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Review

Mapping the Trend, Application and Forecasting Performance of Asymmetric GARCH Models: A Review Based on Bibliometric Analysis

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Abstract: The past few years have witnessed renewed interest in modelling and forecasting asymmetry in financial time series using a variety of approaches. The most intriguing of these strategies is the "asymmetric" or "leverage" volatility model. This study aims to conduct a review of asymmetric GARCH models using bibliometric analysis to identify their key intellectual foundations and evolution, and offers thematic and methodological recommendations for future research to advance the domain. Bibliometric analysis was used to identify patterns in and perform descriptive analysis of articles, including citation, co-authorship, bibliographic coupling, and co-occurrence analysis. The study located 856 research papers from the Scopus database between 1992 and 2021 using key phrase and reference search methods. Publication trends, most influential authors, leading countries, and top journals are described, along with a systematic review of highly cited articles. The study summarises the development, application, and performance evaluation of asymmetric GARCH models, which will help researchers and academicians significantly contribute to this literature by addressing gaps.

Keywords: asymmetric GARCH models; bibliometric analysis; literature review

JEL Classification: C01; C58

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1. Introduction

Since all participants in the financial market are concerned with the risks associated with the assets in which they invest, modelling and predicting the volatility of financial assets is crucial. It is essential for a number of financial operations, including risk management, derivative pricing and hedging, market making, market timing, portfolio selection, and many others. It is a way to gauge how returns across a time series of asset values have changed over time (Aliyev et al. 2020). Volatility clustering, leptokurtosis, asymmetries in volatility, and the leverage effect are frequently used to describe the returns on financial assets. Large changes are followed by other large changes, and small changes are followed by smaller changes. This is known as volatility clustering. Leptokurtosis denotes a fat-tailed distribution of returns (the kurtosis exceeds that of a standard distribution).

Another well-known characteristic of financial time series is asymmetric dynamics. The asymmetry refers to the fact that volatility is higher when returns are negative. It is introduced by (Black 1976) and (Christie 1982). In the literature, the leverage effect and the volatility feedback effect are used to describe the asymmetric volatility attribute (Campbell and Hentschel 1992), (Bollerslev 1987). It is actually negative and positive shocks that are to blame for this volatility clustering. In comparison to a positive shock of equal magnitude, a negative shock produces more volatility. Autoregressive conditional heteroscedasticity or threshold models are effective ways to model these asymmetric and nonlinear dynamics (Aliyev et al. 2020).

Conditional heteroscedastic models are the fundamental econometric tools for estimating and forecasting asset return volatility (Alberg et al. 2008). To describe conditional variance dynamics, Engle (1982) developed the autoregressive conditional heteroscedasticity (ARCH) model, which calculates the variance of returns as a straightforward quadratic function of the lagged values of the innovations. One of its weaknesses is that the ARCH model frequently needs many parameters and a high order q to capture the volatility process. The GARCH model, which is based on an infinite ARCH specification and allows us to restrict the number of estimated parameters by imposing nonlinear constraints, was introduced by Bollerslev (1986) as a solution to this problem. The ARCH and GARCH models both take into account volatility clustering and leptokurtosis; however, because of the symmetry of their distributions (the conditional variance only depends on the magnitude, not the sign of the underlying asset), they are unable to account for the leverage effect (the effect of positive and negative shock on conditional variance). To address this issue, many nonlinear extensions of GARCH models have been proposed, including Exponential GARCH (EGARCH) by Nelson (1991), Threshold GARCH (TGARCH), and Asymmetric Power ARCH (APARCH) by Ding et al. (1993). Similar to GARCH models, high-frequency financial time series have thick tails that are not always properly incorporated into models. To solve this problem, Bollerslev (1987) and Baillie and Bollerslev (1989) used Student's *t*-distribution. The accuracy, usability, forecasting performance, and other characteristics of symmetric and asymmetric GARCH models have been examined in a number of studies, including those by Campbell and Hentschel (1992), Engle (1982), Shahateet (2019), Alberg et al. (2008), Gökbulut and Pekkaya (2014), Maqsood et al. (2013), (French et al. 1987) and (Lee (2017).

This study carries out a twofold analysis of existing literature on asymmetric GARCH models using bibliometric analysis and systematic review. Bibliometric analysis is a crucial technique for statistically analysing a sizable body of prior literature and figuring out how well a particular topic has evolved, while reviewing publications in a field of study is a critical method for locating important research areas. The study used a range of bibliometric tools to map the literature on asymmetric GARCH modelling and to extract insightful conclusions regarding the temporal trends of publishing, prominent authors, key journals, and influential works. This was followed by a thorough literature review of highly cited research papers to determine the forecasting accuracy of different asymmetric GARCH models and to propose the best model to capture the asymmetric effect in the conditional volatility of time series data. Through systematic review, we can obtain insightful knowledge on the most frequently used GARCH models, the major research focus, and the best model proposed by prominent authors in this field of research. In recent years, applying asymmetric GARCH models to model the characteristics of time series data became an interesting field of research, as the financial market witnessed a large number of ups and downs due to positive and negative news/information. On reviewing the literature on asymmetric volatility and GARCH modelling, it was seen that most of the studies focused on modelling asymmetric effects in the conditional volatility of the stock market, and researchers had conflicting opinions on the best GARCH model to capture the same. Since the literature on asymmetric GARCH models has not undergone critical review, a review technique must be used to determine the areas of interest for future research. To the best of our knowledge, no studies have yet thoroughly summarised the asymmetric GARCH literature through bibliometric analysis and review. It will significantly contribute to the literature in this domain by analyzing the evolution and development of, and current trend in, asymmetric GARCH models, along with highlighting the application and forecasting accuracy of these models through review. This will enable both researchers and financial market participants to gain an understanding of this area of study and bridge the knowledge gap.

The primary objectives of this study are:

1. To evaluate the current trend in asymmetric GARCH models in the literature using bibliometric analysis;

2. To provide thorough analysis of the use and forecasting capabilities of asymmetric GARCH models.

This study's remaining sections are structured as follows: The methodology used to extract pertinent literature on asymmetric GARCH models is the main topic of Section 2. Section 3 highlights the bibliometric analysis and findings followed by a systematic review of highly cited research papers, and proposes an agenda for future research, and finally, Section 4 outlines the conclusion.

2. Data and Methodology

We follow the analytical framework followed by Phoong et al. (2022) to present the research objectives along with the methodology adopted to address the research objectives. The above study presented the methodology used to address each of the research objectives in a concise manner using a table. The main objectives of this study, along with the methodology we used to address the same, are presented in Table 1. We used co-authorship, co-occurrence, and bibliographic coupling to provide basic information on the yearly publications and citations and the effectiveness of journals, authors, countries, and search terms in this field of study. Furthermore, a systematic literature review was conducted to address the application and accuracy of those models.

Table 1. Overview of Research Objective and Methodology.

	Research Objective	Research Methodology
Bibliometric analysis	To understand the evolution of and trend in asymmetric GARCH models	Publication trend
	To figure out the leading countries, impactful journals, and influential authors with respect to asymmetric GARCH models	Citation analysis
	To assess the structure and pattern of country collaboration in this field of research	Co-authorship analysis of countries
	To figure out the conceptual structure of keywords in asymmetric GARCH models	Co-occurrence analysis
	To understand countries' coupling structures and how often countries share similar literature in this field of research	Bibliographic coupling of countries
Systematic review	Factor analysis exposing thematic factors in asymmetric GARCH models	Principal Component Analysis
	Factors influencing total citation in publication in asymmetric GARCH models	Correlation and Regression
	To understand the application and forecasting performance of asymmetric GARCH models	Citation analysis of highly cited documents

2.1. Locating Study

An appropriate and trustworthy database is required to ensure the validity and reliability of collected data. To address the research objectives, we used the Scopus database as the source for data collection. We elected to acquire data from Scopus because this database offers the widest coverage of peer-reviewed research in finance (Goodell et al. 2021), a rapid update frequency, and the flexibility to debug and process data (Jain et al. 2021).

2.2. Selection of Relevant Research

The use of the Scopus database initiated the selection process. The 1992–2021 time period was chosen to examine the overall trend in asymmetric GARCH models; we excluded the year 2022 as the publications in this field of research were not yet completed. We used keywords to retrieve relevant articles by examining the literature on asymmetric GARCH models. The actual process for extracting pertinent literature on asymmetric GARCH models for bibliometric analysis is shown in Figure 1.

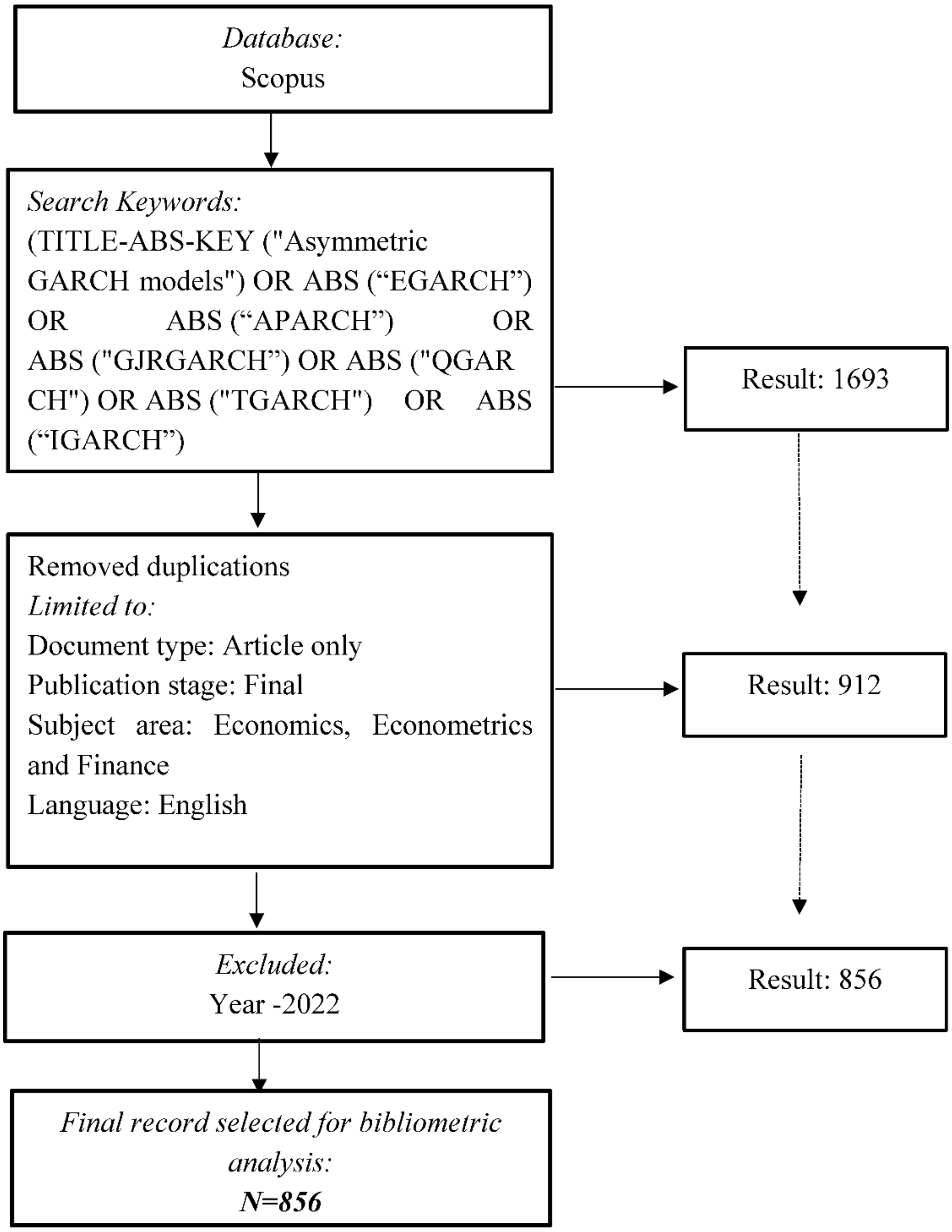

Figure 1. Dataset extraction and processing mechanism for bibliometric analysis.

The dataset for this study, which was retrieved from the Scopus database on June 8 2022, contained 1693 documents. By applying exclusion criteria, 837 of these were removed. This resulted in the final dataset of 856 documents for bibliometric analysis. We used VOS viewer (Visualisation of Similarities) and Excel software to apply bibliographic methods. VOS viewer software was used to construct network mapping, and Excel was used for further filtering and tabulation.

3. Bibliometric Analysis

Bibliometric analysis used a large number of studies to identify popular trends in the literature on asymmetric GARCH models. This section focuses on the outcomes of bibliometric analytic tools.

3.1. Descriptive Analysis

To identify the current trend in this research theme, we used descriptive analysis, which provides a thorough understanding of performance trends for publications and citations regarding asymmetric GARCH models, followed by influential authors, top countries, and impactful journals.

3.1.1. Annual Publication Trend

The annual scientific production of research articles focusing on asymmetric GARCH models provides a comprehensive analysis of the evolution, growth, and current trend in studies using asymmetric GARCH models to model asymmetric financial time series effects. The number of publications from 1992 to 2021 is depicted in Figure 2. In general, the use of asymmetric GARCH models grew steadily over the years. Three papers on asymmetric GARCH models were published in 1992, and the publication trend was not remarkable until 2002. Publications concerned with asymmetric GARCH models increased exponentially after that. This scenario suggests that asymmetric GARCH models gained popularity among academics in recent decades, particularly after 2008. After the stock market crash of 2008–2009, the application of asymmetric GARCH models to evaluate asymmetric effects in time series data became more important, and this trend continued until 2021. Unsurprisingly, there were 202 publications from 2019 to 2021 (the period of the COVID-19 pandemic). The trend in scientific production of asymmetric GARCH models became visible and clear over the years.

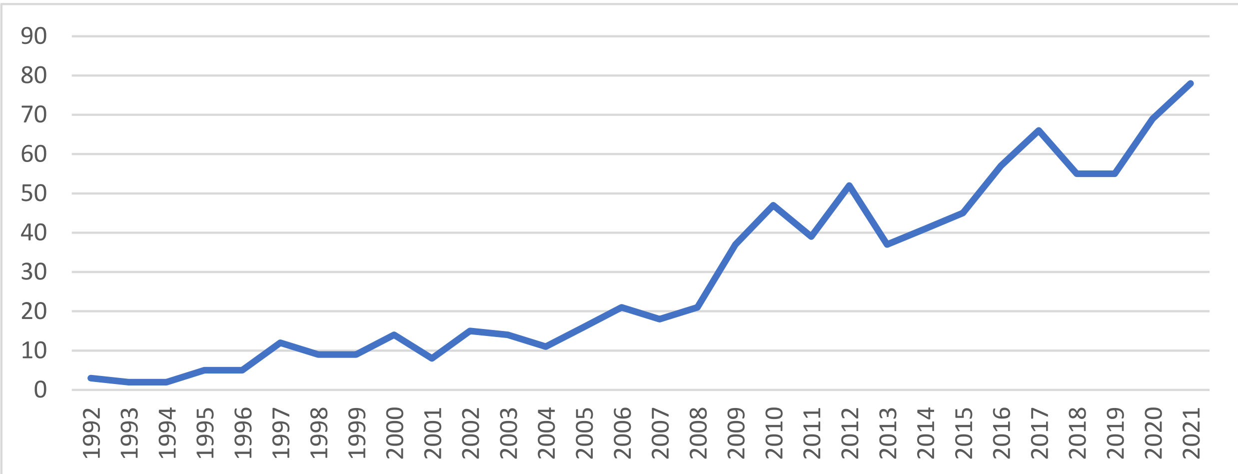

Figure 2. Annual scientific production (1992–2021). Source: Elaborated by authors using data extracted from Scopus.

3.1.2. Leading Countries

The majority of research on asymmetric GARCH models took place in the United States of America, with 176 publications between 1992 and 2021. With 73 publications, India was the second highest contributor, followed by Australia with 72 scientific publications. Figure 3 shows the top countries that contributed to asymmetric GARCH models. The United States had the most citations (7277), followed by Australia (1437) and the United Kingdom (1072). A total of 506 citations were found for Indian publications. It is clear from this that developed countries have the highest numbers of citations, although emerging countries such as India make significant contributions to this field of study.

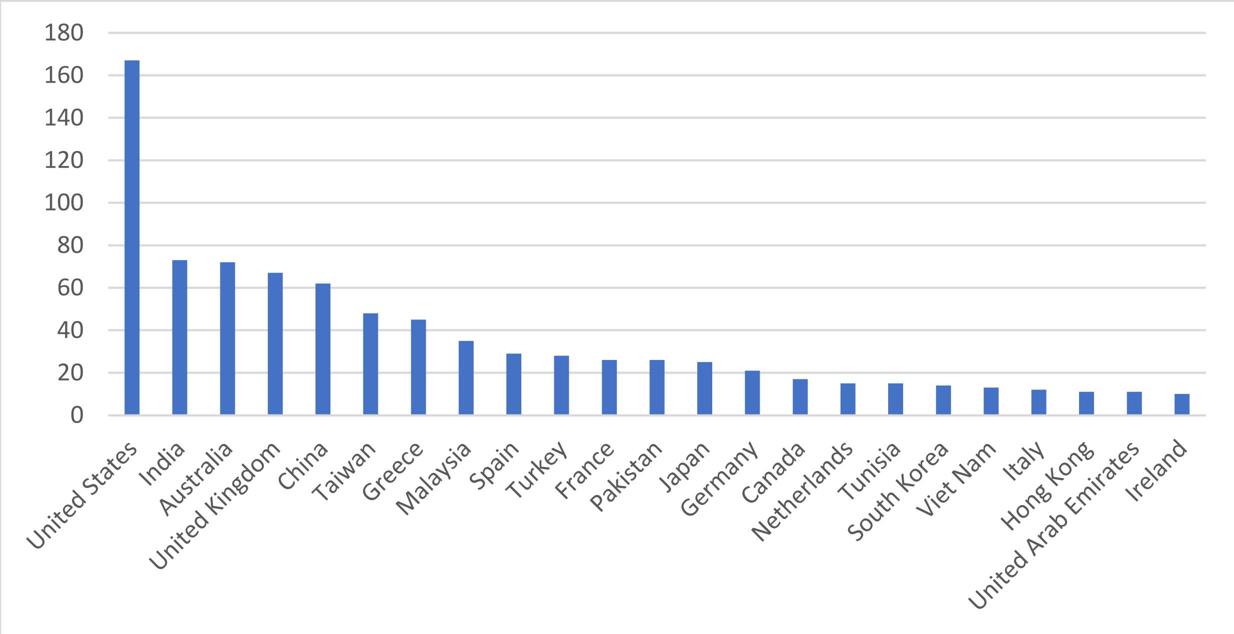

Figure 3. Leading Countries. Source: Elaborated by authors using data extracted from Scopus.

3.1.3. Influential Authors

The top ten influential authors who contributed research articles in this domain (Table 2) can provide a good idea of who contributed significantly to the literature on asymmetric GARCH models. Engle R.F. is the most cited author, with 2796 citations across two papers on asymmetric GARCH. In 1993, V.K. Ng and R.F. Engle co-authored the paper "Measuring and Testing the Impact of News on Volatility". The paper "All in the family: Nesting symmetric and asymmetric GARCH models" by Hentschel (1995) received a total of 1369 citations, followed by Campbell J.Y (1003) and Bollerslev T (719).

Table 2. Influential Authors.

No.	Author	TP	TC
1	Engle R.F.	2	2796
2	Ng V.K.	1	1749
3	Hentschel L.	2	1369
4	Campbell J.Y.	1	1003
5	Bollerslev T.	2	719
6	Mikkelsen H.O.	2	719
7	Laurent S.	4	661
8	Giot P.	3	589
9	Booth G.G.	3	568
10	Koutmos G.	5	428

Source: Elaborated by authors using data extracted from Scopus.

3.1.4. Impactful Journals

Publications in academic journals allow researchers and academicians to share new and useful ideas and knowledge. Researchers can choose the most appropriate and high-quality journals to share their insights by identifying the most impactful journals contributing to a particular field of study. Figure 4 depicts the most productive journals publishing research articles on asymmetric GARCH models. A total of 308 research articles were published in 33 journals during 1992–2021. Applied Financial Economics was the most productive journal, with 31 publications in this field of research. Applied Financial Economics mainly focuses on economics, econometrics, and finance. The second- and third-most productive journals were Energy Economics and Applied Economics with a total of 30 and 29 publications, respectively. In terms of citations, Energy Economics had the highest number of citations (2006), followed by the Journal of Econometrics (1630) and the Journal of Financial Economics (1388). Even though the most productive journal was Applied Financial Economics (31), in terms of total publications as well as total citations, we can conclude that Energy Economics was the most productive and impactful journal in the area of asymmetric GARCH modelling, with 2006 citations for 30 publications during this period.

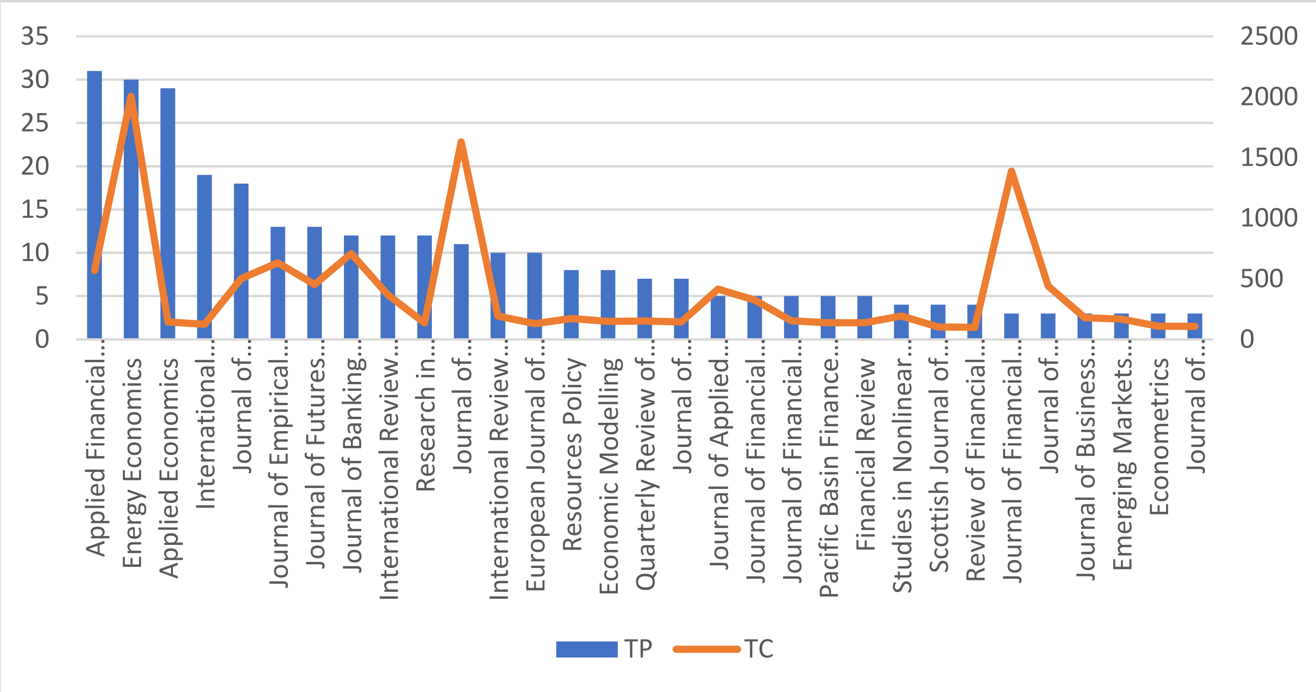

Figure 4. The most impactful journals. Note: TP = Total Publications, TC = Total Citations. Source: Elaborated by authors using data extracted from Scopus.

This article performed ranking analysis by identifying the total number of publications (TP), total number of citations (TC), citations per publication (C/P), ABDC ranking, and H-index. The top 20 journals by number of citations are presented in Table 3. It is seen that only three journals (Energy Economics, Applied Financial Economics, Applied Economics) contributed more than 10% in terms of total publications on asymmetric GARCH models, and two journals (International Research Journal of Finance and Economics and Applied Economics Letters) contributed more than 5%. The top cited journals (Energy Economics and Journal of Econometrics) had the highest H-index. In terms of total citations per publication, the Journal of Econometrics was placed first (C/P = 148.18) as it had the least number of publications (11) with the highest number of citations for those papers.

Table 3. Ranking of top 20 influential Journals.

Rank	Source	TP	P (%)	TC	C/P	ABDC	H
1	Energy Economics	30	10.6	2006	66.86	A*	168
2	Journal of Econometrics	11	3.88	1630	148.18	A*	166
3	Journal of Empirical Finance	13	4.59	632	48.61	A	80
4	Applied Financial Economics	31	10.9	568	18.32	B	57
5	International Review of Financial Analysis	12	4.24	368	30.66	A	69
6	International Review of Economics and Finance	10	3.53	193	19.3	N/A	59
7	Economic Modelling	8	2.82	149	18.62	A	87
8	Applied Economics	29	10.24	144	4.96	A	91
9	European Journal of Finance	10	3.53	129	12.9	A	39
10	International Research Journal of Finance and Economics	19	6.71	124	6.52	N/A	27
11	Applied Economics Letters	19	6.71	99	5.21	B	54
12	Journal of Economics and Finance	9	3.18	79	2.11	B	31
13	Finance Research Letters	9	3.18	66	7.33	A	62
14	International Journal of Financial Studies	8	2.82	53	6.62	B	17
15	Asia-Pacific Financial Markets	12	4.24	50	4.16	C	22
16	Cogent Economics and Finance	11	3.88	49	4.45	B	23
17	Journal of Asian Finance, Economics, and Business	11	3.88	44	4	N/A	20
18	International Journal of Energy Economics and Policy	8	2.82	34	4.25	C	39
19	Investment Management and Financial Innovations	13	4.59	27	2.07	B	20
20	Economics Bulletin	10	3.53	17	1.7	C	34

Source: Elaborated by authors using data extracted from Scopus. Note: TP = Total Publications, P = Proportion (%), TC = Total Citations, C/P = Citations per publication, ABDC = ABDC ranking, H = H Index, N/A = Not Applicable.

3.1.5. Country Collaborations

An assessment of international collaboration based on co-authorship was carried out to understand how countries jointly contribute to the literature on asymmetric GARCH models. Co-authorship analysis by country looked at the strength of collaboration between different countries and provided researchers with a more in-depth understanding of the structure of countries' contributions and collaborations in the related field (Phoong et al. 2022; Tandon et al. 2021). We set the minimum number of documents for a country in this study at four, as every one of the chosen countries had at least four publications. The top ten collaborative nations are listed in Table 4 in order of the strength of all links (Phoong et al. 2022). Among the top ten countries, the United States of America is ranked first in terms of total link strength (79) and published 167 research articles on asymmetric GARCH models in collaboration with other countries. The United Kingdom had the second-highest number of publications (46), followed by Australia and China with 37 and 35, respectively. In addition, in terms of citations, the United States, the United Kingdom, and Australia were ranked first, second, and third, respectively, indicating that researchers frequently cited papers co-authored by authors from these countries.

Table 4. Country Collaborations.

No.	Country	Documents	Citations	Total Link Strength
1	United States	167	7277	79
2	United Kingdom	67	1072	46
3	Australia	72	1437	37
4	China	62	896	35
5	Spain	29	366	29
6	Taiwan	48	542	28
7	Netherlands	15	808	26
8	Pakistan	26	202	18
9	Turkey	28	239	18
10	Greece	45	641	15

Source: Elaborated by authors using data extracted from Scopus.

We further provide network visualisation of country co-authorship to identify the main clusters among countries (Figure 5). The number of published documents in a nation is represented by the node size in the network visualisation. The number of documents published by a nation increases with node size. These countries could be divided into six clusters, each of which is represented by a different colour. Of the top 10 collaborating countries, the USA, the UK and Greece belong to cluster 3, and China, Spain, Taiwan, and the Netherlands are included in cluster 1. The extent of collaboration or co-authorship is determined by the thickness of the link between two countries. The network analysis confirmed that the extent of international collaboration between the USA and the UK in asymmetric GARCH model literature was relatively higher compared with other countries. In the case of India, authors from the United States, Pakistan, Spain, Bangladesh, Germany, and Saudi Arabia collaborated to contribute to this field of research.

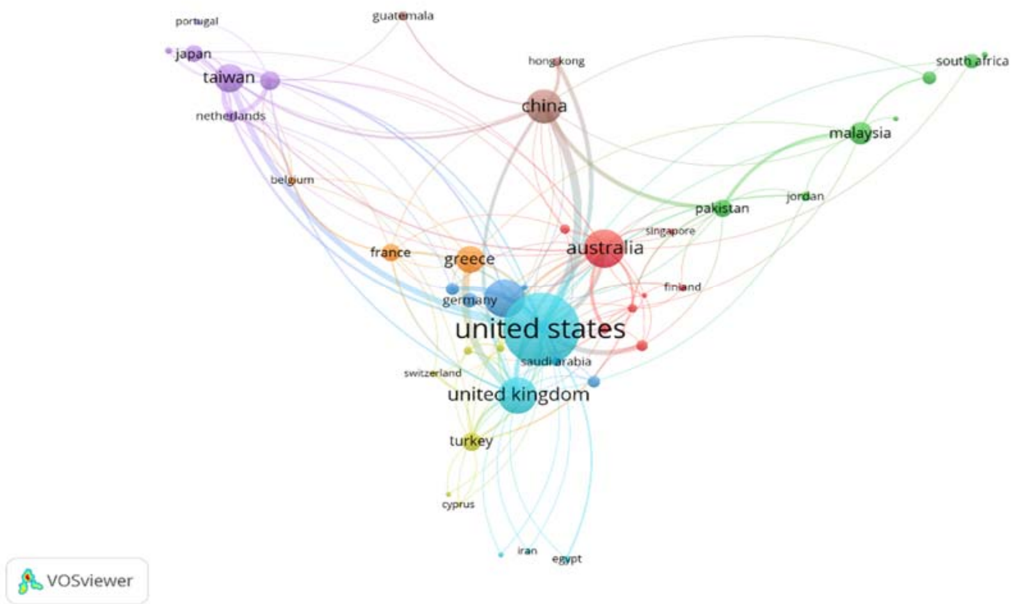

Figure 5. Network visualisation of country collaborations. Source: Elaborated by authors using data extracted from Scopus.

Overlay visualisation of country collaboration was used to examine year-by-year progress in country collaboration. Figure 6 illustrates an overlay view of country co-authorship, with colour variations indicating the year the country began collaboration with other countries. As demonstrated in the picture, Singaporean authors started collaborating with authors from other nations in the early 2000s. Between 2005 and 2010, authors from the United States, Hong Kong, and Japan (light blue) began to work with other countries. Similarly, in late 2010, countries such as the United Kingdom, Australia, Belgium, the Netherlands, and Finland (sea blue colour) began publishing works on asymmetric GARCH models in conjunction with authors from other countries. Countries depicted in light green and yellow have most recently initiated international collaborations.

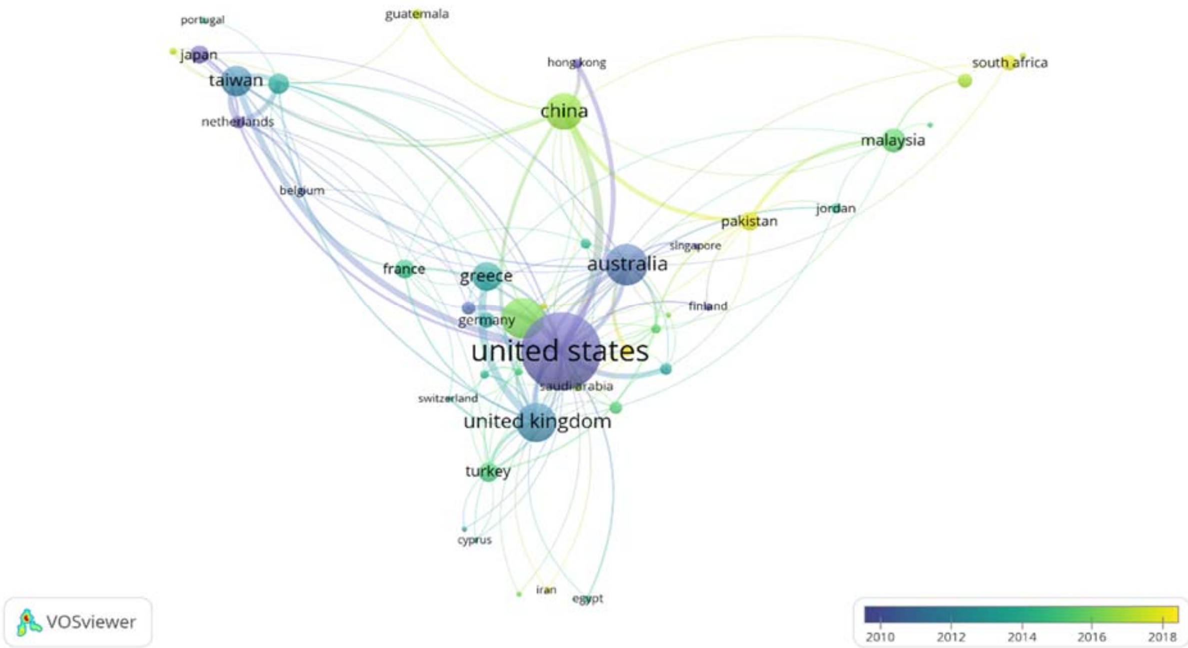

Figure 6. Overlay visualisation of country collaborations. Source: Elaborated by authors using data extracted from Scopus.

3.1.6. Co-Occurrence of Author Keywords

We further looked at author keyword co-occurrence analysis to uncover the most important research topics in the field. In order to identify essential keyword occurrence in the literature on asymmetric GARCH models, we set the minimum occurrence at four. The top ten author keywords in terms of total link strength are shown in Table 5. Volatility (135) was the most frequently used author keyword, with a total link strength of 270. The keyword EGARCH, which had the second highest link strength of 262, also appeared 135 times. With a link strength of 256, the keyword GARCH was ranked third, appearing 114 times, followed by GARCH models and asymmetry. In addition to these, EGARCH models, the leverage effect, asymmetric GARCH, volatility spillover, and asymmetric volatility occurred more than 15 times. As seen in Figure 7, network mapping can also be used to display the occurrence of author keywords. The colours represent the clusters, and the size of the node reflects the frequency with which each keyword appeared in the asymmetric GARCH model literature.

Table 5. Co-occurrence of author keyword.

No	Keyword	Occurrences	TLS
1	Volatility	135	270
2	EGARCH	130	262
3	GARCH	114	256
4	GARCH Models	29	50
5	Asymmetry	28	64
6	EGARCH Model	27	35
7	Leverage Effect	27	55
8	Asymmetric GARCH	23	55
9	Volatility Spillover	22	45
10	Asymmetric Volatility	16	38

Source: Elaborated by authors using data extracted from Scopus.

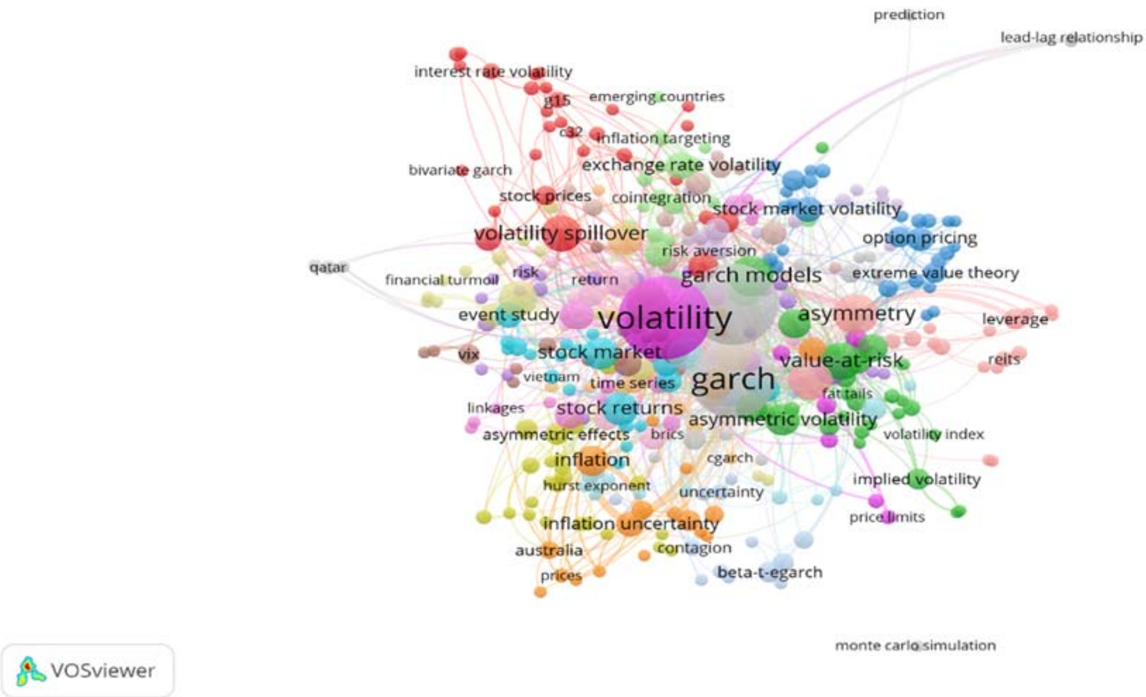

Figure 7. Co-occurrence of author keywords. Source: Elaborated by authors using data extracted from Scopus.

3.1.7. Factor Analysis Exposing the Thematic Factors of Asymmetric GARCH Models

In accordance with Pattnaik et al.'s (2020) recommendations, we examined thematic variables using SPSS, using 40 starting themes that were published in at least five works on asymmetric GARCH models. The correlation matrix for asymmetric GARCH models was subjected to Principal Component Analysis, which produced significant KMO statistics, and Bartlett's test of sphericity results, which confirmed the relevance of exploratory factor analysis.

The primary analysis indicated seven theme components, which together accounted for nearly 97% of the thematic variation, using Varimax rotation and Kaizer normalisation. By setting the absolute value below to 40, we could suppress small coefficients and prevent cross-loadings. Forty thematic items were loaded under four components. The communalities and loading of the theme items relative to their respective components are shown in Tables 6 and 7, respectively. The themes were divided into four thematic components. The first component is the theme of financial modelling. The second component, titled "financial assets", is the modelling of various financial asset characteristics. The third component is the modelling of financial time series characteristics centred on various financial markets. The fourth and final thematic component is the same in light of the financial crisis, including the recent COVID-19 crisis.

Table 6. Communalities of asymmetric GARCH models themes.

Communalities							
SI		Initial	Extraction	SI		Initial	Extraction
1	Crisis	1.000	0.719	21	Exchange Rate	1.000	0.864
2	ARCH	1.000	0.736	22	Forecasting	1.000	0.860
3	GARCH	1.000	0.818	23	Risk Assessment	1.000	0.991
4	Europe	1.000	0.965	24	Price Dynamics	1.000	0.914
5	Uk	1.000	0.636	25	Financial Uncertainty	1.000	0.949
6	Asymmetry	1.000	0.656	26	APARCH	1.000	0.969
7	Volatility Forecasting	1.000	0.973	27	Oil Price	1.000	0.994
8	China	1.000	0.993	28	Eurasia	1.000	0.997
9	Forecasting Model	1.000	0.997	29	EGARCH	1.000	0.983
10	Gold	1.000	0.673	30	TGARCH	1.000	0.994
11	Japan	1.000	0.993	31	COVID-19	1.000	0.991
12	Asymmetric Volatility	1.000	0.993	32	Global Pandemic	1.000	0.995
13	Econometrics	1.000	0.912	33	Leverage Effect	1.000	0.996
14	GARCH Models	1.000	0.956	34	Causality	1.000	0.984
15	United States	1.000	0.969	35	Regression Analysis	1.000	0.969
16	Time Series Analysis	1.000	0.921	36	Financial Crisis	1.000	0.995
17	Stock Returns	1.000	0.993	37	Interest Rate	1.000	0.988
18	Far East	1.000	0.985	38	Volatility Clustering	1.000	0.985
19	Asymmetric Effect	1.000	0.994	39	Asymmetric Volatility	1.000	0.994
20	Volatility Persistence	1.000	0.997	40	Volatility Spillover	1.000	0.881

Source: Authors calculation.

Table 7. Rotated Component Matrix and factor loadings of thematic components.

	Components			
	Forecasting Models	*Financial Assets*	*Financial Markets*	*Financial Crisis*
ARCH	0.994			
GARCH	0.994			
EGARCH	0.994			
TGARCH	0.994			
GARCH Models	0.994			
Asymmetry	0.994			
Leverage Effect	0.994			
Forecasting model	0.994			
Time Series Analysis	0.993			
Volatility Forecasting	0.955			
Risk Assessment	0.954			
Econometrics	0.954			
APARCH	0.954			
Forecasting	0.953			
Asymmetric Effect		0.986		
Asymmetric Volatility		0.984		
Causality		0.984		
Oil Price		0.984		
Exchange Rate		0.983		
Gold		0.980		
Stock Returns		0.979		
Volatility Persistence		0.941		
Volatility Spillover		0.850		
Interest Rate		0.845		
Asia			0.956	

Table 7. *Cont.*

	Components			
	Forecasting Models	*Financial Assets*	*Financial Markets*	*Financial Crisis*
Europe			0.956	
Far East			0.955	
United States			0.955	
Japan			0.895	
China			0.872	
United Kingdom			0.812	
Eurasia			0.771	
COVID-19				0.992
Regression Analysis				0.992
Financial Crisis				0.992
Price Dynamics				0.992
Financial Uncertainty				0.986
Asymmetric Volatility				0.979
Global Pandemic				0.805
Crisis				0.712
Extraction Method: Principal Component Analysis. Rotation Method: Varimax With Kaiser Normalisation.				

Source: Authors' calculations.

3.1.8. Bibliographic Coupling of Countries

Bibliographic coupling analysis reveals the similarities between two countries (Phoong et al. 2022). It shows how frequently countries share similar bibliographies, allowing us to discover publication similarities. The bibliographic coupling visualisation map could be displayed in a variety of colour and node patterns. The node size represents each country's contribution, and different colours denote different clusters. Figure 8 depicts network visualisation of country clustering.

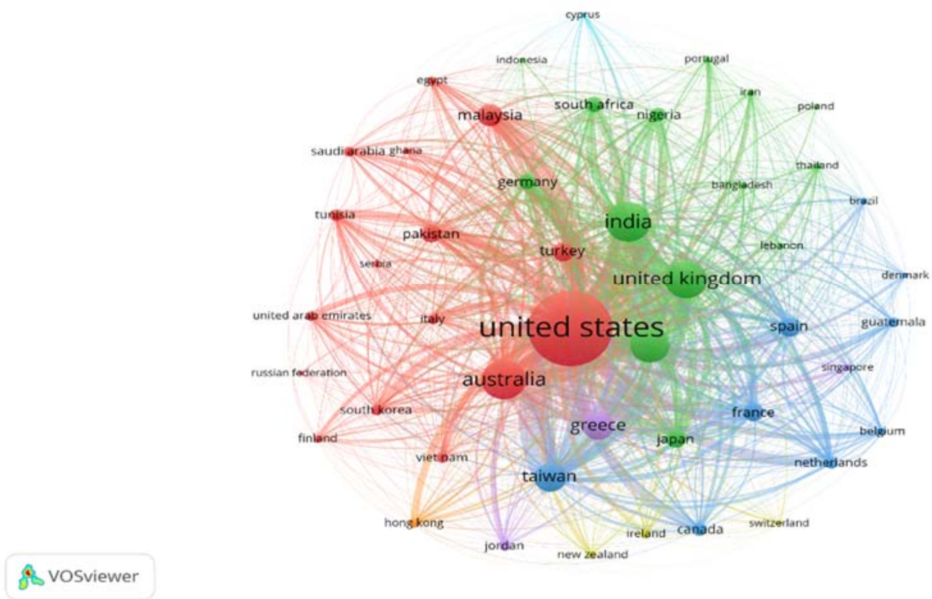

Figure 8. Bibliographic coupling of countries. Source: Elaborated by authors using data extracted from Scopus.

3.1.9. Factors Influencing Citation: Correlation and Regression

Descriptive statistics, correlation analysis, and regression analysis of variables affecting the total citations (TC) of publications on the asymmetric GARCH model are shown in

Tables 8–10. The dependent variable is Total Citations (TC), and the independent variables are LA (Length of the article), NA (Number of authors), AC (Authorship classification; single-authored or co-authored), SAA (Single Authored Articles), and M1, M2, M3 and M4, the models used (GARCH, EGARCH, TGARCH/GJR GARCH, or Other GARCH models).

Table 8. Descriptive Statistics.

	N	Mean	Std. Deviation
TC	856	22.42	62.54
LA	856	12.00	5.43
NA	856	2.92	0.97
AC	856	2.17	0.33
SAA	856	1.08	0.15
M1	856	0.82	0.21
M2	856	0.83	0.24
M3	856	0.25	0.25
M4	856	0.47	0.72

Source: Authors' calculation. Note: TC = Total citations, LA = Length of the article, NA = Number of authors, AC = Authorship classification (Single authored or co-authored), SAA = Number of single-authored articles, and M1, M2, M3, and M4 are the econometric models used: GARCH, EGARCH. TGARCH and Other models, respectively.

Table 9. Correlation matrix of variables.

		TC	LA	NA	AC	SAA	M1	M2	M3	M4
TC	r	1								
LA	r	0.22 **	1							
		0.000								
NA	r	0.21 **	−0.03 **	1						
		0.000	0.000							
AC	r	0.21 **	−0.02 *	0.03 **	1					
		0.000	0.020	0.000						
SAA	r	0.12 **	0.13 *	0.14 *	−0.05 *	1				
		0.030	0.030	0.020	0.026					
M1	r	0.15 **	−0.03	0.21	−0.06	0.871 **	1			
		0.001	0.211	0.112	0.062	0.075				
M2	r	0.020 **	0.255	0.288	0.350	0.785 **	0.748 **	1		
		0.002	0.425	0.363	0.265	0.002	0.005			
M3	r	0.195 **	0.214	0.249	0.296	0.764 **	0.725 **	0.987 **	1	
		0.004	0.504	0.435	0.351	0.004	0.008	0.000		
M4	r	0.288 *	0.310	0.337	0.342	0.737 **	0.741 **	0.870 **	0.925 **	1
		0.064	0.327	0.284	0.277	0.006	0.006	0.000	0.000	

Source: Authors' calculation. Note: TC = Total citations, LA = Length of the article, NA = Number of authors, AC = Authorship classification (Single authored or co-authored), SAA = Number of single-authored articles, and M1, M2, M3, and M4 are the econometric models used: GARCH, EGARCH. TGARCH and Other models, respectively. **. Correlation is significant at the 0.01 level (2-tailed), *. Correlation is significant at the 0.05 level (2-tailed).

The descriptive statistics show the mean and standard deviation of each factor. Each of the articles chosen for the regression obtained, on average, roughly 26 citations. The dependent variable, total citations, had a mean value of 22.42 with a variation of 62.54. The mean of independent variables length of the article (LA) and number of authors (NA) were 12 and 2.92, respectively, with variations of 5.43 and 0.97, respectively. The majority of articles shortlisted used the GARCH and EGARCH models for forecasting the characteristics of time series data (mean = 0.82 for GARCH and 0.83 for EGARCH).

The magnitude and direction of the relationship between the dependent and independent variables are presented in the correlation matrix. It is clear from the table that all independent variables had a significant positive relationship with the dependent variable (TC). Furthermore, regression analysis confirmed this relationship.

Table 10. Regression analysis of variables.

Variables	Beta	*t* Statistics	Sig. Value
(Constant)		−2.21	0.01
LA	0.31	1.21	0.01
NA	0.40	1.02	0.00
AC	0.21	0.89	0.01
SAA	0.41	0.11	0.00
M1	0.03	2.02	0.03
M2	0.04	2.01	0.02
M3	0.02	1.32	0.12
M4	0.01	1.22	0.13
R^2 = 0.42			
Adj. R^2 = 0.411			

Source: Authors' calculation. Note: TC = Total citations, LA = Length of the article, NA = Number of authors, AC = Authorship classification (Single authored or co-authored), SAA = Number of single-authored articles, and M1, M2, M3, and M4 are the econometric models used: GARCH, EGARCH. TGARCH and Other models, respectively. Confidence interval 95%, p value ≤ 0.05.

4. Systematic Review of Highly Cited Articles and Critical Evaluation

In this section, we conducted a systematic review of highly cited articles in this domain. This may give researchers a general idea of the current trend in this field of research and aid them in their investigation so that they can significantly contribute to the literature by filling a gap.

The top research articles in terms of citations are presented in Table 11, along with their major research focus, the GARCH model used, and research contributions. An article's impact is significantly influenced by its total number of citations because a work with high citations is generally considered to be high-quality work. Among those articles, the most cited article is "Measuring and Testing the Impact of News on Volatility" by Engle and Ng (1993), with a total of 2012 citations. Using daily Japanese stock return data, they compared and estimated a number of new and old ARCH models, including a partially nonparametric model. According to their conclusions, Glosten, Jagannathan, and Runkle's model was the most effective one. Although there is evidence that the conditional variance implied by EGARCH has too much variability, EGARCH can also capture the majority of asymmetry. Additionally, their study highlighted the asymmetry of the volatility response to news by presenting new diagnostic tests. Concurrently, "No news is good news. An asymmetric model of changing volatility in stock returns", published in The Journal of Financial Economics by Campbell and Hentschel (1992), also reported a high number of citations (1003). To simulate the volatility feedback effect in U.S. monthly and daily stock returns over the period 1926–1988, they used a QGARCH model.

"Modeling and pricing long memory in stock market volatility" by Bollerslev and Mikkelsen (1996), published in the Journal of Econometrics, had 628 citations. In order to characterise long-run dependencies in US stock market volatility, they used a new class of fractionally integrated GARCH (FIGARCH) and Exponential GARCH (EGARCH) models. "Asymmetric volatility transmission in international stock markets" by Koutmos and Booth (1995a) ranked the fourth most cited article (404), published in the Journal of International Money and Finance. They modelled the asymmetric effect of good news and bad news on volatility transmission using an extended multivariate EGARCH model. This was followed by Hentschel (1995), "All in the family: Nesting symmetric and asymmetric GARCH models" with 366 citations. Using daily data on U.S. stock returns, they developed a family of the most common symmetric and asymmetric GARCH models.

Table 11. Systematic review of highly cited papers.

Document	Citation	Title	Journal	Major Research Focus	GARCH Models Used	Major Research Finding (s)/Contribution (s)	Forecasting Accuracy of GARCH Models
(Engle and Ng 1993)	2012	Measuring and Testing the Impact of News on Volatility	The Journal of Finance	Several models of predictable volatility were discussed, and the concept of a news impact curve was put forth. In order to account for asymmetry in the impact of news on volatility, they compared the GARCH (1, 1) model with a number of other volatility models.	GARCH (1,1), EGARCH, GJR-GARCH, AGARCH, VGARCH, NGARCH	The standard indicator of how news is incorporated into volatility estimates is the news impact curve. According to all models, negative shocks increase volatility more than positive ones.	The best model is the one proposed by Glosten, Jagannathan, and Runkle (GJR Model).
(Campbell and Hentschel 1992)	1003	No news is good news: An asymmetric model of changing volatility in stock returns	Journal of Financial Economics	Used QGARCH to estimate a model of volatility feedback in stock returns.	QGARCH, GARCH-M, QGARCH-M	The QGARCH model, in contrast to the simple GARCH model, produces residuals with means that are close to zero and fits the negative correlation between stock returns and the future volatility of returns.	No best model
(Bollerslev and Mikkelsen 1996)	628	Modeling and pricing long memory in stock market volatility	Journal of Econometrics	Proposed a new class of more adaptable fractionally integrated EGARCH models to describe the long-run determinants of volatility in the US stock market.	GARCH (1,1), EGARCH, IEGARCH, FIEGARCH	The Standard and Poor's 500 composite index's conditional variance is best modelled as a mean-reverting fractionally integrated process.	No best model
(Koutmos and Booth 1995a)	404	Asymmetric volatility transmission in international stock markets	Journal of International Money and Finance	Spillovers in price and volatility across the three main stock markets, New York, Tokyo, and London, were modelled. The volatility transmission mechanism was explicitly modelled in the paper to account for any potential asymmetries.	Multivariate EGARCH	Using the benchmark EGARCH model, all linear and nonlinear dependencies in the return series are successfully taken into account. The mechanism for transmitting volatility is asymmetric.	The EGARCH model performs better than the Quadratic GARCH model because the latter tends to underpredict volatility associated with negative innovations.
(Hentschel 1995)	366	All in the family Nesting symmetric and asymmetric GARCH models	Journal of Financial Economics	The paper developed a family of models of generalised autoregressive heteroskedasticity (GARCH) that encompasses all the popular existing GARCH models.	GARCH, EGARCH, TGARCH, AGARCH, NAGARCH, GJRGARCH, NARCH, APARCH	The data prefer models in which large shocks increase volatility by more than they would in either the AGARCH or EGARCH models, but by less than they would in a GARCH model.	The EGARCH model is almost as robust to large shocks.
(Day and Lewis 1992)	329	Stock market volatility and the information content of stock index options	Journal of Econometrics	Analysed the informational value of the ex-ante market volatility estimates implicit in the call option prices on the Standard and Poor's 100 Index.	GARCH (1,1), EGARCH	GARCH models provide better forecasts than EGARCH models.	The GARCH model is the best.
(Sadorsky 2006)	320	Modeling and forecasting petroleum futures volatility	Energy Economics	Compared the forecasting performance of various univariate and multivariate GARCH models.	GARCH, TGARCH, GARCH-M	The TGARCH and GARCH models both provide good fits for the volatility of heating oil, natural gas, and unleaded gasoline.	The TGARCH and GARCH models are the best.

Table 11. *Cont.*

Document	Citation	Title	Journal	Major Research Focus	GARCH Models Used	Major Research Finding (s)/Contribution (s)	Forecasting Accuracy of GARCH Models
(Hammoudeh and Yuan 2008)	206	Metal volatility in the presence of oil and interest rate shocks	Energy Economics	Used three GARCH family models to simulate volatility persistence and the leverage effect in the short and long runs.	GARCH, CGARCH, EGARCH	According to the EGARCH results, the leverage effect is only present and significant for copper, indicating that gold and silver can be good investments in anticipation of difficult times.	No best model.
(Braun et al. 1995)	204	Good News, Bad News, Volatility, and Betas	The Journal of Finance	Estimated time-varying conditional betas using the exponential ARCH (EGARCH) model in a bivariate setting.	EGARCH	These models enable asymmetrical responses to both positive and negative market and portfolio returns for market volatility, portfolio-specific volatility, and beta.	The EGARCH model can build better estimates of beta and volatility than rolling regressions.
(Mohammadi and Su 2010)	197	International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models	Energy Economics	The study extended the works on estimating the time series properties of crude oil price.	GARCH, EGARCH APARCH FIGARCH	The conditional variance of oil returns shows volatility that changes over time. Asymmetric effects are present in conditional variance.	The APARCH forecasts outperform those of the GARCH, EGARCH andFIGARCH models.
(Tse 1999)	166	Price Discovery and Volatility Spillovers in the DJIA Index and Futures Markets	Journal of Futures Markets	By analysing the common stochastic trend between the DJIA cash and futures prices, they investigated the intraday price discovery process and volatility spillover mechanism.	EGARCH	More than positive news, unfavourable innovations in either market will increase volatility in the stock and futures markets.	No best model.
(Booth et al. 1997)	163	Price and volatility spillovers in Scandinavian stock markets	Journal of Banking and Finance	Investigated the potential interaction between four Scandinavian stock markets.	EGARCH	The presence of volatility clustering and the leverage effect is found, except in the case of Denmark.	The four markets are well described by an EGARCH model with autoregressive returns.
(Kanas 2000)	136	Volatility spillovers between stock returns and exchange rate changes: International evidence	Journal of Business Finance and Accounting	Analysed the interdependence of stock returns and exchange rate.	EGARCH(1,1) EGARCH (2,1)	The study found evidence of symmetric volatility spillover from stock returns to exchange rate for all markets, except in the case of Germany.	EGARCH (1,1) is best for US, UK, France, and Canada, whereas EGARCH (2,1) is best for Germany and Japan.
(Narayan et al. 2008)	113	Understanding the oil price-exchange rate nexus for the Fiji islands	Energy Economics	Examined the connection between oil prices and the exchange rate between the dollars of Fiji and the US.	GARCH, EGARCH	The Fiji dollar appreciates as exchange rate volatility rises, and shocks to exchange rate volatility have asymmetries in their effects.	No best model.
(Heynen et al. 2016)	111	Analysis of the Term Structure of Implied Volatilities	Journal of Financial and Quantitative Analysis	Compared the mean-reverting, GARCH, and EGARCH model assumptions for stock return volatility behaviour.	GARCH, EGARCH	Based on Akaike's information criterion, the EGARCH (1,1) model fits the daily stock returns better than the other two models.	The EGARCH gives the best description of asset prices and the term structure of options implied.

Table 11. *Cont.*

Document	Citation	Title	Journal	Major Research Focus	GARCH Models Used	Major Research Finding (s)/Contribution (s)	Forecasting Accuracy of GARCH Models
(Alberg et al. 2008)	107	Estimating stock market volatility using asymmetric GARCH models	Applied Financial Economics	The Tel Aviv Stock Exchange (TASE) indices' mean return and conditional variance were empirically examined using a variety of GARCH models and the three different density functions: normal, Student's *t*, and asymmetric Student's *t*.	GARCH, EGARCH, GJRGARCH APARCH	An asymmetric GARCH model with fat-tailed densities for calculating conditional variance was advised as a way to enhance overall estimation. Comparing the asymmetric GARCH, GJR, and APARCH models for forecasting TASE indices, the asymmetric EGARCH model is a better predictor.	The EGARCH model using a skewed Student's *t* distribution is the most successful for forecasting TASE indices.
(Lee et al. 2001)	106	Stock returns and volatility in China's stock markets	Journal of Financial Research	In four of China's stock exchanges, the time-series characteristics of stock returns, volatility, and the relationship between returns and volatility were examined.	GARCH, EGARCH	Application of GARCH andEGARCH models provides strong evidence of time-varying volatility and shows volatility is highly persistent and predictable.	The EGARCH model provides a better result.
(McAleer et al. 2007)	91	An econometric analysis of asymmetric volatility: Theory and application to patents	Journal of Econometrics	Provided an econometric analysis of the symmetric and asymmetric volatility in patent shares.	GARCH; GJRGARCH EGARCH;	For Australia, it was determined that the asymmetric GJR (1,1) model was appropriate, whereas the symmetric GARCH model was preferred for Switzerland and the Netherlands (1,1). For Canada, France, Germany, Italy, Japan, Korea, Sweden, and Taiwan, it was discovered that the alternative asymmetric model EGARCH (1,1) is appropriate.	Overall, EGARCH (1,1) is found to be suitable for most countries.
(Cao and Tsay 1992)	76	Nonlinear Time-Series Analysis of Stock Volatilities	Journal of Applied Econometrics	Compared the threshold autoregressive model's forecasting precision to that of models from the ARCH family.	TAR, GARCH, EGARCH	In comparison to the widely used GARCH(1,l) and EGARCH(1, O) models, TAR models may be useful in providing volatility forecasts, especially for large stock returns.	The TAR models provide better forecasts than the GARCH and EGARCH models.
(Huang and Zhu 2004)	63	Are Shocks Asymmetric to Volatility of Chinese Stock Markets?	Review of Pacific Basin Financial Markets and Policies	Studied the impact of leverage and the risk associated with holding A- and B-shares in the Chinese stock market.	GARCH, EGARCH, GJR GARCH	The GJR-GARCH and EGARCH are two examples of nonlinear GARCH models that are inappropriate for estimating the volatility of the Chinese stock market. Therefore, the GARCH model would be adequate and suitable to describe Chinese stock returns. The impact of leverage is absent.	A better model to fit Chinese B-share stock returns seems to be the GARCH model, rather than the nonlinear GARCH model.

By evaluating the frequency of GARCH models used to estimate and forecast the characteristics of time series data (Figure 9), we found that most of the highly cited articles used Exponential GARCH (EGARCH) (Nelson 1991), followed by GJR-GARCH (Glosten et al. 1993). Furthermore, many of the studies applied APARCH/AGARCH, NGARCH, and TGARCH models along with the EGARCH model. Many studies compared the forecasting accuracy of GARCH models and recorded divergent opinions on the best fitting model to capture the asymmetric/leverage effect. Some authors (Koutmos and Booth 1995a; Hentschel 1995; Braun et al. 1995; Booth et al. 1997; Kanas 2000; Heynen et al. 2016; Alberg et al. 2008; McAleer et al. 2007) proposed that EGARCH was the best fitting model. In contradiction to this, (Lee et al. 2001) suggested that EGARCH did not provide better estimation than the GARCH model.

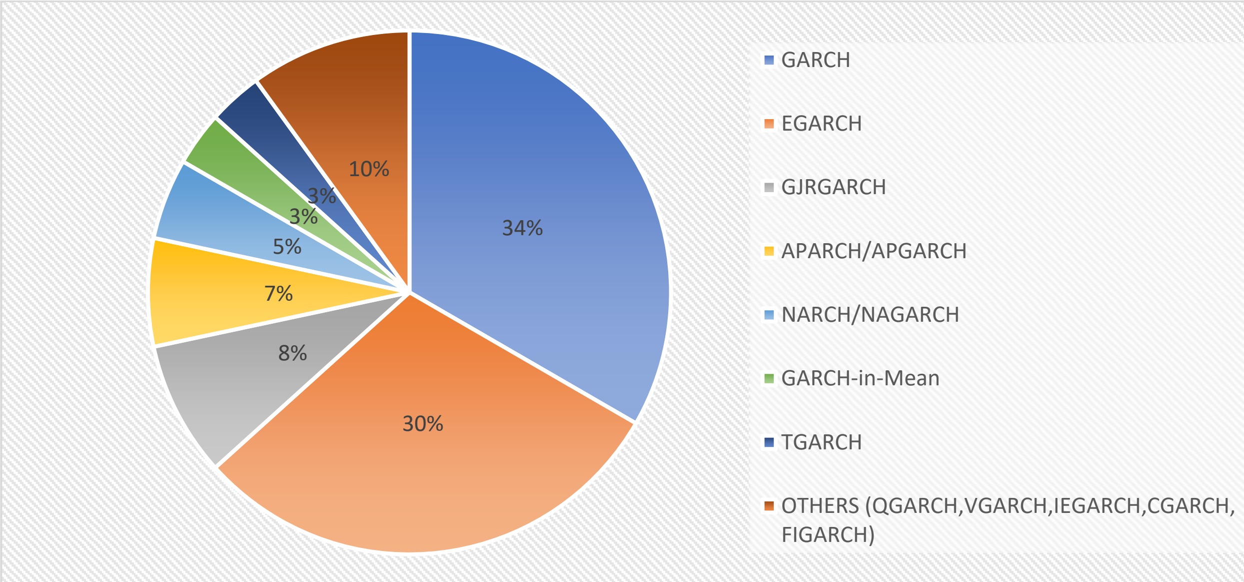

Figure 9. Frequency of GARCH models used. Source: Authors' calculation.

A Critical Evaluation of GARCH Models

Critical analysis is required in order to summarise the works in this field of research and to identify research gaps (Virbickaite et al. 2015; Cochrane 1991). In order to determine the superiority of more sophisticated and complicated models, this section critically evaluates the primary forecasting methodologies. Its primary goal is to provide evidence in support of an argument: When evaluating the volatility of returns on groups of stocks with thousands of data points, GARCH is the best suitable model to employ; when the GARCH model is compared to any other alternative model, the model's suitability is assessed from a single direction based on the accuracy of the volatility forecast it provides. There have been several improvements made to this method for modelling conditional volatility since the introduction of Autoregressive Conditional Heteroscedasticity (ARCH) by Engle (1982) and its generalization by (Bollerslev 1987). Both ARCH and GARCH models fail to capture the asymmetric effect in conditional volatility as their distributions are symmetric. To overcome this, various nonlinear/asymmetric GARCH models were introduced: exponential GARCH by Nelson (1991), threshold GARCH by (Zakoian 1994) GJR GARCH by Glosten et al. (1993), etc.

On critically examining the highly cited papers in this field, most of the studies used EGARCH for modelling the asymmetric volatility effect, while when comparing GARCH models, many of the authors proposed that EGARCH was the best one to capture the asymmetric response of stock returns to negative and positive news/information (Koutmos and Booth 1995a; Hentschel 1995; Braun et al. 1995; Booth et al. 1997; McAleer et al. 2007; Alberg et al. 2008). At the same time, there are contradicting arguments (Day and Lewis 1992; Sadorsky 2006; Mohammadi and Su 2010; Engle and Ng 1993) that other models, i.e., GJR GARCH, APARCH, and TGARCH, perform better than the EGARCH model. Some authors (Day and Lewis 1992; Huang and Zhu 2004) propose that no asymmetric GARCH models are better than symmetric GARCH models. Still, the issue regarding a better model is debatable. The transitions from ARIMA to ARCH, ARCH to GARCH, and GARCH to nonlinear GARCH models have highlighted the need for methodological advancements in GARCH modelling to address the shortcomings of earlier models. Understanding of the causes of volatility in financial time series is not considerably improved by the ARCH model. It merely offers a mechanical approach for describing the behaviour of conditional variance. Furthermore, to accurately represent the volatility process of an asset return, the

ARCH model requires a large number of parameters. The GARCH model, in contrast to ARCH, only has three parameters and a finite number of squared roots that might affect the current conditional variance. However, the GARCH model cannot capture asymmetric or leverage effects in the conditional variance. Further enhancements can be seen with nonlinear extensions, such as EGARCH, TGARCH, GJR GARCH, QGARCH, CGARCH, etc.

Through critically evaluating these papers, studies revealed the "best" or "worst" volatility forecasting models in different research scenarios. When examining the studies that propose that the EGARCH model is best, it was found that most of these studies focused on modelling the stock market's volatility. Similarly, studies proposing a best model other than EGARCH focused on other financial markets, i.e., the derivatives market. The contradiction in the "best fitting model" is due to changes in distribution, study period, data type, and even modelling software. In order to quantify the benefits of some models over others, it is necessary to perform more empirical research in this field.

5. Recommendations for Future Research

In this study, we identified the developments and trend in asymmetric GARCH models in the finance literature. Through a systematic review of highly cited research papers, we came to know that the EGARCH model is the most widely used asymmetric GARCH model. Similarly, the accuracy of the EGARCH model to estimate and forecast asymmetric/leverage effects in time series data was confirmed by many authors via comparison with other GARCH models.

In terms of future research opportunities, the extensive literature review using bibliometric analysis pointed to some key future research directions. Firstly, the present study theoretically contributed to the asymmetric GARCH literature by showing the forecasting accuracy of GARCH models. Thus, future research should focus on empirical verification of asymmetric GARCH models to confirm that the EGARCH model is the best to capture asymmetric effects in time series data from the lens of different asset classes as well as with regard to different countries. In addition to this, previous academic literature on asymmetric GARCH modelling utilised low-frequency data, i.e., daily, monthly, and annual data. Researchers' interest in intraday trading increased as a result of the rise of algorithmic trading in recent years. However, there are not many studies that use high-frequency data to focus on short-term asymmetric volatility. As a result, investigations in this field should concentrate on modelling asymmetric volatility using high-frequency data. Similarly, researchers could also investigate if the contradiction in the best-fitting asymmetric GARCH model is brought on by the software or the properties of the distribution.

The majority of existing studies modelled asymmetric volatility/leverage effects in the stock market, even though investors are concerned with not only the stock market but also other financial markets. In this regard, future studies should focus on modelling the asymmetric volatility effect in different financial markets, which will help investors reduce their risk through portfolio diversification. Most of the existing studies used EGARCH, APARCH, QGARCH, TGARCH, and GJR GARCH in modelling the asymmetric effect in conditional volatility. Various extensions of asymmetric GARCH models, including multivariate GARCH models, are used as a result of methodological developments in econometric modelling, but research studies utilising these extended models are very few. Therefore, a Systematic Literature Review could be conducted to critically evaluate each asymmetric GARCH model and unveil the research gap in this field more specifically. Thus, future works should utilise multivariate GARCH models in modelling time series data and should compare the forecasting accuracy of univariate and multivariate GARCH models. Furthermore, this work is based on bibliometric analysis, which could give a comprehensive summary of literature on asymmetric GARCH modelling.

6. Discussion and Conclusions

Using bibliometric analysis, this study addressed the research trend, applications, and forecasting performance of the asymmetric GARCH model in literature between 1992–2021.

Bibliometric analysis using 856 articles extracted from the Scopus database showed the evolution and trend in this field of research. Asymmetric GARCH models gained popularity among academics in recent decades, particularly after 2008. Unsurprisingly, there were 202 publications from 2019 to 2021 (the period of the COVID-19 pandemic). The trend in scientific production of asymmetric GARCH models became visible and clear over the years. Significantly contributing 176 publications with the highest number of citations between 1992 and 2021, the USA was found to be the leading country contributing to asymmetric GARCH model literature. Engle R.F. was the most cited author, with 2796 citations across two papers, and Applied Financial Economics was the most impactful journal having 31 publications recorded with 568 citations, followed by Energy Economics and Applied Economics.

The most cited article was "Measuring and Testing the Impact of News on Volatility" by Engle and Ng (1993), with a total of 2012 citations, published in the Journal of Finance. An assessment of international collaboration based on co-authorship was carried out to understand how countries jointly contribute to the literature on asymmetric GARCH models, and it was found that the United States of America was ranked first in terms of total link strength (79), with 167 research articles on asymmetric GARCH models in collaboration with authors from other countries. In the case of India, authors from the United States, Pakistan, Spain, Bangladesh, Germany, and Saudi Arabia collaborated with Indian authors in this field of research. Volatility and EGARCH were the most popular author keywords. Further analysis using factor-analysis study found four main thematic components: studies focused on forecasting models, financial assets, financial markets, and financial crises. Using correlation and regression, we found factors influencing total citations. Given the number of countries that collaborated with the USA, the USA had the greatest impact on the literature on asymmetric GARCH models. Through a systematic review, we learned that most of the highly cited articles used the EGARCH model to capture the asymmetric effect. Similarly, most authors suggested that the EGRACH model is the best fitting model among the various asymmetric GARCH models. In addition to this, many authors significantly contributed to the literature by modelling the asymmetric characteristics of time series data, comparing GARCH models, and expanding their theoretical background. Theoretical contributions were made by (Teräsvirta 2009; Virbickaite et al. 2015; Hentschel 1995; Lundbergh and Teräsvirta 2002; Bauwens et al. 2006; Charles and Darné 2019a; Alberg et al. 2008; Lee 2017; Charles and Darné 2019b; Naik and Reddy 2021; Srinivasan and Ibrahim 2010; Aliyev et al. 2020) modelled and compared different GARCH models.

Our study has some significant academic and managerial implications. In terms of academic implications, this study provides some important insights regarding gradual progression, prolific authors, impactful journals, and important studies in asymmetric GARCH literature. Apart from this, the study thoroughly reviewed highly cited papers to identify the frequently used GARCH models and the best model proposed by prominent authors in this field. This study significantly advances this field of research by highlighting the development and current structure of asymmetric GARCH models in the estimation and forecasting of asymmetric effects in the conditional volatility of time series data. From a managerial perspective, our study attempts to present a thorough grasp of the idea of asymmetric volatility that can aid managers, investors, and other market participants in comprehending the concept while making investment decisions and diversifying portfolios. Furthermore, it will help econometricians improve their GARCH modelling methodology.

This study is subject to some limitations. Firstly, the sources that were used to extract the datasets have an impact on the accuracy of the results. The datasets for this study were taken from the Scopus database. However, some of the top research on asymmetric GARCH models might not have been included due to the use of a single scientific database. To obtain a significant amount of literature on asymmetric GARCH models, other well-known databases, such as Web of Science, could be added to Scopus. It might improve the generalizability, accuracy, and reliability of the findings. Furthermore, this study covered the literature on asymmetric GARCH models from 1992 to 2021, as this study utilized a single database. There may be studies significantly contributing to this literature before 1992.

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