatility prediction is becoming a revolutionary but methodologically disjointed field. Cross-country and sectoral analyses also require further panel-data-based investigations to reveal structural asymmetries in spillovers. Future studies are also required to work towards improving model robustness and interpretability to maintain viability in quickly changing financial environments. Overall, this study provides valuable insights, signalling the dynamic nature of SMV research and outlining promising avenues for scholars to delve deeper into the intricacies of volatility phenomena.

5. IMPLICATIONS AND LIMITATIONS

Volatility, a phenomenon and a concept remains central to both contemporary financial markets and academic research. The past few decades saw an explosion of literature on testing the stock market's efficiency. The assertion about the validity of the SMV and its determinants has remained the subject of several investigations. These frequently expressed assertions about "SMV" have implications for stock market investigators, market professionals, practitioners, and regulators. A thorough understanding of SMV can form the basis for efficient price discoveries, implying predictability, which is embraced by both traders and investors. Portfolio managers, risk arbitrageurs, and corporate treasurers can closely watch these trends because price fluctuations may have a significant impact on their decision-making about investments and risk management. This study aims to provide a comprehensive understanding of stock market volatility (SMV) to financiers and stock market enthusiasts. The study covers the underlying philosophies, historical developments, and empirical findings related to SMV. It seeks to attract the attention of both academics and practitioners. Additionally, the study emphasises the need for regulators to play a responsible role in reducing stock market volatility. Although the paper has contributed scientifically to the recognition of wider stock market forces, researchers' bias in the selection of databases and inclusion-exclusion checks can limit its use. The study is restricted to the SCOPUS repository, but it does not cover all journals in any discipline. Hence, the biggest shortcoming of this paper is limiting the coverage. To identify the most accurate issues in SMV, this study could furthermore extend to encompass more nonspecific keywords from social sciences journals, such as equity volatility, market shocks, stock mis valuation, and Market instability (Buldyrev *et al.*, 2021). Further different diagnosis-deductive reasoning approaches for qualitative content analysis can illuminate many hidden or less explored dimensions of the domain. Though it is believed that the aggregation of the conceptual essence of the SMV presented through this study remains comparable for subsequent investigations as well.

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