ANALYZING FINANCIAL MARKETS EFFICIENCY: INSIGHTS FROM A BIBLIOMETRIC AND CONTENT REVIEW

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Abstract
The nonlinear nature of financial data series and the intricate incorporation of data into market prices necessitate a comprehensive exploration of key research findings, prevailing trends, intense debates, and subfields in the market behavior realm. Studies exploring the way in which technical analysis can exploit the deviation from market efficiency in stock markets, based on new prediction techniques (machine learning, deep learning, and artificial intelligence), are lacking. This study presents a comprehensive bibliometric assessment of market behavior using the Scopus database from 1972 to 2022. A thorough assessment process, which included keywords, filters, and data cleaning, was employed to narrow down the literature from 30,551 to 8,289 relevant papers. The research framework delineates seven primary themes that underpin this study: market efficiency, behavioral finance, technical analysis, volatility, fractals, asset pricing, and price discovery. For practitioners, investors, and policymakers, our study presents evidence regarding emerging themes, such as technical analysis, adaptive market hypothesis, and machine learning, which diverges from the findings of the proponents of equilibrium models based on investors' rationality. Moreover, an in-depth inquiry into the role of technical analysis in shaping portfolio investment presents a promising future research avenue.

Keywords
Bibliometric analysis, market efficiency, technical analysis, forecast, machine learning, asset pricing.

JEL Classification
G10, G11, G12, G14

Introduction
Informational efficiency in financial markets has many facets and has been the focus of extensive research for decades. The Efficient Market Hypothesis (EMH), formulated by Fama in 1970, was a significant step toward understanding financial markets'

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informational efficiency; however, it has been criticized in other research streams. The behavioral finance school, Fractal Market Hypothesis, Adaptive Market Hypothesis, and econophysics are examples of the many alternative theories and critical views that have emerged.

Our study follows a two-step strategy. First, it undertakes a bibliometric exploration of the field to identify and create space for a more objective analysis. Second, building upon insights gleaned from information retrieval from titles, abstracts, keywords, and identification of key journals and authors, we meticulously select the most relevant 51 papers for an in-depth analysis.

At least two significant gaps can be identified in the literature. The first gap is related to the way in which technical analysis can exploit deviations from market efficiency in stock markets based on new prediction techniques (machine learning, deep learning, and artificial intelligence). Second, the analysis regarding the consequences of using different technologies in trading (high-frequency trading, algorithmic trading based on evolutionary algorithms for trading rule selection, and portfolio optimization) is currently fragmented; a complete picture is yet to emerge.

This study's research design, based on a bibliometric approach and a close reading of the relevant literature, helps us answer questions regarding the evolution of the field, the most influential and productive authors and journals, the trending topics, thematic mapping, and the field's intellectual landscape. Thus, a bibliometric analysis provides a rigorous and objective approach to mapping scientific production based on statistical measures in the field of interest (Aria and Cuccurullo, 2017, p.959; Donthu et al., 2021, p.285) . However, applying machine learning models to the bibliometric approach forms a pivotal element of our second strategy, facilitating the systematic selection of the most pertinent papers based on objectivity. The resulting selection, when scrutinized in depth, offers insights into various aspects, including the types of data employed and methodologies utilized in the identified pivotal papers.

Our study makes several contributions to the existing literature: (i) it is the sole research endeavor examining informational efficiency across the entire market; (ii) it applies a two-step methodology, applying a quantitative method (bibliometric) and expert judgment analysis stemming from the comprehensive literature review; and (iii) it paves the way for an emergent research trajectory regarding informational efficiency in the market.

The rest of the paper is organized as follows: Section 1 presents the review of scientific literature regarding bibliometric studies on the subject; Section 2 describes research design and methodology; Section 3 delves into results and discussions; Section 4 conducts an in-depth content analysis of the most influential papers; and finally, section 5 encapsulates concluding remarks, study limitations, and future research direction.

1. Review of the scientific literature

Recent bibliometric studies have identified topics closely associated with or integral to informational efficiency in markets. Behavioral finance—encompassing extensive analyses of investor sentiment and sentiment analysis, market microstructures, asset price predictions, and stock forecasts—has emerged within this domain. Hence, this subject's intricate nature and extensive research history emphasize the significance and need for a study that systematically maps the principal themes, subthemes, literature gaps, and future research avenues in this field as a whole.

Within the behavioral finance realm, several bibliometric studies on informational efficiency have been identified. For example, bibliometric analyses extensively scrutinize themes, such as investor sentiment or sentiment analysis, reflecting their connection with informational efficiency in the market. Notable authors in this realm include López-Cabarcos et al. (2020); Bagane et al. (2021); Garg and Tiwari (2021); Kamath et al. (2022); Kamath, S. Shenoy and Kumar N. (2022);. Further, Paule-Vianez, Gómez-Martínez and Prado-Román (2020) significantly contributed by depicting 13 themes associated, to varying extents, with informational efficiency.

Tripathi, Vipul and Dixit (2020) examine other pertinent subjects, employing bibliometric techniques to systematically review the literature concerning market microstructure and its implications for market efficiency. Akram, RamaKrishnan and Naveed (2021) examined stock manipulation, while Ali and Bashir (2021) noteworthy bibliometric study addressed asset pricing. An expanding body of work also centers on stock prediction using machine learning or other artificial intelligence models, with contributions from Janková (2021), Tupe-Waghmare (2021), Ahmed et al. (2022), and Kumbure et al. (2022). Our study employs the same methodology as that of Paule-Vianez, Gómez-Martínez and Prado-Román (2020) to identify the themes that encompass behavioral finance, with a distinct focus on studying informational efficiency holistically and a content review of the most influential papers. Contrarily, other studies delve into themes or subthemes of informational efficiency, albeit not in their entirety.

2. Research methodology

The study systematically explored the Scopus database, widely recognized as one of the most comprehensive databases for peer-reviewed social science papers. Scopus is better suited than the Web of Science for quantitative analyses, including bibliometric investigations (Bartol et al., 2014, p.1502). Moreover, combining searches from two databases (e.g., Web of Science and Scopus) can introduce variations in the analysis results (Baker, Kumar and Pattnaik, 2020, p.8; Donthu et al., 2021, p.293). Additionally, Scopus provides detailed bibliometric data, unlike Google Scholar, and ensures the exclusion of predatory journals (Paul et al., 2021, p.8).

The foundation of our search for relevant papers is a set of keywords that accurately and comprehensively characterizes our research topic. The examination of the related literature largely drove the keyword selection process. As such, the final keyword list was compiled based on an extensive literature review and was organized into two categories. The first group encompasses keywords linked to market efficiency references: “efficient market hypothesis,” “informational *efficiency,” and “market *efficiency.” The second group centers around the concepts that criticize or exploit informational inefficiency: “criti*” and “*efficient market”; “adaptive market*”; “fractal*” and “financial market*”; “behavioral finance”; and “stylized facts” and “technical analysis.”

Following the first round of the Scopus database inquiry in December 2022, we collected 30,551 articles. We applied several filters in the second round of queries to refine our dataset and enhance focus on our topic. Initially, we narrowed our scope solely to subjects related to the stock market by using the following words: “stock market*,” “financial market*,” “equity market*,” “capital market*,” “stock*,” or “equit*.” Furthermore, for our search, we relied solely on journal-published articles because these can be regarded as “certified knowledge” (Ramos-Rodríguez and Ruíz-Navarro, 2004, p.982). We also restricted our search to publications in English, considered as a *lingua franca* in science and international business (Rogerson-Revell, 2007, p.103; Cullen, 2017, p.437). Interestingly, applying additional data cleaning measures, such as removing duplicates and excluding papers not related to the research topic, yielded a database containing 25,170 papers.

To further refine our sample to the most germane scientific output, we applied a Bradford filter, based on Bradford law, which led to the final database of 8,289 papers (Handro, 2023) published between 1972 and 2022. Bradford law (Bradford, 1934) suggests that information is concentrated in core journals. Specifically, only a few journals contribute significantly to the field and are considered core sources with high productivity on the subject. The law can be described using formulas, such as 1:n:n^2, meaning that the number of articles is sorted into three groups, and consequently, the number of journals is proportional to the formula mentioned.

The total number of authors contributing to this scientific production was 11,240, with 1,334 being sole authors. Of the 8,289 papers, 1,630 were single-authored, while the remaining 6,659 involved multiple authors. The average number of co-authors per paper was 2.41. The papers spanned across 44 journals, encompassing 259,818 references cumulatively. For analysis and data visualization, we employed the bibliometrix R package developed by Aria and Cuccurullo (2017).

3. Results and discussions: Bibliometric analysis

3.1 Evolutionary approach to the field

Our initial examination of the dataset provides insights into informational efficiency's evolutionary trajectory in the market. The results reveal sustained scientific production in the intervals following 2000 (Figure 1). Notably, a discernible upsurge in scientific output becomes evident after the two major crises of the 2000s (the dot-com bubble and global financial crisis). The modern era, characterized by heightened communication and periodic crises, has intensified the debate on informational efficiency and price formation mechanisms. Additionally, since 2010, this topic has consistently garnered notable interest within the scientific community.

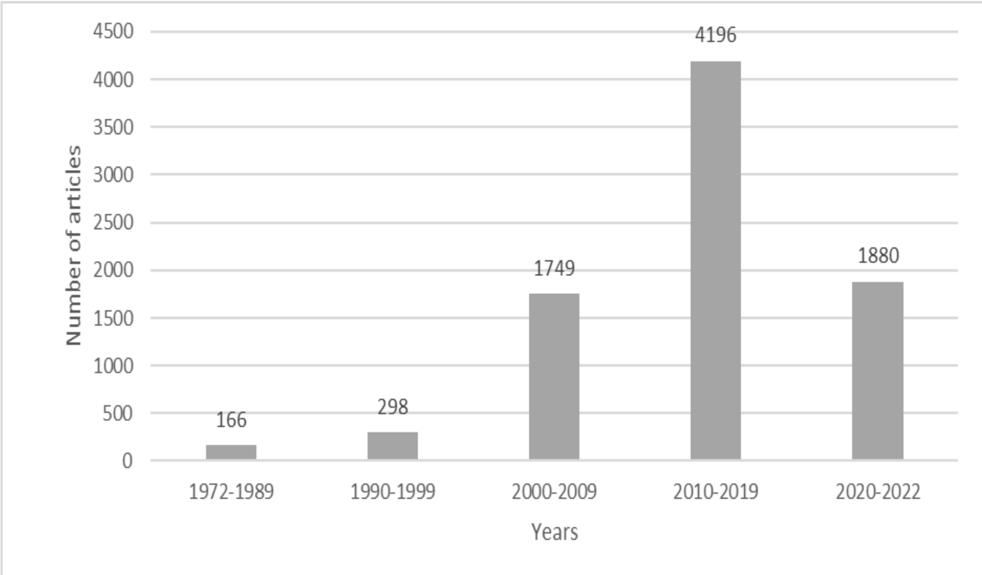

Figure no. 1: Annual publication by year (1972–2022). Data were analyzed with bibliometrix package.

Source: Authors' own computation based on Biblioshiny.

A pivotal aspect of our evolutionary investigation entails scrutinizing citation patterns in the domain. Despite the relatively lower scholarly output in 1972–1989 and 1990–1999, the most cited writings were created during these periods. Notably, three pivotal works experienced peak citations since 1976, all of which were published in the *Journal of Financial Economics*. First, "The pricing of commodity contracts" by Black (1976) provides important evidence for understanding the role of future contracts, forward contracts, and commodity option prices in risk management, portfolio diversification, and informational efficiency in the markets. Second, "The option pricing model and the risk factor of stock," by Galai and Masulis (1976) aims to enhance the understanding of stock prices by combining the option prices model with the capital asset pricing model (CAPM). Third, "Capital market seasonality: The case of stock returns" by Rozeff and Kinney Jr. (1976) provides empirical evidence for seasonality in monthly stock returns, discusses this phenomenon's statistical significance, and explores its implications for the CAPM, market efficiency, and other related theories. As early research in the field—and by exploring different subjects, such as risk management and derivatives, the integration of option pricing models with the CAPM, and the presence of seasonality in stock returns—these studies reveal essential insights for understanding how financial markets operate and whether they conform to the market efficiency principle.

As Figure 2 illustrates, prominent peaks in the number of citations occurred in 1981, 1985, 1992, and 1993, owing to several significant contributions. Banz's (1981) work in

"The relationship between return and market value of common stocks," published in the *Journal of Financial Economics* provides evidence about the questionable relation between size effect and the CAPM, highlighting a potential limitation or misspecification of the CAPM, leaving room for further research. De Bondt and Thaler's (1985) investigation in "Does the stock market overreact?"—published in the *Journal of Finance*—raises questions regarding investors' rationality. Bollerslev, Chou and Kroner (1992) comprehensive review in "ARCH modeling in finance: A review of the theory and empirical evidence," published in the *Journal of Econometrics*, enriches the field of finance by reviewing statistical models that help improve predictions for better financial decision-making. Fama and French's (1992) seminal work, "The cross-section of expected stock returns," published in the *Journal of Finance*, focuses on identifying key variables that can explain variations in stock returns. They conclude that factors like size and book-to-market equity play a crucial role in understanding why some stocks perform better or worse than others. Fama and French's (1993) exploration in "Common risk factors in the returns on stocks and bonds," published in the *Journal of Financial Economics*, depicts the cross-asset relationship; challenges traditional models, like the CAPM; and acknowledges that risk factors, such as the overall market size and book-to-market equity, can influence stock returns and maturity, and that default risk can influence bond returns. Jegadeesh and Titman's (1993) pioneering analysis, "Returns to buying winners and selling losers: implications for stock market efficiency," published in the *Journal of Finance*, provides evidence that, on the short horizon, winner or loser stocks in the past can show some predictable direction in the future.

Overall, Fama and French (1992, 1993) add more context to market efficiency's multifaced nature, by introducing new factors in their models and explanations. However, from the mid-1980s, different research streams emerged, opening discussions about market efficiency and investor behavior, as well as providing new statistical models that provide fresh insights.

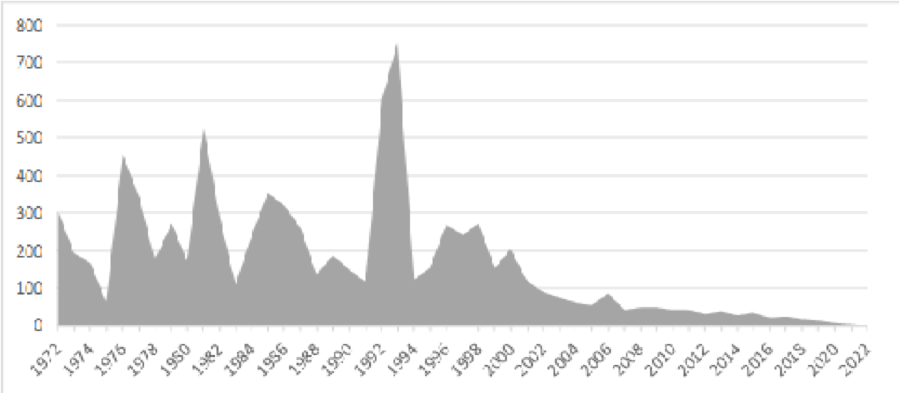

Figure no. 2: Average number of citations per year.
Source: Authors' own computation based on Biblioshiny

3.2 Most influential authors

Our bibliometric study identified the most influential authors based on the number of citations and a range of other metrics, such as *h*-index, *g*-index, and *m*-index. The *m*-index, introduced by Hirsch (2005), measures an author's productivity and the impact of their research, considering both the quantity and quality of their publications. Analogously, the *g*-index (Egghe, 2006) considers the number of citations garnered by the most highly cited papers. Specifically, the *m*-index is calculated as the ratio of the *h*-index of an individual researcher to the number of years of their scientific activity. Furthermore, article fractionalization measures the number of authors contributing to a single article.

According to our bibliometric analysis of 25 authors with the most citations, Fama EF and French KR are the most highly cited authors (Table 1). Although the former received significantly more citations than the latter (14,554 versus 12,726), most of their papers are co-authored. Their research has significantly impacted the finance field and is highly regarded by fellow researchers. Harvey CR secures the third position in our dataset. Although his citation count (5,833) trails behind that of the first two authors, his contributions bear weight and position him as a prominent contributor within the field. Other authors, such as Subrahmanyam A and Chordia T, have received relatively low levels of citations; however, this could be because their research endeavors commenced later than those of their contemporaries.

Conversely, a closer inspection of our data reveals *h*-index values between 7 and 19 and years from the first publication ranging from 1976 to 2016. In this context, introducing new metrics, such as the *m*-index (*h*-index divided by career duration from our dataset), can provide a more accurate picture of the most influential authors. Although Fama EF and French KR received a high citation number and a high *h*-index value, comparing these values vis-à-vis time shows lower *m*-index values (0.404 and 0.432) relative to those for other more recent authors, such as Plastun A and Zaremba A, or Urquhart A, who display values above 1. In summary, this difference indicates that although some classical authors have a higher *h*-index relative to their career duration, they are not as productive or influential as newer researchers.

3.3 Authors with prolific output

Following Zabavnik and Verbič's (2021) methodology, we analyzed authors' productivity using our datasets. Leveraging the capabilities of bibliometrix, Figure 3 provides a visual representation of authors' productivity over time. The lines in the figure denote the research activity durations, while the bubbles and color density correspond to the number of articles and citations for each author per year, respectively.

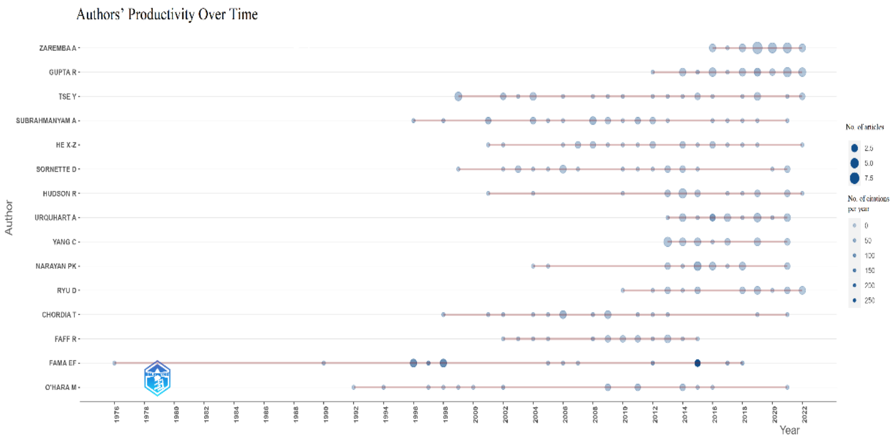

Figure no. 3: Authors' Productivity Over Time
Source: Authors' own computation based on Biblioshiny

Fama EF, one of the most productive authors in the sample, appears to have had a consistent presence in the field since 1976. Notably, the number of publications fluctuates from year to year, with some years having slightly lower or higher numbers of publications than others. A discernible upward trajectory in scientific output over time is evident, with a pronounced surge commencing around 2013. This upward trend aligns with other prolific researchers' contributions, including Tse Y, Gupta R, Subrahmanyam A, and Zaremba A, who have substantively enriched the field with numerous publications.

3.4 Most relevant sources

In this section, we identify the most significant journals that have published and shaped research directions and knowledge dissemination regarding informational efficiency in markets. Our scrutiny encompasses journals that have not only published a substantial number of papers but also accrued considerable citations.

Figure 4 illustrates the top five journals by publication count in this field. Remarkably, these journals have exhibited a sustained upward trajectory in article numbers over the last two decades, a surge that has intensified significantly in the last three years. Notably, *Physica A: Statistical Mechanics and its Applications* stands out for its remarkable growth rate since 2006, an ascent that has continued. This swift progression in the journal's prominence may be attributed to an increasing interest in topics encompassing mathematical and statistical models that consider the decryption of complex systems, the study of nonlinear data systems, and the analysis of transitional and critical phenomena to measure participants' behavior in financial markets.

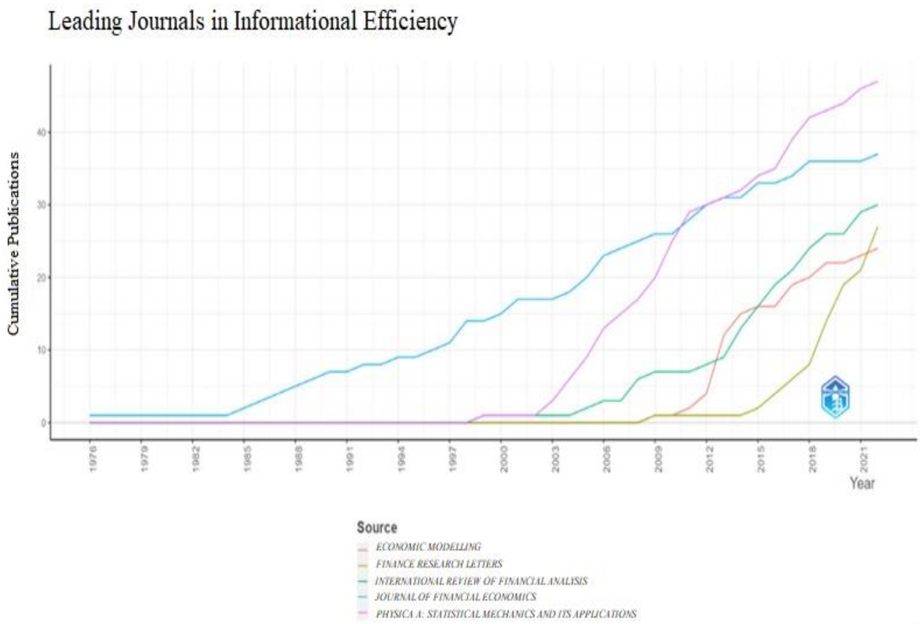

Figure no. 4: Leading journals in informational efficiency research.
Source: Authors' own computation based on Biblioshiny

Additionally, we examined the top five academic journals' performance based on their *h*-index, *g*-index, total number of citations, and commencement year. An analysis of the data from Table 2 indicates that the *Journal of Financial Economics* has the highest *h*-index, but regarding the *g*-index and *m*-index, the second-ranked journal from our sample, *Physica A: Statistical Mechanics and its Applications*, performs better, confirming the trend mentioned earlier. Considering journal age, *Finance Research*

Letters seems to be another important player in this field, registering an *m*-index of 0.933, an *h*-index of 14, and a *g*-index of 27, indicating that the latest papers had significantly higher numbers of citations.

3.5 Trending topics

One of the advantages of employing bibliometric methods lies in their capacity to identify trending topics and create thematic maps using advanced techniques. In this section, we use authors' keywords, which are words or phrases used by researchers to underline the content of their papers and identify core topics and themes. In bibliometric techniques, authors' keywords are as effective as keywords in examining the studied field's knowledge base (Zhang et al., 2016). This approach provides additional insights into understanding the trending topics and themes (Donthu et al., 2021) and the architecture of the relationships between different topics and themes.

Our analysis of authors' keywords shows an upsurge in papers over the last three years focusing on subjects, such as “COVID-19,” “machine learning,” “cryptocurrency,” “bitcoin,” and “deep learning” (Figure 5). Conversely, in reference to the more recent trending topics, the keywords representing subjects related to “cointegration,” “exchange rates,” and “learning” have the most continuous and long-lasting usage in our sample. The enduring usage of “cointegration” shows the scientific community's constant exploration of the interdependency between diverse asset classes or markets and how information is incorporated into the price formation mechanism.

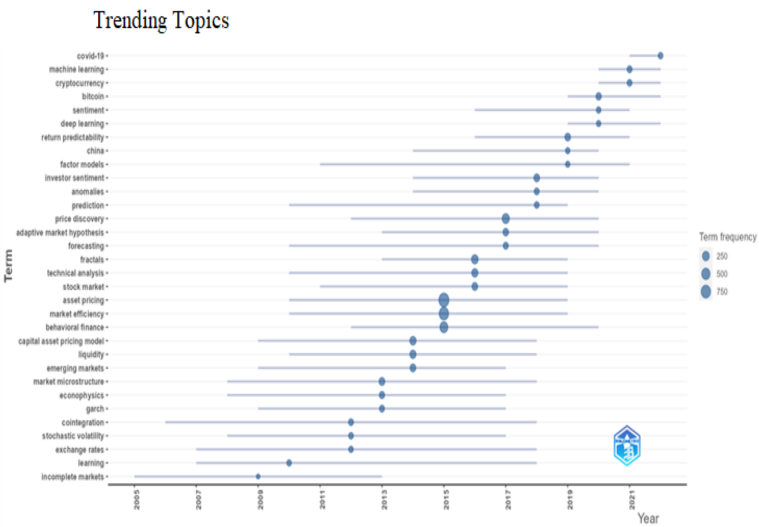

Figure no. 5: Trending topics based on authors' keywords.
Source: Authors' own computation based on Biblioshiny

The keyword “learning” appears frequently in our sample and may be related to informational efficiency in several ways. For example, reinforcement learning and least-squares learning are algorithms that can analyze financial data and identify patterns or trends relevant for understanding market efficiency. Other terms, such as “technical trading” and “technical analysis,” which also appear in our sample, are strategies that may be used to speculate short-term market mispricing and may also suggest market inefficiencies.

A lower frequency of published papers and a relatively extensive range of publication years are displayed by keywords such as “market microstructure,” “factor models,” and “forecasting.” Most papers were published between 2008 and 2021. Among other topics, “behavioral finance,” “asset pricing,” and “market efficiency” have appeared in papers across several years, with peaks in 2015. These themes have been observed in the literature for approximately 8 to 9 years, although their popularity has recently dwindled, notably since 2020.

3.6 Thematic map

In this subsection, we evaluate the main themes of informational efficiency based on a clustering process using a simple center algorithm that automatically labels clusters (Cobo et al., 2011). The simple center algorithm produces networks through a dual-pass approach, adding internal and external links (Coulter, Monarch and Konda, 1998, p.1209). Additionally, following the procedure outlined by Callon, Courtial and Laville (1991), we use a strategic diagram (Figure 6) to visually represent different thematic clusters based on the most frequently used keywords. The diagram uses the concepts of centrality and density to provide a simplified representation of the network morphology, offering insights into the network's structure and behavior. Centrality measures a cluster's importance and strategic position within a network, based on the strength of its links with other clusters. In the strategic diagram, the centrality and significance of a research theme are represented on the x-axis. Density measures the strength of the links inside the clusters and provides information on how tightly they are connected. The y-axis represents the density or evolution of a theme.

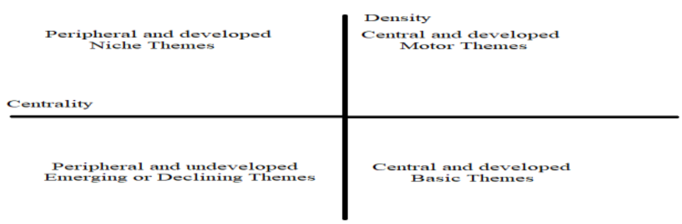

Figure no. 6: Strategic diagram.

Source: Authors' adaptation of Callon, Courtial and Laville 's (1991) procedure

The diagram classifies clusters into four themes (niche, motor, emerging or declining, and basic) and four general categories. The clusters located in the diagram's upper-right quadrant hold a strategic position within the research field, signifying the mainstream research in recent years. These clusters have been thoroughly analyzed by a well-regarded group of researchers, concluding that central and advanced topics correspond to the motor theme. The second category of clusters resides in the lower-right quadrant, characterized by high centrality due to strong inter-cluster connections, but low intra-cluster connections, indicating a lower development level. Clusters located in this quadrant align with the basic theme. The top-left corner represents high density and low centrality, embodying clusters formed around peripheral and developed niche themes. The fourth category of clusters, located in the lower-left quadrant, pertains to emerging or declining themes. These clusters exhibit low centrality and density, suggesting their evolving nature or waning relevance within the field.

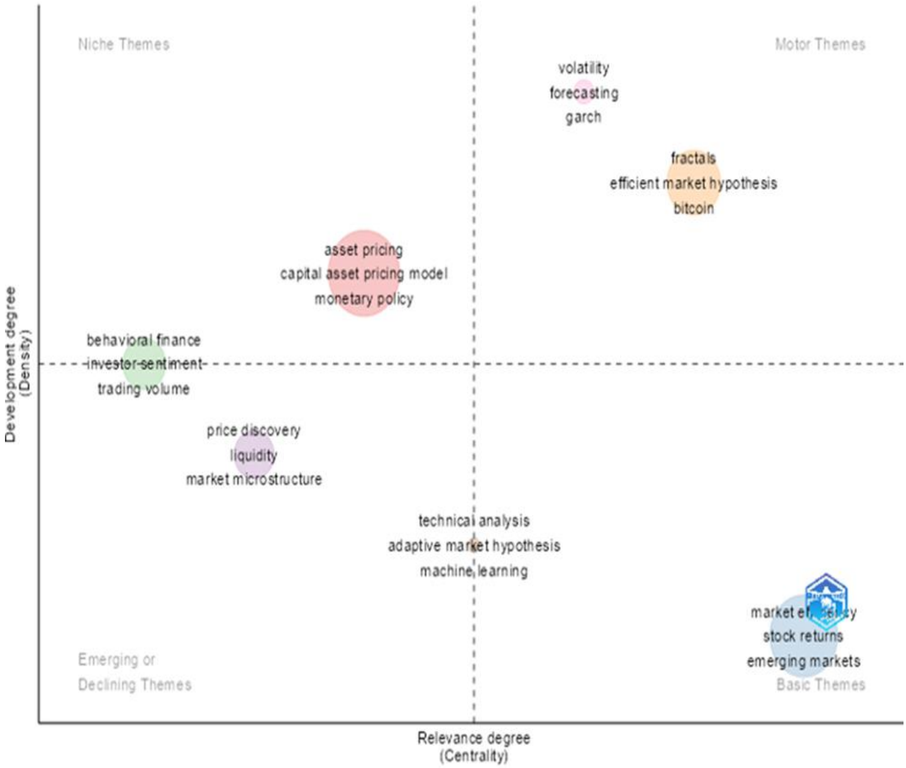

Figure no. 7: Thematic map

Source: Authors' own computation based on Biblioshiny

To further elaborate on the strategic diagram, we created a thematic map to understand the clusters using network analysis of keywords; this was to identify and evaluate the central-theme studies on informational efficiency. Using the capabilities of Biblioshiny, from 12,968 authors' keywords, we selected the 1,000 most frequent words, with the minimum frequency threshold set to five times per thousand documents. Additionally, the labels used to annotate the clusters in the network were set to three and were the first three keywords with the highest occurrence in each cluster. The label size was set to a threshold of 0.3, indicating that the label required at least 30% of the total number of nodes in the network to be valid. For clustering, we used the Louvain algorithm (Blondel et al., 2008), with the community repulsion parameter set to 1, for better separation and reduction of the overlap between communities. The outcome revealed seven distinct clusters: asset pricing, market efficiency, behavioral finance, price discovery, fractals, technical analysis, and volatility (Figure 7).

Following the theme identification, we assessed each theme's development level and impact on the field. The themes were organized in a strategic diagram based on their centrality and density. The "fractals" and "volatility" clusters in the diagram emerge as motor themes, displaying high interconnectivity and development. The "fractals" cluster shows that research interest in the fractal nature of financial markets and their behavior was captured. This cluster's second and third most frequent keywords are "efficient market hypothesis," with 108 occurrences, and "bitcoin," with 91 occurrences, respectively. The connection between these keywords suggests intense research interest in the fractal nature of financial markets, technological innovation in markets, and how information is reflected in prices.

"Volatility" is the second cluster located in the motor theme quadrant. Along with "volatility" which has the highest occurrences (132), other frequently occurring keywords include "forecasting," "GARCH," "implied volatility," and "stochastic volatility." The combination and association of these keywords may reflect intense research interest in developing models and methods for predicting and analyzing stock market volatility. Moreover, the appearance of "informational efficiency" in this cluster indicates research interest in understanding how efficiently the stock market processes and incorporates volatility-related information.

The second quadrant accommodates basic and transversal themes with high centrality (connection with other clusters) but low density (low intra-cluster connection). The cluster, labeled as "market efficiency" in our thematic map, seems to be a well-defined research area focusing on understanding financial market efficiency, particularly concerning the predictability of "stock returns" (126) and the existence of "momentum" (107) and "anomalies" (66), which represent other keywords from the cluster. The high number of occurrences (763) for the term "market efficiency" indicates that this topic is widely studied. The presence of terms, such as "emerging markets" (124) and "event study" (51), hints that the research in this area extends beyond developed economies and includes an interest in understanding the impact of events on market efficiency in different contexts. However, the relatively low occurrence of other keywords in this cluster suggests that there is room for further research. Additionally, the fact that this cluster has high centrality but low density indicates a well-connected theme with other research areas. However, this cluster may have less collaboration or overlap between authors.

The third quadrant contains two clusters that harbor well-established themes peripheral to our central theme—informational efficiency in markets. The first cluster, labeled as "asset pricing" (947), also contains other keywords related to asset pricing models, such as the "capital asset pricing model" (180), indicating a primary focus on pricing financial assets. Moreover, keywords such as "equity premium" (61), "risk aversion" (48), and "risk premium" (42) may suggest an exploration of risk-return relationships in financial markets. The presence of keywords such as “learning” (45) and “heterogeneous beliefs” (44) implies investigation into how financial market agents form expectations and make decisions. The keyword “monetary policy” appears with a moderate frequency (88), suggesting some degree of research interest in how monetary policy affects asset price formation.

The last quadrant comprises two clusters of emerging themes. The first cluster in the fourth quadrant, the “price discovery” theme, dominates the cluster with 309 occurrences. Other keywords that populate the cluster, such as “liquidity” (159), “market microstructure” (127), and “cointegration” (64), delve into price formation mechanisms, particularly the interplay of market participants in processing new information and buyer–seller dynamics. Moreover, keywords such as “exchange rates” (46) and “high-frequency data” (43) also indicate a focus on the role of information technology and data analysis in the price discovery process. The second cluster in the fourth quadrant is dominated by the “technical analysis” theme with 168 occurrences. Additional related keywords such as “adaptive market hypothesis” (106), “machine learning” (68), and “prediction” (54) indicate that this cluster is centered on using quantitative techniques and algorithms to predict future market trends and identify profitable trading opportunities. Furthermore, the “adaptive market hypothesis” keyword also suggests an interest in the idea that financial markets are dynamic and necessitate adaptable trading strategies.

Overall, with the advent of new processing capacities and machine learning algorithms, themes such as technical analysis are poised to evolve further, attracting more research attention and resources.

3.7 The field's intellectual landscape

Next, we showcase the field's intellectual landscape by analyzing the co-citation network. Co-citation analysis aims to identify the patterns of relationships and influences among scientific papers based on their citation frequency (Small, 1973, p.265). Additionally, co-citation analysis suggests that frequently cited papers are likely to share similar or related content (Zupic and Čater, 2015, p.434). The co-citation method enables us to identify seminal papers that have significantly impacted the research field and its developmental growth owing to their influential contributions. The co-citation analysis results reveal three distinct groups of frequently cited references (Figure 8). These are likely to be the most influential references in the field based on their co-citation frequency. Fama's seminal work dominates the red cluster. For example, “Common risk factors in the returns on stocks and bonds,” co-authored by Fama and French (1993), holds the highest co-citation count, accompanied by other papers authored by Fama (1973, 1992, 1996, 2015), which dominate the cluster. Additionally, papers such as “On persistence in mutual fund performance” by Carhart (1997) and “Illiquidity and stock returns: cross-section and time-series effects” by Amihud (2002) are also relevant in the field. All these studies explore the factors that may influence stock returns and have implications for stock market efficiency. Moreover, Amihud (2002) examines the relationship between stock returns and liquidity, while Carhart (1997) explores mutual funds' performance persistence over different time zones.

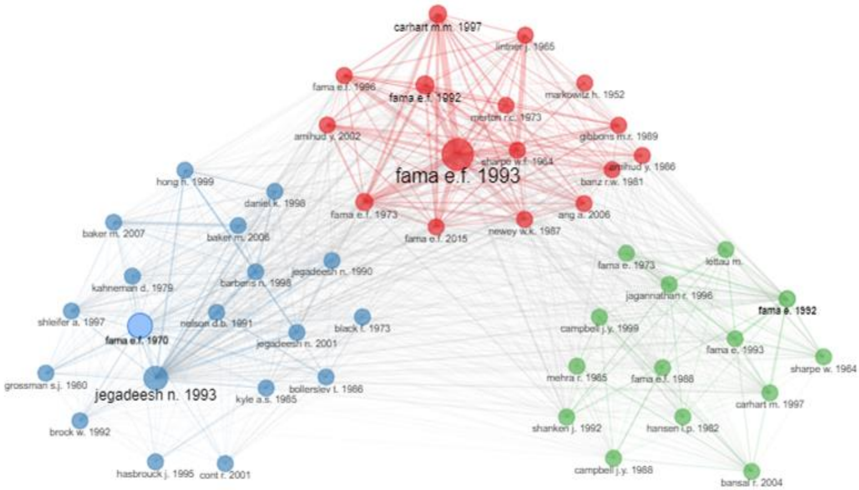

Figure no. 8: Co-citation network that examines informational efficiency.
Source: Authors' own computation based on Biblioshiny

In Figure 8, the blue cluster contains studies that significantly shaped the field of finance, particularly concerning market efficiency. Fama's (1970) seminal work, "Efficient capital markets: a review of theory and empirical work" is the cornerstone of informational efficiency in financial markets. This study introduces three forms of efficiency: weak, strong, and semi-strong. Additionally, another essential paper in this cluster is "Returns to buying winners and selling losers: implications for stock market efficiency," by Jegadeesh and Titman (1993). This study documents a phenomenon where in the short term (3–12 months), buying past winning stocks produces returns, and conversely, selling stocks that performed poorly in the past protects returns; notably, the profit accumulated by the winning stocks is erased in the longer horizon (2–3 years). Black and Scholes's (1973) study on the pricing of options and corporate liabilities develops a theoretical model for pricing financial options and tests it using data on options prices. Their empirical tests reveal systematic variation between the actual prices of options and the values predicted by the formula. Despite this mispricing, the transaction costs in options markets create a challenge for speculators to capitalize on. Kyle's (1985) study on continuous auctions and insider trading investigates the impact of insider trading on market efficiency and liquidity, and the impact of market structure on insiders' ability to profit from their insider information.

The blue cluster also hosts studies utilizing statistical analysis and empirical data to examine asset returns' properties. Bollerslev's (1986) study of generalized autoregressive conditional heteroskedasticity (GARCH) uses data on asset returns to develop a model to analyze asset price volatility over time. Similarly, Nelson's (1991) study on conditional heteroskedasticity in asset returns uses data to examine the relationship between volatility and various factors, such as market level, firm size, and firm industry membership.

Studies that explore the impact of investor sentiment on financial asset prices are also included in this cluster. In this context, Baker and Wurgler (2006), Barberis, Shleifer and Vishny, (1998) and Daniel, Hirshleifer and Subrahmanyam, (1998), who use statistical analyses and empirical data to examine the connection between market participants' sentiment and asset price evolution, are among the most influential studies. These studies contribute significantly to estimating investor sentiment and psychology's influence on financial markets.

The green cluster centers around Fama and French's (1988) pivotal study, where the authors propose a new method for decomposing the returns of financial assets into “permanent” and “temporary” components. This decomposition aids in unraveling the underlying factors that drive asset prices. Other key contributions from this cluster include studies by Campbell and Cochrane (1999) and Bansal and Yaron (2004). The former's findings hint at consumption habits' influence on stock market behavior, while the latter posits that the disparity between predicted and observed financial asset returns could arise from investors potentially not fully understanding or appreciating the risks associated with long-term investments. Additional clusters converge around studies by Fama and MacBeth (1973), Fama and French (1992, 1993), and Sharpe (1964). These studies analyze the role of risk in financial markets and its effects on financial asset prices.

The co-citation analysis results reveal three distinct groups of references that are commonly cited together, indicating their influential status within the field. These studies span diverse themes, including market risk and size risk, market efficiency forms, investor sentiment, asset returns' properties based on statistical methods, and the decomposition of returns into permanent and temporary components. Moreover, these studies have contributed to a better understanding of financial markets and how various factors, such as investor sentiment and market structure, can impact market efficiency and liquidity.

4. Results and discussions: In-depth reading

In this section, we analyze, in depth, the most relevant papers in the field. To create our dataset, we applied techniques previously used by other researchers (e.g.,Zabavnik and Verbič, 2021). This approach led us to select 51 papers (Table 3) based on their highest citation count per year. By applying this filter, we included both earlier and recent influential studies (Ahmad et al., 2020, p.12). The resulting sample was examined from several perspectives: chronologically and thematically, authors' data and methodologies, and their key contributions to the existing knowledge within this field.

Organizing our selection in ascending order of publication year revealed that more than half of the most influential papers—27 out of 51—were published between 2011 and 2021. The remaining 24 papers were published over 28 years, between 1981 and 2009. This suggests noteworthy advancements in the field in recent years, affirming our evolutionary analysis. It also underscores the enduring impact of previous research and the continued relevance of earlier findings.

Interestingly, most of the highly cited papers from our sample focus on fundamental indicators, market risk, and price statistics of stocks (bid-ask, returns based on open-price, and close-price), reaffirming the predilection of academics around the EMH. Moreover, owing to Eugene Fama's extensive academic career, as seen in Subsection 3.3, his papers are present both in the first and second parts of our sample (five and four papers, respectively), denoting a monopolization of the academic community more around fundamental factors and less around the technicality of security prices.

As the first literature stream that challenges Fama's theory, behavioral economics is present in our sample starting from 1985, with De Bondt and Thaler's (1985). Their seminal paper regarding market participants' overreaction to news, or other unexpected events, emphasizes investors' irrationality and highlights the so-called overreaction hypothesis, tested by the authors. The second pivotal paper from our sample pertaining to the behavioral stream is Baker and Wurgler's (2006) paper. This paper contradicts the classical view and provides some evidence for investor sentiment playing a role in determining price movements. Similarly, Hirshleifer (2001) considers that, besides only considering risk, a new approach should consider behavioral and psychological factors. Furthermore, Coval and Moskowitz's (1999) study explores investment managers' biases, concluding that they prefer to choose stocks based on distance (usually opting for companies closer to their location) and the number of small, highly leveraged firms in the area, which contradicts the investors' rationality hypothesis. In addition, a new approach to choosing stocks may be influenced by social, environmental, and governance responsibility goals: Renneboog, Ter Horst and Zhang, (2008) show that companies that follow environmental and social governance experience superior flows of funds and provide superior, abnormal returns.

The older part of our sample includes important authors whose work underpins the two clusters from the thematic map and is also visible in our field's intellectual landscape. Bollerslev, Chou and Kroner (1992), drawing from the work of Bollerslev (1986) and Engle (1982), conduct a thorough survey of auto-regressive, heteroscedastic family model evolution, emphasizing the importance of using accurate models in forecasting volatility, also considering the stylized facts from the financial time series. Moreover, Cont's (2001) provides important clarification regarding the properties of data from financial time series, the so-called stylized statistical facts, proving deviation occurs from linearity in the financial data.

These examples are in line with the results from the thematic maps that characterize the behavioral and sentimental analysis at the border of emerging themes and niche themes, which means that emerging themes need scholarly attention and niche themes require additional connections with other themes from the strategic map. Moreover, volatility, forecasting, and GARCH are included in the thematic map, positioned in the upper right quadrant, signifying the mainstream research in recent years.

The second part of the sample covers the period from 2011 to 2022 and presents a different type of focus. Eugene Fama's work appears here as well, but other valuable themes are the focus of the papers. In this period, the rise of a new asset class (i.e., cryptocurrency, namely, bitcoin) attracted attention in the academic space. In this regard, Urquhart (2016), Bariviera (2017) and Nadarajah and Chu (2017) depict bitcoin inefficiencies. Moreover, we find some new subjects regarding political uncertainty and its impact on the stock market. Pástor and Veronesi (2012) develop an asset pricing model to analyze political uncertainty's effects on stock prices through the lens of a general equilibrium model of government policy choice. Brogaard and Detzel (2015) develop a more elaborate model to capture economic policy uncertainty in the United States and to forecast and understand market returns, based on a combination of market data (index evolution with and without dividends), business cycle variables, and sentiments from the news. A new approach concerning sentiments that can influence stock movement is presented by Da, Engelberg and Gao, (2015), who construct an index of sentiments based on household internet searches. Their study presents consistency in predicting an increase in volatility, short-term return reversals, and flows from high-risk asset class funds to lower-risk asset funds.

Among the most cited papers from our sample are Gu, Kelly and Xiu, (2020), Cao, Li and Li, (2019), and Kim and Won (2018). The first summarizes the literature on machine learning used in prediction models and demonstrates a larger profit for investors based on machine learning forecasting, which outperforms regression-based models from the literature. The second uses two hybrid models, based on machine learning techniques, that produce improved prediction results in the short term, compared with other models. The third uses machine learning and multiple GARCH-type models to forecast volatility. Patel et al. (2015) use more complex models, with two methods for data input: (1) based on raw statistical price data and (2) based on technical analysis indicators. The experiment results show that prediction models outperform technical indicator models. Another stream explores market microstructure topics by analyzing high-frequency trading with price discovery and efficiency Brogaard, Hendershott and Riordan, (2014); Hendershott, Jones and Menkveld, (2011) provide empirical evidence regarding the contribution of algorithmic trading to (1) improving liquidity and (2) increasing the informativeness of buying and selling quotes.

A major shift in this part of our sample is reflected by the emergence of more sophisticated models based on new soft computing techniques. Machine learning, deep learning, evolutionary algorithms, and fuzzy logic are some of the techniques that help construct models or systems that can incorporate more fundamental, technical, business cycle, or sentiment data. Furthermore, the rise of algorithmic trading and high-frequency trading is part of the market microstructure theme. As observed in the thematic map, both machine learning and market microstructure are emerging themes and need attention from the scientific community based on our analysis.

4.1 Thematic assessment

The initial section of our selection encompasses a broad timeframe and covers subfields such as asset pricing models, behavioral finance, market efficiency, and statistical models, or combinations thereof. Fama's work revolves around evolving asset pricing models and defending his theory of informational efficiency in markets. Notably, some of the most widely used asset pricing models are based on the CAPM, simple one-factor models, three-factor models, or five-factor models.

Another prominent research stream in this category addresses financial asset liquidity from the perspective of the bid-ask spread or other new measures, such as the illiquidity of a financial asset. Most studies examine the relationship between the asset pricing process and various risk domains such as market, systematic, company-specific, industry-specific, macroeconomic, or liquidity risks.

Behavioral finance forms another prominent theme in several studies. Generally, these studies address the price puzzle of financial assets due to investors' different behavioral, psychological, and cognitive biases. Factors such as home bias, sentiment-driven stock returns, and news overreaction can impact investment decisions and generate market anomalies that challenge the market efficiency hypothesis. The subsequent cluster of papers focuses on market efficiency and asset pricing models. A few delve into the relationship, both in emerging and developed markets, between the transparency level in a country's financial system and the stock price synchronicity (as measured by R2) and the frequency of significant negative returns for individual stocks. Furthermore, the connection between stock return performance and price-to-earnings ratios or financial statement transparency is analyzed using data spanning the entire decade, leading to the conclusion that the EMH does not comprehensively explain this phenomenon.

The last cluster contains papers that debate statistical models or their limitations owing to certain statistical properties of financial time series. One seminal article offers an overview of the theory and methodology of autoregressive conditional heteroskedasticity (ARCH) family models, evaluating their empirical performance. Another seminal article discusses stylized facts or regularities observed in the distribution of asset returns, such as fat tails, long memories, and volatility clusters. This study underlines the limitations of standard statistical methods for modeling asset returns and the need for more sophisticated methods to capture the complex and nonlinear nature of financial time series. The subsequent 27 papers (2011–2021), more recently published, span a range of themes, including the intersection of asset pricing models with behavioral finance, statistical models, informational efficiency, and other new emerging topics, such as bitcoin. Additionally, a new stream of studies exploring the stock prediction theme employs more sophisticated techniques, such as machine learning, which are combined with technical indicators to predict the return and volatility of assets.

A few studies address emerging themes, including government policy effects, and niche themes such as intangible asset integration into stock valuation. These studies discuss the effects on stock prices that result from uncertainty about future changes or the effects of the announcement of a policy change. Moreover, another study provides empirical support for the market's failure to incorporate assets such as employee satisfaction into stock valuations.

Another group of studies focuses on investment strategies, with several discussing the time-series momentum effect and value-momentum correlation structure, while others examine the use of leverage or beta as investment strategies. Recent years have witnessed a growing trend of using machine learning techniques and technical indicators for stock prediction, with papers discussing trend-deterministic data preparation and financial time-series forecasting.

Furthermore, a cluster of papers focuses on market efficiency, with several studies examining the role of high-frequency trading in price discovery, the efficiency of the bitcoin market, and the roughness of financial market volatility. Pedersen, Fitzgibbons and Pomorski, (2021), in their study on responsible investing and the Environment, Social, and Governance-efficient frontier, emphasize the significance of incorporating environmental, social, and governance considerations into investment decisions.

4.2 Methodologies of highly cited articles

Our collection of highly cited articles showcases a diverse range of methodologies, often employing multiple approaches. Foremost among these is the application of econometric models to study financial time series. Regression analysis, particularly Fama-MacBeth (1973) regression, a two-step regression approach to estimate the risk premium associated with different factors (Amihud, 2002; Asness, Moskowitz and Pedersen, 2013; Fama and French, 1992; Harvey and Siddique, 2000), features prominently, appearing in 19 studies. Panel regression is present in 15 studies, while time series, cross-sectional, and ordinary least squares are also utilized.

A few studies have captured and debated stock market volatility. Autoregressive family models are used to depict volatility, highlighting their usefulness in predicting expected returns and stock price volatility. Moreover, combining these models with other statistical methods, such as regression and deep learning techniques, can lead to more accurate predictions and a better understanding of asset pricing (e.g., Cochrane, 2011; Daniel and Moskowitz, 2016; Harvey and Siddique, 2000; Kim and Kim, 2019). In addition to the classical models used to predict volatility, a relatively new class of models similar to GARCH has been proposed in the literature. This includes rough fractional stochastic volatility, which is based on the concept of roughness and can capture the stylized facts of financial volatility (e.g. Gatheral, Jaisson and Rosenbaum, 2018).

Recently, new methods have been proposed to improve price prediction accuracy. The first approach is based on the hybrid model of Cao, Li and Li (2019), which combines empirical mode decomposition with long short-term memory (LSTM). This combination is used to predict each function, and the final prediction is obtained by reconstructing each prediction. The second approach is to improve the accuracy of price forecasts and risk premium predictions by utilizing machine learning techniques, such as sample splitting and tuning via validation, simple linear, penalized linear, dimension reduction, generalized linear, boosted regression trees, random forests, and neural networks. Additionally, these methods use statistical models that describe the general functional form of risk premium predictions, an objective function for estimating model parameters with a focus on minimizing the mean squared prediction error, and computational algorithms for identifying the optimal specification among model permutations (Gu, Kelly and Xiu, 2020).

4.3 Data in highly cited articles

Most studies use the Center for Research in Security Prices or Compustat as primary data sources and Bloomberg or Yahoo Finance as secondary databases. The data encompass various typologies across different locations and periods. Of the 51 analyzed articles, 43 contribute empirically, 2 employ questionnaires, 2 review specialized literature, and 4 provide theoretical insights.
Advanced economies, particularly the USA, feature predominantly in empirical and theoretical studies of financial market behavior. Of the studies on advanced economies, 26 are centered on the US financial market because of its potential for financial growth, accessible data resources, and market scale. Another five articles comparatively analyze data from the US and other developed or emerging markets. Finally, 10 of the most influential articles use global data, and only 4 studies focus on a country other than the USA.
Concerning the duration of empirical investigations, most studies concentrate on timeframes exceeding a decade, with the longest period spanning 86 years (Daniel and Moskowitz, 2016), and the shortest being 4 years (Chong, Han and Park, 2017). Time frequencies typically exceed a hundred periods, encompassing intraday, daily, and monthly intervals, with annual data reaching up to 86 years.

Conclusions

Our thorough research design, which includes bibliometric analysis and an in-depth examination of pertinent papers, has provided valuable insights into the dynamics of the informational efficiency landscape. By employing the bibliometric approach, we sought to answer a broad array of questions **regarding the evolution of the field, the most influential and productive authors and journals, the trending topics, thematic mapping, and the field's intellectual landscape.** Additionally, the in-depth analysis of the pivotal papers offers insights regarding the thematic approaches, data employed, and methodological choices.
Scientific production in this domain has increased significantly since 2000. Notably, between 2010 and 2019, researchers intensified their work by doubling the number of studies focusing on liquidity, behavioral finance, and cryptocurrency. Regarding authors, Fama EF and Subrahmanyam A demonstrate the highest *h*-index and *g*-index values. Fama EF has been one of the most productive authors and has had a constant presence in the field since 1976. Additionally, the field has recognized a significant increase in publications since 2013. Part of this increase can be attributed to the efforts of a group of scholars, including Urquhart A, Plastun A, Yang C, and Zaremba A.

Regarding the journals in which informational efficiency topics have been published, out of the 44 sources, our analysis of the top five journals based on the number of publications and citations revealed a consistent growth trend in recent years, with *Physica A: Statistical Mechanics and its Applications* showing the most significant growth rate. Further analysis based on the *h*-index, *g*-index, *m*-index, and total citation count confirmed that the *Journal of Financial Economics* exhibits the best performance.
Regarding the analysis of the most influential articles, the first group of papers with a high citation count include "Multifactor explanations of asset pricing anomalies," cited 2,852 times, "Industry costs of equity," cited 2,798 times, "A five-factor asset pricing model," cited 2,304 times, and "Market efficiency, long-term returns, and behavioral finance," cited 2,126 times. Notably, these contributions are authored by Fama and French (1996, 1997, 2015).
Furthermore, our analysis revealed that papers with a high number of citations per year in the last five years are associated with current trending topics. For example, Gu, Kelly and Xiu, (2020), in "Empirical asset pricing via machine learning," find that machine learning techniques can significantly improve prediction accuracy and deliver substantial economic gains to investors, receiving an elevated number of citations in a relatively short period. Moreover, Chong, Han and Park, (2017) and Cao, Li and Li, (2019) explore the use of deep learning and financial time-series forecasting techniques, which may have enhanced the understanding of how market prices reflect available information. Additionally, in the last five years, a significant number of highly cited papers have focused on understanding cryptocurrency market efficiency.
The intellectual landscape reveals three distinct clusters of authors that are regularly cited together. We noticed that Fama's work is present in all the three clusters. Moreover, we revealed that the studies span diverse themes, including market and size risk, market efficiency forms, investor sentiment, the properties of asset returns, based on statistical methods, and the decomposition of returns into permanent and temporary components.
The thematic approach found in the highly cited articles reveals a wide range of themes. Initially, these papers focus on asset pricing models and liquidity, while also delving into the exploration of behavioral biases and challenging the traditional notion of market efficiency. Moreover, emerging topics, such as government policy effects and responsible investing or the transparency level in a country's financial system, are also present. The preoccupation regarding investment strategies based on prediction—with the help of statistical models, or more sophisticated models, such as machine learning—is also present as a theme in the pivotal papers.
Methodologies used in the field vary, with econometric model-based regression analysis being a common approach. Volatility studies often employ autoregressive family models. More sophisticated models combining fundamental indicators and technical analyses have recently been used to predict stock market prices and measure informational efficiency. By far, the USA and developed markets dominate the data used in the studies, and intraday data are used more frequently.
Our study found that technical indicators are less frequently utilized in the content analysis of the most relevant studies than fundamental indicators when constructing an investment portfolio. This finding is consistent with the observation of Lo, Mamaysky

and Wang (2000, p.1705): “While charting has been utilized in financial practices for many years as part of technical analysis, it does not receive the same level of scrutiny and recognition as fundamental analysis”. Technical analysis is based on the interpretation of charts and statistical data to identify future security price directions, whereas fundamental analysis examines the underlying economic and financial factors that drive asset value. The new trend in machine learning techniques is the use of chart recognition to predict future prices and construct new investment portfolios.

We focused on revealing informational efficiency's role in financial markets. Our study makes significant contributions to this field of research. First, to the best of our knowledge, this is the only study that examines informational efficiency as a whole. Second, the analysis of paper trends facilitated the assessment of the research contributions of authors and journals. Third, we identified seven themes that underpin the field: *volatility, fractals, market efficiency, behavioral finance, asset price, price discovery,* and *technical analysis.* Finally, we performed a content review of the most cited papers, which can be a valuable tool for novice researchers.

For practitioners, investors, and policymakers, our study provides evidence about emerging themes, such as technical analysis, adaptive market hypothesis, and machine learning. Our findings diverge from those of the classical proponents of equilibrium models based on investors' rationality, which consider technical analysis as a waste of time and money. For scholars, our paper presents valuable analysis about trends and emerging themes, which provide both explanations and context to conduct new studies regarding market efficiency.

Moreover, our findings are in line with those of Brock, Lakonishok and LeBaron, (1992, p.1733), underlining that it is premature to conclude that technical analysis is useless, as earlier studies have considered. Additionally, Malkiel (2003, p.80) concludes that, with the improvement of data processing and larger databases, new studies empirically documenting the deviation from market efficiency will emerge. More recent studies (see Dima, Dima and Ioan, 2021, p.2) acknowledge that improved price predictability may be related to informational inefficiencies in markets.

In this vein, the actual learning capacity of the new systems—based on a combination of deterministic data inputs, such as technical indicators and sentiment data derived from fundamental indicator interpretation—can enhance prediction accuracy and improve investment decisions. Selecting and optimizing the inputs in the models/systems with the help of evolutionary algorithms or other deep learning algorithms can create additional efficiency. In the meantime, these developments need attention from researchers, policymakers, and investors.

Despite our access to an extensive database of published papers, our analysis has some limitations. First, our study considered only Scopus-indexed publications; other databases that could be included are WoS and Dimensions. Second, our study only accessed articles published in journals; by applying a database reduction filter (e.g., Bradford filter), we limited our analysis to core sources.

Our study reveals at least two types of future research directions; one resulting from the bibliometric sections and the second from the content review. One avenue of future research is to extend our research to other zones of the Bradford filter to select journals outside the core Bradford zone, potentially yielding valuable contributions. Another

avenue for future research is to access other multidisciplinary databases to obtain different citation statistics, access other journals, and compare the results with those of the present study. Moreover, to enhance our study, future research could employ other bibliometric software, such as CiteSpace, Vosviewer, Gephi, or similar tools capable of conducting semantic and conceptual text analyses.
On the other hand, the content review analysis revealed two significant future research directions. The first, is related to the way in which technical analysis can exploit deviations from market efficiency in stock markets based on new prediction techniques (machine learning, deep learning, and artificial intelligence). Second, the analysis regarding the consequences of using different technologies in trading (high-frequency trading, algorithmic trading based on evolutionary algorithms for trading rule selection, and portfolio optimization) is currently fragmented; a complete picture is yet to emerge.

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Table 1. Most influential authors

Rank	Author	No of Articles	Co-authored	Single-author	Articles Fractionalized	*h*-index	*g*-index	*m*-index	Times Cited	NP	First Year of Publication
1	Fama EF	17	12	5	11,00	19	19	0,404	14554	19	1976
2	French KR	14	13	1	7,50	16	16	0,432	12726	16	1986
3	Harvey CR	15	12	3	8,25	14	14	0,400	5833	14	1988
4	Subrahmanyam A	24	22	2	9,42	18	24	0,667	3856	24	1996
5	Chordia T	17	17	0	5,83	15	17	0,600	3605	17	1998
6	O'hara M	16	16	0	6,25	15	16	0,484	2731	16	1992
7	Hommes CH	15	14	1	3,17	6	7	0,240	2702	7	1998
8	Tse Y	27	24	3	12,08	13	27	0,542	1989	27	1999
9	Ferson WE	17	15	2	7,83	14	15	0,389	1938	15	1987
10	Urquhart A	19	16	3	8,98	11	19	1,100	1586	19	2013
11	Tabak Bm	15	14	1	6,07	11	15	0,579	1374	15	2004
12	Gupta R	27	27	0	7,67	14	27	1,077	1177	32	2010
13	Yoon S-M	15	15	0	5,03	12	15	0,857	1157	15	2009
14	Narayan PK	19	18	1	6,92	13	18	0,684	1110	18	2004
15	He X-Z	21	21	0	8,25	15	23	0,682	1087	23	2001
16	Sornette D	21	21	0	8,07	15	21	0,625	1065	21	1999
17	Faff R	23	22	1	6,58	10	17	0,476	1049	17	2002
18	Zhou W-X	16	16	0	5,97	13	16	0,650	1023	16	2003
19	Ryu D	17	16	1	7,17	12	18	0,923	844	19	2010
20	Westerhoff F	17	14	3	5,83	8	12	0,400	767	12	2003
21	Plastun A	16	16	0	4,23	8	14	1,143	758	14	2016
22	Hudson R	20	20	0	7,08	9	17	0,409	745	19	2001
23	Yang C	19	19	0	8,92	9	16	0,818	743	23	2012
24	Zaremba A	31	27	4	13,58	9	11	1,286	734	31	2016
25	McMillan DG	17	13	4	7,83	7	10	0,318	731	12	2001

Source: Authors' own research based on the Scopus database

Table 2. The 25 most relevant sources

Rank	Source	*h*-index	*g*-index	*m*-index	Times Cited	NP	First Year of Publication
1	*l of Financial Economics*	34	37	0,708	17906	37	1976
2	*a A: Statistical Mechanics and its Applications*	25	47	1	2282	47	1999
3	*tional Review of Financial Analysis*	16	30	0,64	1142	30	1999
4	*e Research Letters*	14	27	0,933	786	27	2009
5	*l of Economic Dynamics and Control*	13	16	0,5	1930	16	1998
6	*of Financial Studies*	13	14	0,481	2011	14	1997
7	*l of Finance*	12	12	0,429	7500	12	1996
8	*nic Modelling*	11	20	0,733	416	24	2009
9	*Journal of Banking and Finance*	11	16	0,367	699	16	1994
10	*Journal of Economic Behavior and Organization*	11	14	0,524	528	14	2003
11	*Journal of Futures Markets*	11	18	0,44	752	18	1999
12	*Pacific Basin Finance Journal*	11	19	0,5	370	19	2002
13	*Computational Economics*	10	11	0,455	329	11	2002
14	*Journal of International Financial Markets, Institutions and Money*	9	14	0,429	332	14	2003
15	*North American Journal of Economics and Finance*	9	14	0,9	270	14	2014
16	*Energy Economics*	8	10	0,5	1108	10	2008
17	*Journal of Empirical Finance*	8	9	0,258	680	9	1993
18	*Journal of Financial and Quantitative Analysis*	8	8	0,25	455	8	1992
19	*Quantitative Finance*	8	16	0,348	538	16	2001
20	*Management Science*	7	8	0,269	505	8	1998

21	*Research in International Business and Finance*	7	12	0,389	249	12	2006
22	*Applied Economics*	6	13	0,316	194	18	2005
23	*Applied Financial Economics*	6	10	0,261	120	11	2001
24	*Economics Letters*	6	8	0,333	970	8	2006
25	*The Journal of Finance*	6	6	0,162	1627	6	1987

Source: Authors' own research based on the Scopus database

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
1	Banz RW	The relationship between return and market value of common stocks	*Journal of Financial Economics*	1981	2440	58	Relationship between the return on common stocks listed on the NYSE	CAPM does not adequately capture the relationship between risk and return for a small sized firm
2	De Bondt WFM; Thaler R	Does the stock market overreact?	*The Journal of Finance*	1985	3056	80	Stock market overreaction hypothesis	Empirical evidence in support of the overreaction hypothesis
3	Amihud Y; Mendelson H	Asset pricing and the bid-ask spread	*Journal of Financial*	1986	2229	60	Relationship between stock return, relative	The influence of bid-ask spreads on the returns of

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
			Economics				risk (beta), and bid-ask spread.	securities; the role of liquidity in asset pricing
4	Bollerslev T; Chou RY; Kroner KF	ARCH modeling in finance. A review of the theory and empirical evidence	*Journal of Econometrics*	1992	2445	79	ARCH model in finance	Overview of the theory and methodology of the ARCH model
5	Fama EF; French KR	The cross-section of expected stock returns	*The Journal of Finance*	1992	7337		Stock return prediction	The development of a three-factor model (market risk, size, and value on stock returns) for

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
								predicting stock returns
6	Fama EF; French KR	Common risk factors in the returns on stocks and bonds	*Journal of Financial Economics*	1993	11330	378	Asset pricing	Anomalies explained by additional factors, such as size and value, in asset pricing models
7	Jegadeesh N; Titman S	Returns to buying winners and selling losers: implications for stock market efficiency	*The Journal of Finance*	1993	4670	156	Behavioral finance and market efficiency-momentum investment strategy	Stocks with higher returns in the past tend to maintain the trend in the future

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
8	Fama EF; French KR	Multifactor explanations of asset pricing anomalies	*Journal of Finance*	1996	2852	106	Asset pricing anomalies	Multifactor model for explaining various asset pricing anomalies or deviations
9	Fama EF; French KR	Industry costs of equity	*Journal of Financial Economics*	1997	2798	108	Industry cost of equity	Industry-level variables: market-to-book ratio and the dividend payout ratio estimate the cost of equity
10	Fama EF	Market efficiency, long-	*Journal of*	1998	2126	85	Market	Evidence backs

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
		term returns, and behavioral finance	*Financial Economics*				efficiency anomaly	market efficiency; deviations arise from behavioral influences
11	Coval JD; Moskowitz TJ	Home bias at home: local equity preference in domestic portfolios	*Journal of Finance*	1999	1211	50	The phenomenon of home bias	Home bias affects investments, asset prices, and performance—influenced by proximity, information, and firm characteristics
12	Morck R; Yeung B; Yu W	The information content of stock markets: why do emerging markets	*Journal of Financial Economics*	2000	1394	61	Informational efficiency in different stock	Emerging market stock prices exhibit

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
		have synchronous stock price movements?					markets	synchrony—limited information potentially responsible
13	Harvey CR; Siddique A	Conditional skewness in asset pricing tests	*Journal of Finance*	2000	1157	50	Asset pricing and skewness	The role of skewness in asset pricing, including implications in asset management and portfolio construction

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
14	Graham JR; Harvey CR	The theory and practice of corporate finance: evidence from the field	*Journal of Financial Economics*	2001	2388	109	Alignment between the theory and practice regarding prediction models	Internal view of executives can influence stock price evolution
15	Cont R	Empirical properties of asset returns: stylized facts and statistical issues	*Quantitative Finance*	2001	1518	69	Limitations of standard statistical methods in modelling financial time series	Fat tails and long memory observed in asset returns distribution

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
16	Hirshleifer D	Investor psychology and asset pricing	*Journal of Finance*	2001	997	45	Behavioral finance and asset pricing	Insights on psychology-based asset pricing—potential future research directions
17	Amihud Y	Illiquidity and stock returns: cross-section and time-series effects	*Journal of Financial Markets*	2002	3937	187	Relationship between stock return and liquidity	Assets with high bid-ask spreads tend to have lower returns
18	Shleifer A; Vishny RW	Stock market driven acquisitions	*Journal of Financial Economics*	2003	959	48	Asset pricing models and behavioral	Model explores equity overvaluation incentives for

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
							finance	stock-funded acquisitions
19	Acharya VV; Pedersen LH	Asset pricing with liquidity risk	*Journal of Financial Economics*	2005	1149	64	Relationship between asset prices, liquidity risk, and illiquidity	Model of asset pricing that incorporates liquidity risk
20	Baker M; Wurgler J	Investor sentiment and the cross-section of stock returns	*Journal of Finance*	2006	2459	145	Stock returns and investor sentiment	Investor sentiment affects stock prices, returns, and dividend policy

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
21	Jin L; Myers SC	R2 around the world: new theory and new tests	*Journal of Financial Economics*	2006	1072	63	Relationship between the level of transparency in a country's financial system and the level of stock price synchronicity	Control rights and information influence risk division between managers and investors
22	Renneboog L; Ter Horst J; Zhang C	Socially responsible investments: institutional aspects, performance, and investor behavior	*Journal of Banking and Finance*	2008	736	49	Behavioral finance and asset pricing models	Critical literature review of socially responsible investments

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
23	Hutton AP; Marcus AJ; Tehranian H	Opaque financial reports, R2, and crash risk	*Journal of Financial Economics*	2009	917	66	Relationship between the transparency of financial statements and stock returns	Opaque firms were found to be more prone to stock price crashes
24	Goyenko RY; Holden CW; Trzcinka CA	Do liquidity measures measure liquidity?	*Journal of Financial Economics*	2009	622	44	Asset pricing and liquidity	Low-frequency measures capture high-frequency transaction costs
25	Edmans A	Does the stock market fully value intangibles?	*Journal of Financial*	2011	709	59	Asset pricing's relationship	High employee satisfaction

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
		Employee satisfaction and equity prices	*Economics*				with employee satisfaction	yields superior long-horizon returns
26	Hendershott T; Jones CM; Menkveld AJ	Does algorithmic trading improve liquidity?	*Journal of Finance*	2011	656	55	Market microstructure	Algorithmic trading at the NYSE improves liquidity
27	Cochrane JH	Presidential address: discount rates	*Journal of Finance*	2011	604	50	Asset pricing research	Importance of discount rate variation in the long term

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
28	Fama EF; French KR	Size, value, and momentum in international stock returns	*Journal of Financial Economics*	2012	826	75	International stock returns	The patterns in average returns in developed markets
29	Pástor L; Veronesi P	Uncertainty about government policy and stock prices	*Journal of Finance*	2012	780	71	Government policy effects	Government policy effects on stock prices and equilibrium model predictions
30	Moskowitz TJ; Ooi	Time-series momentum	*Journal of Financial*	2012	571	52	Investment strategy—Time-	New evidence challenges the

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	YH; Pedersen LH		*Economics*				series momentum effect	random walk hypothesis
31	Asness CS; Moskowitz TJ; Pedersen LH	Value and momentum everywhere	*Journal of Finance*	2013	954	95	Investment strategy—Value-momentum correlation structure	Common global risks found
32	Pástor Ľ; Veronesi P	Political uncertainty and risk premia	*Journal of Financial Economics*	2013	789	79	Government policy effects	Political uncertainty effects

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
33	Novy-Marx R	The other side of value: the gross profitability premium	*Journal of Financial Economics*	2013	679	68	Investments strategy—Profitability premium analysis improves the value strategy	Profitability as another dimension of value—adds growth strategy
34	Frazzini A; Pedersen LH	Betting against beta	*Journal of Financial Economics*	2014	693	77	Investment strategy—using leverage or beta	Relationship between leverage and margin constraints and the returns of high-beta and low-beta assets
35	Brogaard J;	High-frequency trading	*Review of*	2014	433	48	Market	How high-

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No.	**Authors**	**Title**	**Source**	**Year**	**Times Cited**	**Avg TC Per Year**	**Theme**	**Key Contribution**
	Hendershott T; Riordan R	and price discovery	*Financial Studies*				microstructure —High-frequency trading's role in price discovery	frequency trading affects market structure and performance
36	Fama EF; French KR	A five-factor asset pricing model	*Journal of Financial Economics*	2015	2304	288	Five-factor asset pricing model	The model builds on the three-factor model by adding two additional factors: profitability and investment
37	Da Z; Engelberg J; Gao P	The sum of all FEARS investor sentiment and	*Review of Financial*	2015	557	70	Search data analysis and	Novel sentiment measures from

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
		asset prices	*Studies*				stock return	high-frequency search data literature
38	Brogaard J; Detzel A	The asset-pricing implications of government economic policy uncertainty	*Management Science*	2015	554	69	Political uncertainty and asset price	Government policy's impact on asset prices
39	Patel J; Shah S; Thakkar P; Kotecha K	Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques	*Expert Systems with Applications*	2015	502	63	Stock prediction	Converts technical indicators to trend deterministic data for prediction

Table 3. The 51 most influential articles

No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
40	Urquhart A	The inefficiency of bitcoin	*Economics Letters*	2016	609	87	Market efficiency and bitcoin	Significant inefficiency in the bitcoin market
41	Daniel K; Moskowitz TJ	Momentum crashes	*Journal of Financial Economics*	2016	359	51	Investment strategy	Evidence that momentum crashes are predictable
42	Chong E; Han C; Park FC	Deep learning networks for stock market analysis and prediction:	*Expert Systems with Applications*	2017	387	65	Stock prediction and deep learning	Deep learning for stock market analysis—

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
		methodology, data representations, and case studies						effective for prediction
43	Nadarajah S; Chu J	On the inefficiency of bitcoin	*Economics Letters*	2017	348	58	The efficiency of the bitcoin market	Significant inefficiency in the bitcoin market
44	Bariviera AF	The inefficiency of bitcoin revisited: a dynamic approach	*Economics Letters*	2017	315	53	The efficiency of the bitcoin market	Bitcoin is not a reliable investment owing to its lack of efficiency

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
45	Fama EF; French KR	International tests of a five-factor asset pricing model	*Journal of Financial Economics*	2017	303	51	Five-factor asset pricing model	Five-factor model, including market beta, size, value, profitability, and investment, used to explain the returns of a given asset
46	Kim HY; Won CH	Forecasting the volatility of stock price index: a hybrid model integrating LSTM with multiple GARCH-type models	*Expert Systems with Applications*	2018	309	62	Volatility prediction	Model combining a neural network model with multiple econometric models

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
47	Fama EF; French KR	Choosing factors	*Journal of Financial Economics*	2018	251	50	Five-factor asset pricing model	Developing insights about the maximum squared Sharpe ratio
48	Gatheral J; Jaisson T; Rosenbaum M	Volatility is rough	*Quantitative Finance*	2018	226	45	The roughness of financial market volatility	Volatility exhibits persistent roughness in all markets
49	Cao J; Li Z; li J	Financial time-series forecasting model based on CEEMDAN and LSTM	*Physica A: Statistical Mechanics and its*	2019	241	60	Financial time-series forecasting and machine	Forecast financial time-series data by decomposing them into

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
			Applications				learning	intrinsic mode functions
50	Gu S; Kelly B; Xiu D	Empirical asset pricing via machine learning	*Review of Financial Studies*	2020	259	86	Asset pricing and machine learning	Machine learning algorithms can be used to identify patterns in financial data and make predictions
51	Pedersen LH; Fitzgibbons S; Pomorski L	Responsible investing: the ESG-efficient frontier	*Journal of Financial Economics*	2021	109	55	Responsible investing	Insights to construct portfolios that are both financially

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No.	Authors	Title	Source	Year	Times Cited	Avg TC Per Year	Theme	Key Contribution
								efficient and have a positive environmental, social, and governance impact

Source: Authors' own research based on the Scopus database