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Bibliometric Analysis of Fractal Patterns in Stock Markets: Trends and Perspectives

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Abstract

Traditional financial models fail to capture the nonlinear, self-similar patterns in stock markets, whereas the Fractal Market Hypothesis (FMH) provides a more robust framework. This study aimed to carry out a comprehensive bibliometric analysis to map the intellectual structure and evolution of research on stock markets with fractal patterns. Based on 1,280 documents obtained from the Scopus database (1982–2025), bibliometric analyses were conducted, including co-authorship and co-word analysis, as well as thematic evolution with the Bibliometrix R package. Despite limitations in study design, results indicated a significant shift from basic to their applied interdisciplinary research. The multifractal approach has emerged as the leading methodology with around 42% studies after 2005. Research output is led by China, India and the USA with increasing interest in financial crises, cryptocurrencies and hybridizing fractals with artificial intelligence. The bibliometric results yield empirical evidence that reinforces the applicability of the FMH in addressing market complexity and aligning with contemporary financial phenomena. Analysis of common themes in literature highlights certain knowledge deficiencies, predominantly regarding comparative studies between developed and emerging markets, dynamic performance under systemic shocks of fractal structures and the utility function analysis based on where fractal-based trading strategies are implemented. This is clearly a stepping stone for more extensive research on that topic, but it also highlights how fractal approaches can span across academic fields in finance.

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1. Introduction

Financial markets are examples of complex adaptive systems with nonlinear dynamics, feedback processes, and changing interdependencies. Sector luminaries such as Fama (1970) rendered textbook paradigms, including the Efficient Market Hypothesis (EMH), which state that prices instantly and completely reflect all available information and asset returns are essentially random. Although the EMH presents a foundational understanding of contemporary finance, the underlying assumptions regarding perfect rationality and equilibrium-based efficiency cannot account for these anomalies or inefficient patterns, volatility clustering, and long-memory effects (Onali and Goddard, 2011; Brătian et al., 2021). The repetitive occurrence of crises, speculative bubbles and asymmetric information flows only serves to reinforce the notion that market behavior does indeed differ from the EMH theoretical ideal (Karp and Van Vuuren, 2019).

Given these empirical failings, the Fractal Market Hypothesis (FMH) did not just represent an alternative, but a necessarily progressive development of financial ideas. Drawing from Mandelbrot’s (1972) idea of self-similarity and Peters’ (1989) initial fractal approach to the structure of market data, FMH redefines financial markets as self-organized structures governed by investors with heterogeneous time horizons. Whereas EMH assumes informational homogeneity, FMH allows for the insights that stability and liquidity require a balance between long- and short-term investment perspectives. This balance gets disrupted, as in the crisis markets display a multifractal scaling nature that elicits nonlinear responses and extreme volatility (Berghorn et al., 2019; Okorie and Lin, 2021). Therefore, FMH delivers a more accurate explanation by combining heterogeneity, memory and dynamic adjustment found in data that EMH has systematically neglected.

In the past four decades, the collaborative effort of multifractal analysis, econophysics and computational finance has been iterative to form FMH (Jiang et al., 2019; Zhou et al., 2024), pushing further theoretical study and empirical modeling from regime paradigm to complexity in a market. Further modern analysis also displays that FMH identifies structural shifts in markets affected by global shocks like the COVID-19 pandemic and new developing phenomena in digital assets and decentralized finance (Okorie and Lin, 2021; ElNabulsi and Anukool, 2025). Additionally, the relationship of fractal modeling with artificial intelligence and quantum computation renders FMH as a comprehensive approach for exploring financial systems operating under uncertain conditions where nonlinear interactions take place (Popovska Georgieva-Tsaneva 2024; Kehinde et al., 2023).

Despite these developments, some research gaps remain. Existing studies comparing the performance of emerging and developed markets are limited, as is the dynamicity behind the multi-fractal structures' response to systemic shocks. Moreover, a potential area for future research is the marriage of FMH-based indicators with machine learning and big data analytics methodologies to achieve real-time forecasting and risk management (Leventides et al., 2024). To tackle these problems, we need a broad understanding of how the FMH has developed conceptually and empirically over time.

The current study fills these gaps by using a bibliometric method to explore the intellectual structure and evolution of research on fractal stock markets between 1982 and 2025. Bibliometric analysis has been acknowledged as a qualitative and quantitative approach that can identify multiple research trends, conceptual clusters and knowledge gaps by examining scientific publication data such as articles, citations through papers' keywords, and collaboration networks (Nourahmadi and Rasti, 2025; Nourahmadi, 2024). Specifically, it investigates the following four research questions:

1. What are the temporal trends in FMH-related publications, and how do thematic pathways evolve across different periods?

2. Which authors, countries, and journals have the strongest influence based on co-authorship networks, citation counts, and collaboration patterns?
3. What conceptual clusters can be identified through keyword co-occurrence and thematic mapping, and how do they relate to emerging research fronts?
4. What are the knowledge gaps based on bibliometric evidence and what suggestions for future directions could inform interdisciplinary and applied research in FMH?

This study addresses these questions and helps consolidate existing knowledge, while identifying promising ways forward for interdisciplinary and applied research.

2. Theoretical framework

2.1. Origins of fractal geometry and its introduction to financial economics

In 1975, Benoit Mandelbrot introduced the amazing mathematical construction of fractals, coining a new term (now it does). He was also remarkably interested in using mathematical language to describe unusual patterns found at various scales in nature, such as coastlines, clouds and mountains whose apparent complexities resist Euclidean geometry. He introduced the idea of fractals, shapes that exhibit similar features at various scales, a property called self-similarity. Now this idea was used not only in natural science but also in social and economic spheres. In his early work, including a 1972 paper, Mandelbrot demonstrated that cotton prices in financial markets exhibit fractal characteristics and that their fluctuations follow non-Gaussian distributions (Mandelbrot, 1972). Fractal geometry fundamentally changed financial modeling by providing a quantitative link between market irregularities and scaling behavior, enabling researchers to capture nonlinear dynamics and volatility clustering**.**

The late 1980s saw an acceleration in the adoption of fractal geometry as a way to characterize asset price dynamics, notably by the financial economist Edgar Peters. In particular, Peters, in a seminal 1989 article in the Financial Analysts Journal, showed how market price data exhibited fractal structures. Unlike the classical models, like Geometric Brownian motion, financial markets show nonlinear, complex behavior that is better described using fractal instruments (Peters 1989). As a result, Fractal Market Hypothesis (FMH) was created, being proposed as an alternative hypothesis of the Efficient Market Hypothesis (EMH). FMH requires that markets are not perfectly efficient and supports the existence of self-similarity and long memory in price behavior (Evertsz, 1995; Malik, 2011).

Within this framework, price changes should be examined across multiple time scales, as investors with different horizons, short-term (e.g., day traders), medium-term (e.g., institutional investors), and long-term (e.g., pension funds) influence the market. These complex interactions generate fractal patterns in which small daily fluctuations can repeat larger weekly or monthly patterns. This multi-scale behavior forms the basis for modeling volatility and forecasting market regimes.

2.2. Efficient market hypothesis versus fractal market hypothesis

The Efficient Market Hypothesis (EMH) claims that the price of any asset fully reflects all known information at any point in time, which was proposed by Eugene Fama in the 1970s. The EMH hypotheses that states that no investor should be able to achieve a systematic return greater than the market due to price movement being a random and therefore unpredictable process that can exist in a weak, semi-strong or strong form (Fama, 1970). In contrast, experience during the last thirty years has demonstrated some consistent structural inefficiencies in markets, e.g., calendar effects, price bubbles and financial crises. These inefficiencies show that markets always efficiently weigh all of the available information and investor irrationality as a major factor (Onali and Goddard, 2011).

By contrast, in FMH, price data exhibit the fractal structures that are financial markets being made up of investors with a diversity of time horizons (Peters, 1989). FMH espouses the long memory and self-similarity of market volatility— that is, the behavior of markets across different time intervals is similar, if not in intensity or magnitude. In FMH, financial markets operate under different regimes: when the market is in a normal state, stable market conditions prevail due to the stabilizing effect of diverging investor horizons, and crises are characterized by an (over)concentration on short-term investment goals resulting in high returns volatility (Berghorn et al., 2019). In contrast to EMH, the FMH incorporates resetting feedback loops, the memory effect and dynamics adaptation, resulting in a more general conceptual apparatus for modeling market imbalance phenomena (Karp and Van Vuuren 2019; Okorie and Lin 2021).

Empirical studies confirm FMH's superiority in explaining crisis dynamics and volatility clustering in emerging markets (ElNabulsi and Anukool, 2025).

2.3. Key concepts in fractal theory

In this section, we provide an overview of essential concepts that form the basis for the analysis of fractal markets to connect theoretical foundations with analytical tools.

Self-Similarity: The property of having repeating patterns across different time scales, which carries over to financial markets as well, where price behavior across days, weeks, or months is similar but the distribution of prices is different (Evertsz, 1995).

Long Memory: The Hurst exponent is used in measuring long memory. If $H > 0.5$, there is a tendency for trends to persist, and if $H < 0.5$, then mean reversion is expected (Yu et al., 2006). This is a key property in FMH's predictive power.

Fractal Dimension: measures how complex/rough a time series; higher numbers express more volatile and irregular market structures (Bayraktar et al., 2004). This metric allows for clearly distinguishing between market efficiency in various regions.

Richtigen: MFDFA and MFDCCA methods show asymmetries and nonlinear patterns (Jiang et al., 2019; Zhou et al., 2024). Multifractality is especially effective in detecting regime shifts and systemic risks.

2.4. Analytical frameworks

In this section, we present statistical models, which are based on fractal theory, that can be used in financial analysis.

ARFIMA Model: Autoregressive Fractionally Integrated Moving Average models are capable of modeling long memory processes typical in financial time series (Panas, 2001). They extend ARIMA to allow for fractional differencing, which makes them applicable where there are pronounced trends.

Wavelet Analysis: Extracts multi-scale features from complex time series, working great when dealing with high-frequency data, especially to analyze volatility and fractal dimension (Bayraktar et al., 2004).

MFDFA and MFDCCA: Multifractal Detrended Fluctuation Analysis and its cross-correlation variant have been applied extensively to discover multifractal structures as well as dependencies between assets (Zhou et al., 2024). The combination of these methods may augment the ARFIMA phenomenon and wavelet analysis to identify several new facts with a scale sensitive interests about market.

To improve clarity, Section 2.5 focuses on geometric and dynamic models, while Section 2.4 emphasizes statistical and time-series approaches.

2.5. Advanced models

This section introduces dynamic and geometric models that extend fractal analysis into new theoretical domains. Each model is presented using a consistent format.

Fractional Brownian Motion (FBM): Definition: A generalization of classical Brownian motion with long memory. Insights: Models time series and cross-sectional complex dependencies in financial data. Use case: Used to model stock indices more accurately than conventional approaches (Brătian et al., 2021; Gu, 2025).

Geometric Arbitrage Theory: Definition: A geometric structure that models arbitrage as curvature. Goal: Use differential geometry to illuminate market dynamics. Application: Used to identify arbitrage opportunities in cryptocurrency markets (Farinelli, 2015; ElNabulsi and Anukool, 2025).

Higher conceptual coherence and theoretical integration are achieved as this section ensures stylistic consistency among the various models and clarifies the purposes of each model.

2.6. Literature review

2.6.1. Classical studies

Peters (1989) initially introduced fractal structures in financial markets through the early studies. Drawing on Mandelbrot's work in fractal geometry, he showed that asset price variations are self-similar, a property that never quite gets captured with classical models. Then, Evertsz (1995) quantitatively highlighted the relevance of fractal dimensions in financial time series analysis. Huang and Yang (1995) further illustrated by examining multinational markets that structures of stock returns exhibit a multi-scale property. Such studies laid the groundwork that helped establish a new field of research, which over subsequent decades has grown to an increasingly frenetic pace. These works have been cited as foundational for the combination of fractal models with artificial intelligence (Blackledge and Lamphiere, 2021) in recent reviews. Yet these initial studies, although valuable, did not have strong empirical validation across many states of the market, limiting generalizability.

2.6.2. Developed vs. emerging markets

The distinction between developed and emerging markets has been a key focus of fractal research. Bianchi and Frezza (2017) showed that market efficiency is dynamic, and fractal characteristics can reveal the relative efficiency or inefficiency of markets. Samadder et al. (2013) concentrated on Indian stock market indices and discovered strong self-similarity of price series. More recently, Xu et al. In their research, (2022) found asymmetric fractal features for the style indices of China are present, indicating that market efficiency plays a significant role under certain conditions. These have shown that EMs tend to be more complex and multifractal, indicating structural inefficiencies and weak information flow. Evidence from the MFDFA of African markets affirmed these disparities and indicated to policymakers that they could also utilize these tools for improved efficiency (Moradi et al., 2021). However, comparative studies tend to be limited in both methodology and data granularity, so conclusions across markets are tentative.

2.6.3. Market efficiency and asymmetry

A wide range of fractal data has been used to test the Efficient Market Hypothesis (EMH). Onali and Goddard (2011) studied European markets, finding significant inefficiencies in many indices that can be detected using fractal techniques. Gayathri et al. (2013) investigated the Indian market and demonstrated that fractal dimensions can significantly explain non-linear market dynamics. Grönlund et al. (2012) developed a "Fractal Profit Landscape," which means that trading systems are developed in an environment determined by fractals (2012). Together, these studies have shown that the markets are not fully efficient, especially during times of volatility or crisis and fractal analysis offers a useful tool for detecting such inefficiencies. More recent work using this approach incorporates information entropy to highlight asymmetries in return distributions (Liu et al. 2025).

To improve thematic flow, the next section builds on these insights by examining how crises and systemic shocks further amplify fractal complexity.

2.6.4. Crises and economic shocks

A critical area of research concerns the impact of crises and systemic events on the fractal structure of markets. Okorie and Lin (2021) demonstrated that the COVID-19 pandemic significantly altered fractal features and increased market complexity. Moradi et al. (2021), who examined several crises for the Tehran and London markets, also suggested that the Fractal Market Hypothesis can help to predict stock returns under high-risk conditions. Yang (2025) took a crack at the "fractal DNA" viral concept to account for Albion pattern-matching crisis arcs evolving hierarchically in fractal time. In studying the effects of mergers and acquisitions on stock prices, Verma and Kumar (2023) analyzed changes in the fractal dimensions concerned with market complexity. Our analysis of the EU trade data provides shock studies and shows that its fractal structures fundamentally change under shocks to give rise to new topological order in both short memory and long memory. Analyzing the multifractality of South African sector indices revealed that higher multifractality was accompanied by crisis periods (Amini et al., 2024). However, studies specifically focusing on crises are frequently retrospective in nature, limiting their predictive power.

2.6.5. Practical applications and trading strategies

Fractal analysis is not only a theoretical concept. The study conducted by Blackledge and Lamphiere (2021) gives an extensive overview of the various applications in FMH for algorithmic trading, showing that fractal patterns can be used in price forecasting/management and risk management. Popovska and Georgieva-Tsaneva (2024) suggested robotic trading strategies considering fractional derivatives and volatility analysis. Gu (2025) proposed multi-timeframe fractal patterns for optimizing cross-asset trading. Liu et al. (2025) “Energy-Spacetime” architecture generalizes as fractal-game theory physics for markets. Recent research proposes to apply fractal analysis in cryptocurrency trading as a way of finding structure within chaotic price movements (Ko and Kuo-Shing, 2025; Kristjanpoller and Tabak, 2025). Additionally, combining fractals and filters based on Fractal Chaos Bands mitigates market noise and promotes multi-timeframe strategies (Blackledge and Lamphiere, 2021; Popovska and Georgieva-Tsaneva, 2024). While very promising, these methods have limited validation in real time and may struggle to adapt to regime shifts.

2.6.6. Market modeling and simulation

Researchers have sought to simulate markets using fractal-based models to better understand complex behavior. Leventides et al. (2024) simulated the Athens Stock Exchange using fractional Brownian motion. Amini et al. such as (2024) proposed a model explaining volatility clustering using fractals. A fresh approach using fractal-based qualitative financial modelling under high-risk scenarios was introduced in ElNabulsi and Anukool (2025). These approaches suggest that financial markets need to be represented not just as aggregates of trades, but rather as complex systems with behaviors across multiple scales. When modeling financial markets, Laplace–Mittag-Leffler distributions have proven useful (Kristjanpoller and Tabak, 2025). However, simulation models are typically never compromised due to parameter calibration and real-world comparability.

2.6.7. Complementary concepts and interdisciplinary approaches

Econophysics has also contributed to the advancement of fractal research. The field applies ideas from statistical physics and chaos theory to better understand how financial systems behave. Formally, financial markets tend to display complex behaviors similar to those of physical systems, such as volatility clustering, fat-tails and non-Gaussianity. Chaos Theory stresses great sensitivity to starting conditions, meaning that marginal variations in input can yield dramatically different results. That view is aligned with fractal geometry, which explains the nonlinearity and complex behavior (Castilhos et al., 2017). In 2025, we applied econophysics based on fractal analysis to African stock markets, as they are stated to have lower efficiency.

Farinelli (2015) used the tools from differential geometry to define arbitrage as the "curvature" of a principal fibre bundle and called this theory his Geometric Arbitrage Theory. This geometrical viewpoint complements the concept of fractals because both seek to uncover hidden order in financial data. Combining these theories can create all-new moulds in the market of stability analysis and arbitrage opportunity finding.

Together, these interdisciplinary frameworks—FMH, chaos theory, econophysics, and geometric modeling—form a conceptual ecosystem for understanding financial complexity. Their integration under the umbrella of fractal analysis enables multi-scale modeling, cross-asset forecasting, and systemic risk detection.

2.6.8. Cryptocurrencies and decentralized finance

In addition, the introduction of cryptocurrencies and blockchain technology has created new paths for fractal research. Considering the extreme volatility and nonlinear behavior of cryptocurrencies, a fractal approach may be sufficient (Jiang et al., 2019). Recent research has suggested that Bitcoin and other cryptocurrencies share multifractal character with long memory, similar to what we see in the traditionalization of emerging market movements. Moreover, with the recent injection of decentralized finance (DeFi), fully algorithm- and smart-contract-driven markets are emerging. By understanding the fractal characteristics of these markets, it is possible to develop new tools for risk management and predictive modelling. Some others have tried to use fractal analysis in cryptocurrency trading, initiating discoveries of structural patterns contained in the price algorithm at a very volatile scale (Ko and Kuo-Shing, 2025; Kristjanpoller and Tabak, 2025).

2.6.9. Methodological challenges and limitations

Despite considerable progress, the use of fractal analysis in finance still has its issues:

- **Data Noise and Nonstationarity**: This is particularly true for financial time series, which are known to be noisy and nonstationary, potentially biasing any estimation of a fractal index like the Hurst exponent (Goyal, 2024).
- **Computational Complexity**: Techniques like MFDFA necessitate significant computational capacities, restricting scalability (Kehinde et al., 2023).
- **Interpretability**: Economic interpretation of fractal indicators does not come so clearly, especially

3. Data and methodology

The Bibliometrix method analyzes various patterns and models in bibliometrics and its applications to study scientific trends, research developments in collaboration with several others (Nourahmadi and Parsi 2025); it also allows scholars and authors to discover high-demand research areas and plan their research aligned with the most up-to-date scientific trends. Using bibliometric analysis, this study systematically analyzes research on fractal patterns in stock markets. Bibliometric analysis is a strong method to map the intellectual structures, identify the key authors and institutions, and trace evolutionary trends in a specific research domain (Donthu et al., 2021). This technique offers extensive descriptive as well as visual insights into the existing literature in this area, especially considering the very small number of publications on fractal finance which have emerged in recent decades.

Methods: The Scopus database, a well-known source for indexing scientific articles, was used to collect relevant scientific data. Data collection occurred in multiple stages:

Keyword Selection: A variety of both theoretical and applied keywords relevant to the research domain of interest were used to provide comprehensive coverage. The main combinations were:

- Fractal Pattern + Fractal Finance
- Fractal Pattern + Self-similarity
- Financial Market + Fractal Market
- Fractal Finance + Multifractal
- Multifractal Analysis + Market Volatility

These combinations span both theoretical dimensions (e.g., self-similarity, fractal dimension) and applied dimensions (i.e., market volatility and option pricing).

3.1. The exact Boolean search query used in Scopus was

("Fractal Pattern" and "Fractal Finance") or ("Fractal Pattern" and "Self-similarity") or ("Financial Market" and "Fractal Market") or ("Fractal Finance" and "Multifractal") or ("Multifractal Analysis" and "Market Volatility").

The data were extracted from Scopus on August 25, 2025.

Initial Data Retrieval: The initial search in Scopus retrieved 1,704 scientific documents, including journal articles, conference papers, book chapters, and reviews.

Data Filtering: The initial steps for ensuring quality and focusing on reliable scientific literature were as follows:

1. Removing duplicate documents resulting from keyword overlaps.
2. Applying a publication window from 1982 to 2025.
3. Excluding irrelevant documents based on title and keyword review.
4. Retaining only articles written in English and excluding publications in other languages.

The final dataset, after applying filtering measures, included 1,280 documents from 569 credible sources; the various types of articles included journal articles, conference papers, book chapters and reviews.

- Data Preparation for Analysis: Table Z-filtered data were exported into BibTeX and CSV formats to guarantee compatibility with bibliometric analysis tools. These comprised authors and co-authorship networks, year of publication, source journals, keywords, abstracts, citation counts and references. This data was used as the basis for descriptive statistics analysis, as well as for network-based analyses such as networks of keyword co-occurrence, thematic maps and temporal trend analyses.
- Analytical approach: We used the Bibliometrix package in R (Aria and Cuccurullo, 2017) for data analysis. Author Co-citation analysis, Collaboration Analysis and Country/Institutional Publication output were performed using the Bibliometrix package in RStudio, whereas its web-based interface, Biblioshiny, was used for interactive visualization as well as analysis. The employed techniques included:
- Descriptive Statistics: Annual growth, average citations and document types, which gives a broad overview of up-to-date trends of publications and impact, and the history of resource

development.

- Co-authorship Analysis: Exploring collaboration trends among authors and nations. This also shows the structure, density, and internationality of research networks in this field.
- Co-word Analysis: Conceptual structure mining in keyword co-occurrence networks. This method reveals co-occurring terms and emerging research fronts, along with intellectual connections.
- Thematic Mapping: Grouping topics into push, foundational, niche and emergent/declining themes. This aids the emergent knowledge domains in identifying their focus areas from the periphery or depreciating topics, thus providing an insight into a research area positioning strategy.
- Tune Released: Histories of the article in different time points, which further illustrate changing thematic priorities over time and highlight newly emerging paradigms or methodological fashions.

4. Findings

Table 1 presents descriptive statistics of the conducted research:

Table 1. Descriptive statistics

Description	Results
General Information about the Data	
Time Span	1982–2025
Sources (Journals, Books, etc.)	569
Documents	1,252
Annual Growth Rate (%)	10.600
Average Document Age	10.7 years
Average Citations per Document	24.310
Content of Documents	
Keywords Plus	5,380
Author Keywords	2,967
Authors	
Total Number of Authors	2,466
Single-Author Papers	155
Author Collaboration	
Single-Author Documents	199
Average Number of Co-authors per Document	2.870
International Collaboration (%)	19.65%
Document Types	
Journal Article	919
Article-Book	1
Article-Book Chapter	1
Article-Conference Paper	1
Book	9
Book Chapter	25
Conference Paper	268
Conference Paper-Article	3
Review	21

The bibliometric dataset comprised 1,252 publications released between 1982 and 2025 from 569 sources. The annual publication growth rate was 10.6%, and the average citations per document amounted to 24.3, reflecting the significant and sustained impact of research in the field of fractal finance. The majority document type was journal articles (919), while only 268 papers were conference documents, which play a complementary role in new topics. These statistics show the persistence of the discipline in terms of scientific growth and significant influence on financial markets using fractals, which should serve as a firm base to further analysis (literature) trends.

4.1. Results and discussion

This section provides an in-depth examination of the bibliometric data, taking each of the four research questions (RQs) stated within the Introduction in turn. Using the Bibliometrix R package, the results, based on 1,280 documents indexed in the Scopus database from 1982 to 2025, show the intellectual structure and some of their influential contributors as well as their thematic evolution in stock markets through fractal patterns. Discussing these findings, they are not only exhaustive results to be interpreted descriptively but rather an empirical material that highlights the increasing relevance of FMH as a competing robust paradigm for financial modelling.

RQ1: What are the temporal trends in FMH-related publications, and how do thematic pathways evolve across different periods?

The aggregate analysis of annual scientific production (Figure 1) demonstrates a constant trend of increase directly, answering RQ1 about the temporal trends. This path is quantitative and qualitative in terms of degenerating traditional paradigms such as Efficient Market Hypothesis (EMH) (Fama, 1970) into the Fractal Market Hypothesis (FMH) (Peters, 1989). Research productivity has been characterized by three separate phases:

- Formation Phase (1982–2000): This was a slow growth period, accounting for fewer than 20 articles annually. It concentrated on heuristic theories from Mandelbrot (1972) and Peters (1989), laying the foundation of ideas such as self-similarity and fractal dimension.
- Expansion Phase (2001–2015): Rapid growth occurred during this period, peaking at around 60 articles published per year, which correlates with the massive uptake of computational tools such as multifractal detrended fluctuation analysis (MF-DFA).
- Maturity and Diversification Phase (2016–2025): The number of annual publications reaches more than 75 per year, corresponding to a cumulative propagation ratio of 10.6% (Table 1). The average citation per document during this phase reached 24.31, indicating the high impact and longevity of the research.

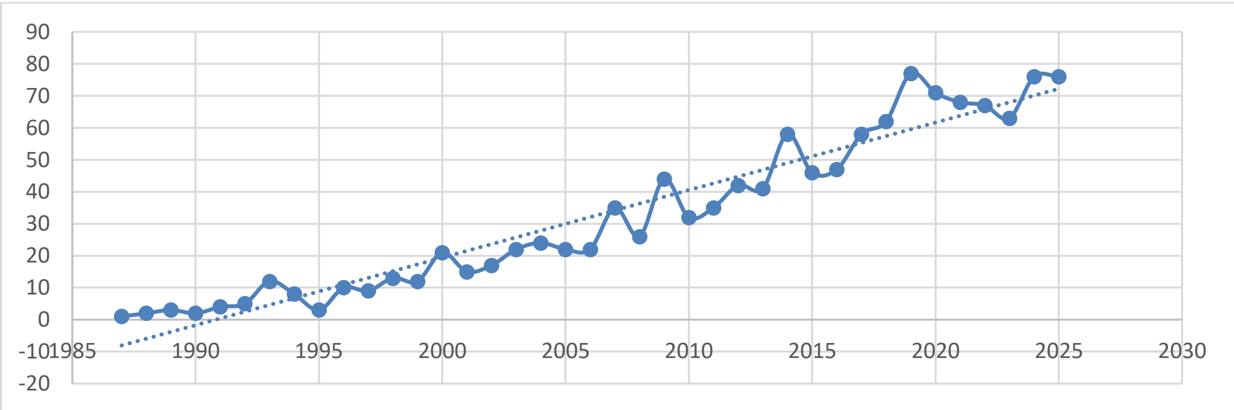

Figure 1. Annual Scientific Production

The three-phase analysis (Figure 1) shows the macro-level growth in publication volume, while a co-occurrence evolution map of themes over time (Figure 2) provides a more zoomed-in view of conceptual shifts that led to this growth. Collectively, they provide a panorama of the field's evolution. The map depicts five specific periods:

1. Period 1 (1982–2007): Focused on foundational mathematical models applied in basic sciences.
2. Period 2 (2008–2014): Marked the pivot toward financial economics, with core concepts like

"fractals" and "self-similarity" gaining prominence.

3. Period 3 (2015–2018): Defined by methodological diversification, integrating wavelet analysis and pattern recognition.
4. Period 4 (2019–2022): Consolidated research by applying advanced tools like detrended cross-correlation analysis (DCCA) to financial markets, particularly during crises like COVID-19.
5. Period 5 (2023–2025): Showcases a convergence with cutting-edge technologies, integrating fractal analysis with concepts from modern physics, artificial intelligence, and decentralized finance (DeFi).

The new themes of FMH from 2018 onwards, finally leading us to the merging with AI and DeFi, are evidence of how adaptable and relevant the FMH can be. This indicates that FMH is not a fixed theory, but a dynamic framework that can accommodate new methodologies to account for increasingly elaborate financial phenomena as an essential feature of theories with their base in complexity science.

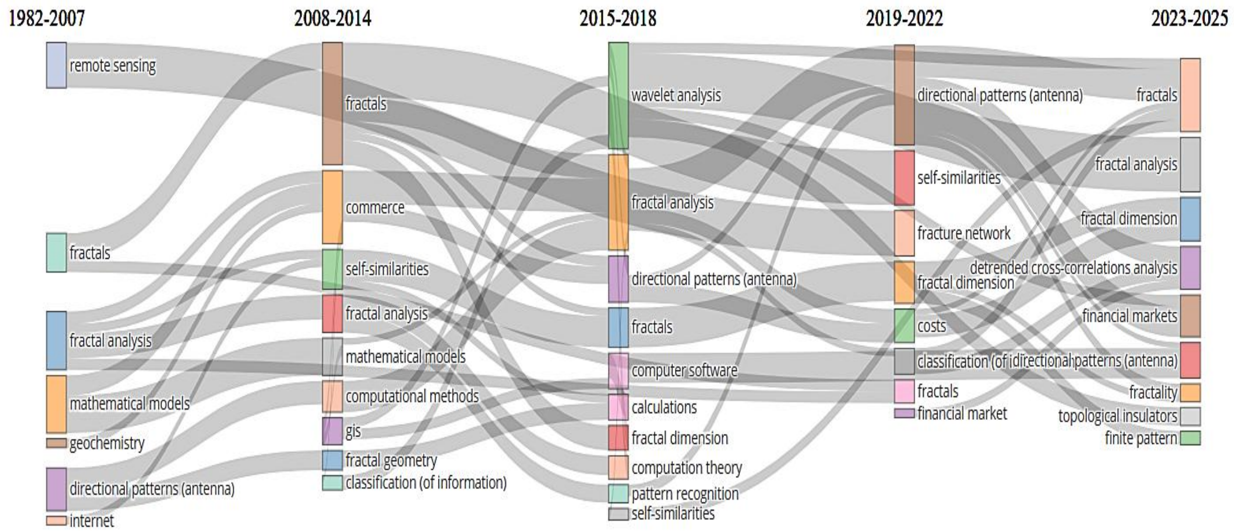

Figure 2. Thematic Evolution

RQ2: Which authors, countries, and journals have the strongest influence based on co-authorship networks, citation counts, and collaboration patterns?

The influence of authors and countries is mapped through the three-field plot (Figure 3) and the corresponding author's country chart (Figure 4). The analysis reveals a pronounced geographic concentration of knowledge production. China is the undisputed leader, with authors like Wang J, Zhou WX, and Jiang ZQ contributing a high volume of work. This prominence can likely be explained by large national investments into data science and econophysics, along with the high-profile teams at universities, and a tactical focus on complex systems. Poland has also shown high contributions (e.g., Drozdz S), whilst Brazil, following China, ranked as a top contributor (e.g., Fernandes LHS).

However, collaboration patterns vary considerably. Where China excels in single-country publications (SCP), countries such as Germany, the UK and Canada show particular willingness to work with other countries (MCP), with more than 47% from these nations co-authored internationally. This suggests that there is some bifurcation of research culture one the one hand, high-volume domestic output (China, India) and on the other hand, building international collaborative networks. This difference significantly affects how knowledge spreads globally and the potential for diverse viewpoints within the field.

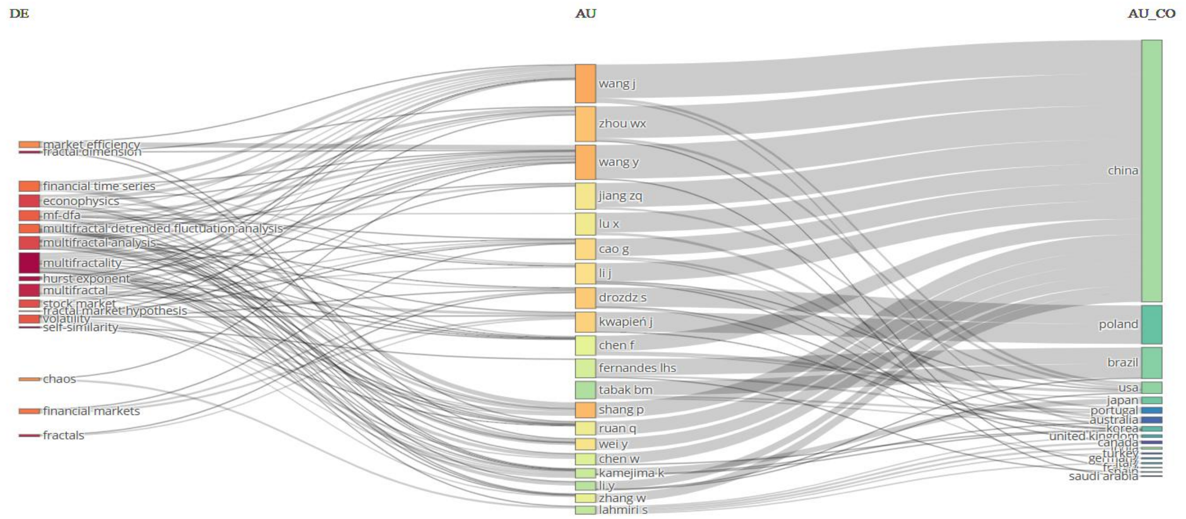

Figure 3. Three field plots

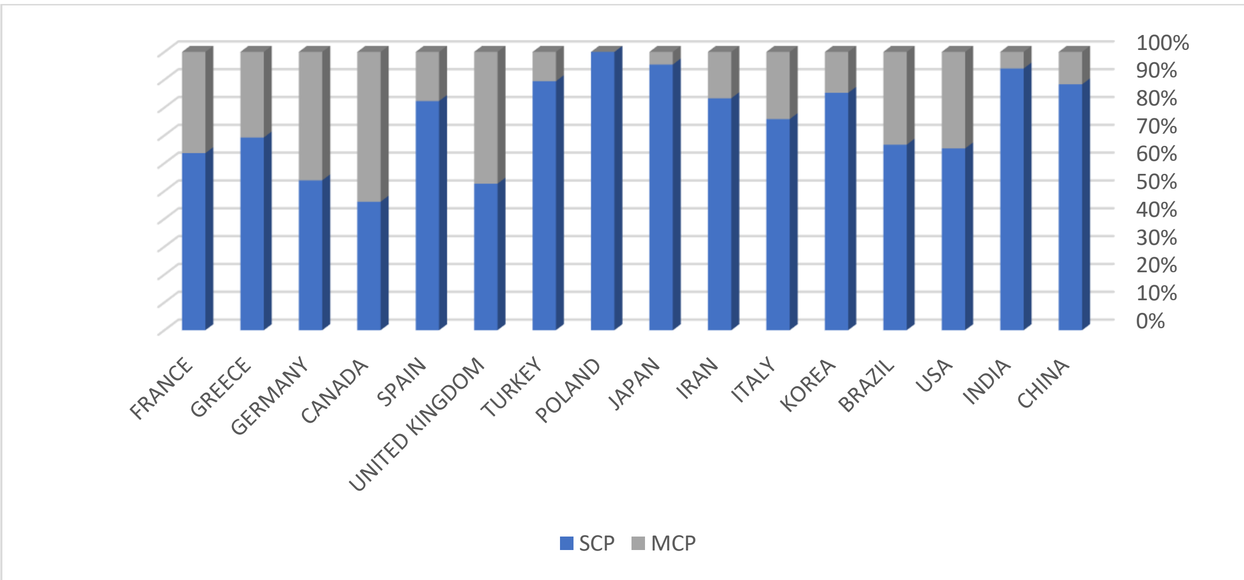

Figure 4. Corresponding author's countries

RQ3: What conceptual clusters can be identified through keyword co-occurrence and thematic mapping, and how do they relate to emerging research fronts?

Keyword analysis (Figures 5, 6, 7, 8, and 9) uncovers a rich conceptual structure with evolved significantly over time. The word cloud (Figure 5) and the trend topics (Figure 6) show a shift in focus. Specifically, the emphasis has moved away from core concepts like "self-similarity" and "fractal dimension" toward more practical areas such as "cryptocurrencies," "forecasting," and "risk management." The prominence of 'cryptocurrencies' and 'deep learning' alongside traditional terms signifies a critical paradigm shift in which the field is moving from pure financial econometrics towards an interdisciplinary convergence with data science, reflecting the need to analyze new, algorithm-driven markets. The emergence of terms like 'decentralized finance (DeFi)' in the most recent period illustrates the field's responsiveness to technological innovations and its expanding scope beyond traditional stock markets.

Figure 5. Word cloud

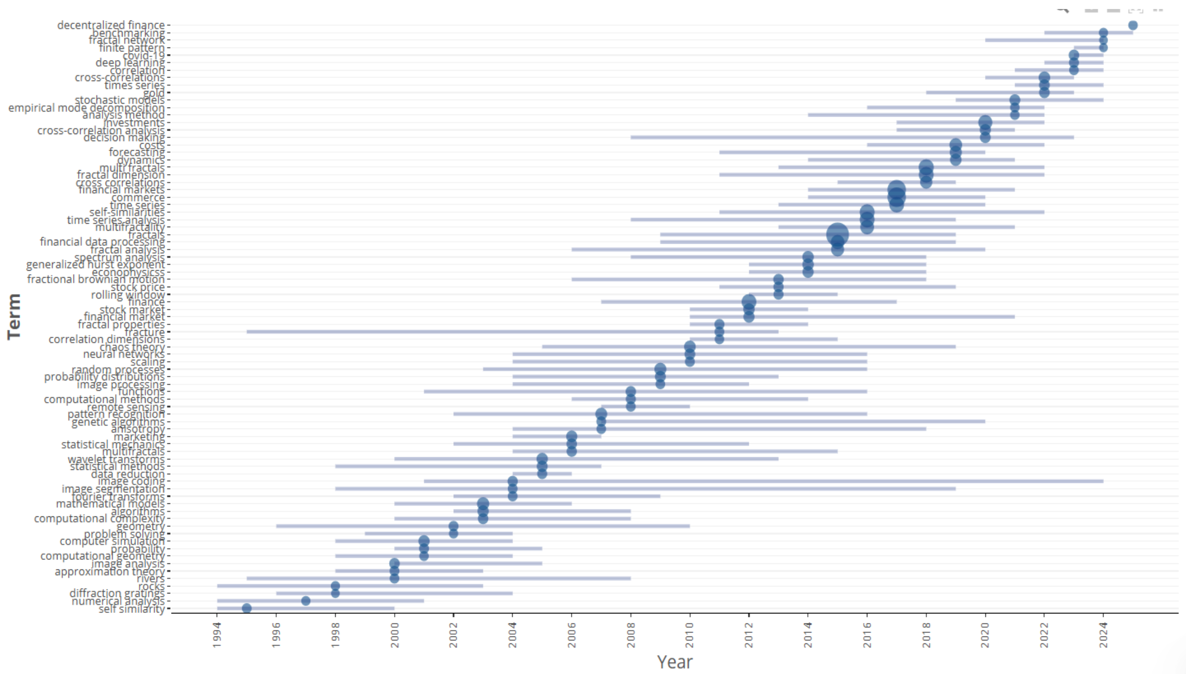

Figure 6. Trend topics

The co-occurrence network (Figure 7) organizes these keywords into four distinct clusters, each with distinct theoretical and practical relevance:

- Blue Cluster (Fundamental Concepts): This cluster represents the theoretical bedrock of the field, providing the fundamental language (e.g., self-similarity, chaos) that challenges the assumptions of traditional finance and underpins the FMH.

- Red Cluster (Applications in Financial Markets): Linking fractal tools directly with the core debates of finance, the Red Cluster is important because it provides empirical evidence contrary to the Efficient Market Hypothesis (EMH) and supportive towards a Fractal Market Hypothesis (FMH) framework (Onali and Goddard, 2011).
- Green Cluster (Multifractal Analyses◦Emerging Applications): The much-needed novelty, the applied evolution of the field, is suggested to be covered in a way offered by the Green Cluster. With a focus on cryptocurrencies and econophysics, it is essentially a research front seeking to model extreme volatility and systemic risk in contemporary, complex financial ecosystems.
- Purple Cluster (Statistical Methods): This smaller cluster focuses on methods highlights a technical side of modern financial analysis, stressing the value in understanding dependencies across asset classes.

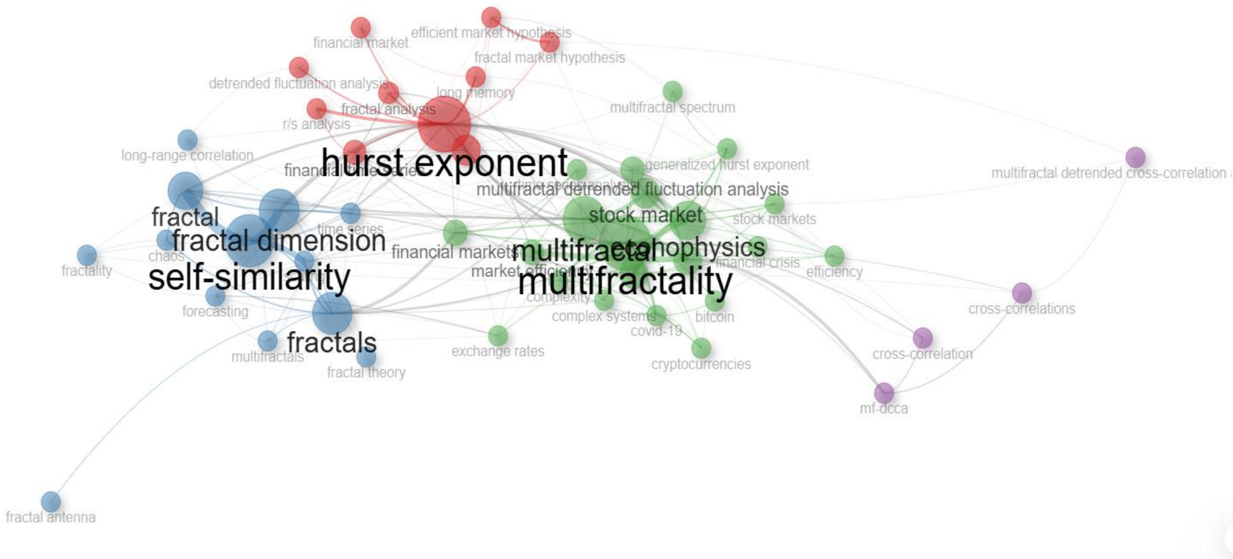

Figure 7. Co-occurrence network

The thematic map (Figure 8) further stratifies these topics by centrality and density. “Multifractality” and “multifractal analysis” emerge as motor themes that are located in the top-right quadrant with high centrality/ density. They remain the methodological and theoretical backbone of the discipline, fundamental to modelling (and thus having potential predictive power over) long-memory and volatility clustering, major cornerstones of FMH. The large number of articles identified as belonging to the multifractal domain might very well have, in themselves, provided strong bibliometric evidence for its role as a main analytical engine of FMH. M(ulti)F(range), representing at least seven measures–the possibility of picking and choosing conveniently from these descriptions, also helps make up for the lack of theoretical clarity underpinning this subdomain. As the key tool for quantifying the long-memory, heterogeneity, and scaling behavior, the FMH posits as fundamental to market dynamics, offering a more nuanced explanation than the EMH ever could.

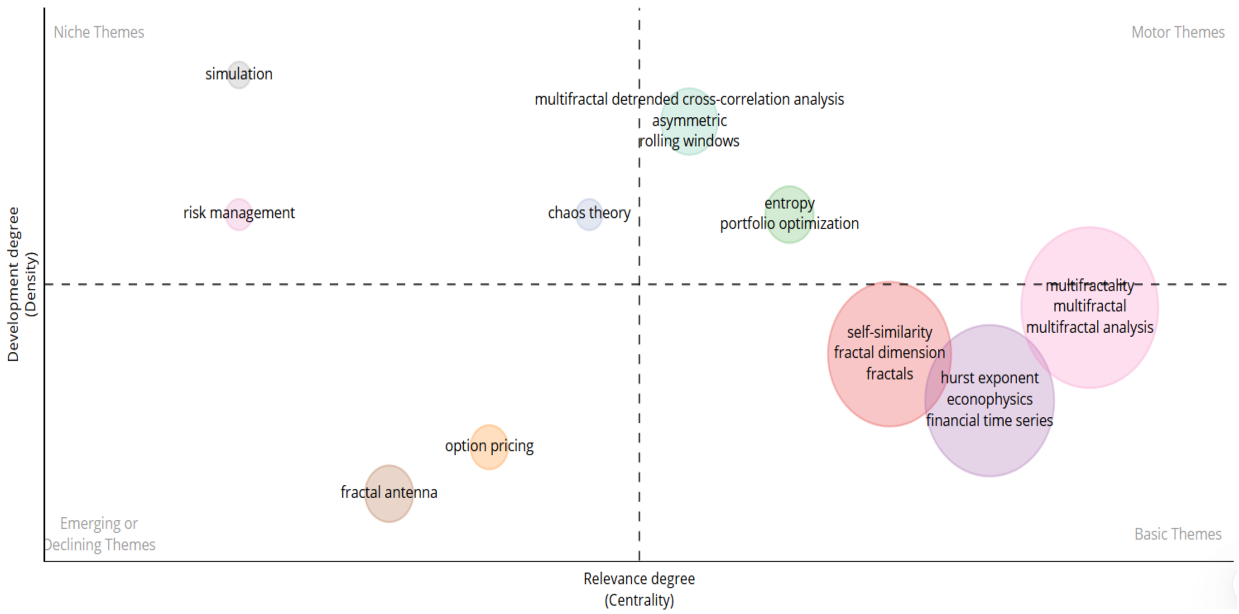

Figure 8. Thematic map

Lastly, the factorial analysis (Figure 9) supports this structure also, indicating a core cluster of applied methods (MF-DFA, cryptocurrencies), a theoretical cluster (EMH, complex systems), and an applied satellite branch (forecasting). With MF-DFA being the dominant method in most of these analyses, it is consistently applied throughout this analysis.

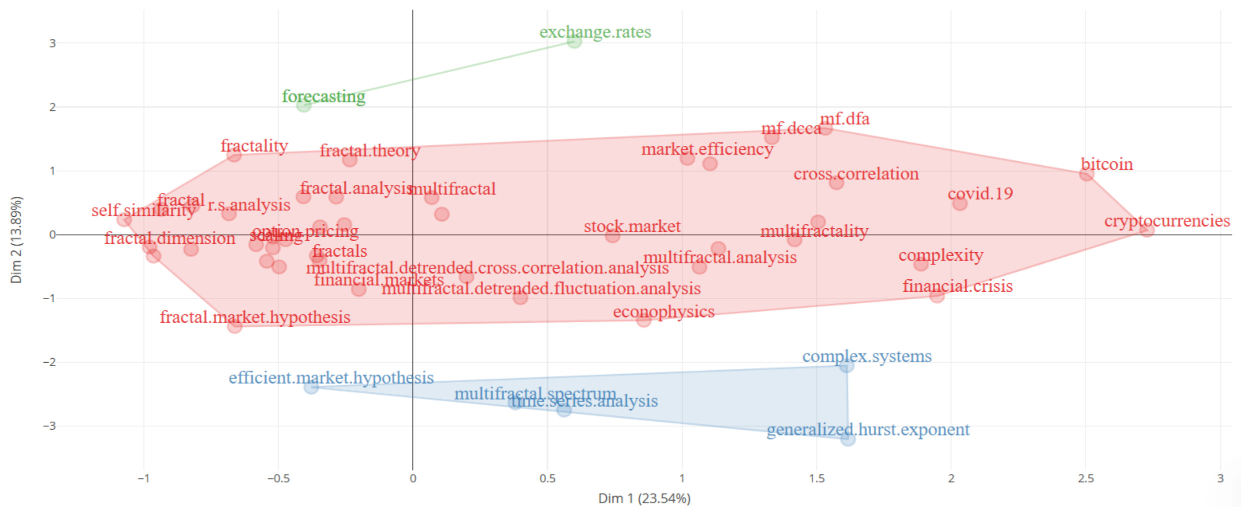

Figure 9. Factorial analysis

RQ4: Based on bibliometric evidence, what knowledge gaps exist, and what future directions are suggested to advance interdisciplinary and applied research in FMH?

Although the bibliometric evidence identified growth in papers that validate FMH, it also showed persistent gaps in our knowledge that must be addressed to move the theory beyond descriptive towards predictive. In the thematic evolution (Figure 7) and cluster analysis (Figure 3), in which we chart changes over time, surveyed studies of crises and cryptocurrencies dominated, but comparative studies between emerging and developed markets remained under-researched. Although research is focused on specific countries, the existing studies fail to generalize the applicability of FMH across economies with varying structures.

Furthermore, the shift toward analyzing systemic shocks (e.g., COVID-19) underscores a second gap; the dynamic impact of these shocks on fractal structures is not fully understood. Most studies are retrospective, limiting their predictive utility. There is a need for real-time, predictive models that can anticipate how fractal patterns will evolve during a crisis.

Lastly, the rise of terms like "deep learning" and "DeFi" suggests yet another gap; there is still a gaping void in practical use, building out trading strategies based on these fractal implications. Although many theoretical models exist, they have not been integrated into machine learning for real-time forecasting and risk management on the ground. Hence, future research should seek to: (1) conduct comparative cross-market analysis; (2) predictive modeling of fractal dynamics in systemic shocks; and (3) hybridization models for actionable financial strategies able to combine fractal indicators with artificial intelligence. Eliminating these gaps will be instrumental in pushing the FMH from a mere descriptive structure to an actual predictive and prescriptive mechanism of current finance.

5. Conclusion and suggestions

This bibliometric analysis provides strong evidence that fractal analysis has been established as an influential paradigm of financial research. Especially noteworthy in this respect has been the development and popularity of multifractal detrended fluctuation analysis (MF-DFA). The identification of multifractality as a motor theme emphasizes not only its methodological importance but also its theoretical role in the approach to long memory and volatility clustering characterizing financial time series (Jiang et al., 2019; Zhou et al., 2024).

The results of our work are in agreement with the previous reviews in economics and complex finance that have acknowledged this failure to describe financial markets from a Gaussian perspective (Peters, 1989; Evertsz, 1995). Recent works indeed have indicated that systemic shocks disrupt the fractal dynamics significantly, which is also in line with our finding on the prominent timescale of inflation, crises and cryptocurrencies in recent literature (Okorie and Lin, 2021; Zhou et al., 2022). On a theoretical basis, the strong multifractality leads to providing empirical evidence against the efficient market hypothesis and strongly supports the fractal market hypothesis (FMH) as a more valid proposition. This validates that market fractality is dynamic, not static, across different investment horizons, and that the observation of investment horizon heterogeneity is the primary motivation of FMH. The amalgamation of fractal methodologies with econophysics, complexity approaches and AI reveals the versatility of the FMH beyond conventional finance.

Fractal research provides useful practical tools from predictive disciplines and applications such as risk management, algorithmic trading, etc. The theoretical rigor of fractal-based systems alongside noise from data and cost-related challenges has limited their real-time applicability in near-scale machine-learning scenarios. Despite the challenges, there is a way forward.

6. Research gaps and future directions

Bibliometric evidence here demonstrates the previous expansion of knowledge, yet also highlights gaps in current understanding. There are several key immediate areas that future work should build on, including:

Systematic comparison of across and between developed, emerging, and frontier markets to test the universality of FMH. These studies are important to detect structural differences in fractal behavior and promote the generalizability of the theory.

Combine fractal indicators with AI using metrics like the Hurst exponent and machine learning, deep learning, and neural networks, allowing for greater predictive power and real-time analysis of dynamic and convoluted movements in the market, which are effectively great in volatile markets such as cryptocurrencies (Kehinde et al., 2023).

Utilizing longitudinal studies of how pandemics, policy changes, and geopolitical events affect fractal market structures to develop predictive models for systemic shocks. Such insights can guide policymakers towards designing more robust market mechanisms.

Real-time applications based on a computationally efficient fractal model with mere insight for algorithmic trading and portfolio optimization. This calls for a reduction in the computational complexity of instruments such as MF-DFA and wavelet analysis to render them practical in high-frequency trading settings (Popovska and Georgieva-Tsaneva, 2024).

The use of fractal finance should also be better defined in different areas, such as cryptocurrencies, DeFi (decentralized finance) and climate-related financial risks. This will elucidate incremental nonlinearities in different levels of market interactions obtained by combining fractal ideas with data science and behavioral economics.

For the first time, this research presents a complete bibliometric analysis of market fractal pattern literature from 1982 to 2025. Identifying trends regarding impactful contributors and the thematic evolution of the field through an analysis of 1,280 Scopus-indexed documents. The results illustrated how remarkably the discipline has diversified when compared to its previous orientation, earlier modelling work and theoretical considerations with current transformational transformations of artificial intelligence/and crisis-influenced subtopologies. The fact that this field of research continues to grow and diversify demonstrates how the fractal market hypothesis remains relevant in its ability to address these complexities within modern financial systems.

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