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Research paper

Mapping portfolio optimisation: a systematic and bibliometric review

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Abstract

Purpose: This study provides a comprehensive analysis of the evolution of portfolio optimization over the last three decades, employing systematic review and advanced bibliometric techniques to map key trends, influential works, and significant contributors in the field.
Design/Methodology/Approach: Adhering to PRISMA guidelines, we conducted a systematic review and bibliometric analysis of 1,000 articles sourced from the Web of Science database, spanning from 1989 to 2023. Advanced bibliometric tools, including citation analysis, co-occurrence analysis, and network visualization, were utilized to identify prominent authors, influential journals, and emerging research themes.
Findings: Our analysis reveals a significant growth in portfolio optimization literature, particularly in recent years. Key findings include the identification of pivotal authors, foundational papers, and leading journals that have shaped the field. The study also traces the methodological evolution from traditional models, like Markowitz's Modern Portfolio Theory, to contemporary approaches incorporating artificial intelligence and machine learning.
Practical Implications: This study offers valuable insights for researchers and practitioners by highlighting critical developments in portfolio optimization. It also suggests areas for future research, particularly in integrating advanced data analytics and AI-driven methodologies into portfolio management.
Originality/Value: This paper stands out by combining systematic review with a comprehensive bibliometric analysis, offering a holistic view of the portfolio optimization landscape. It not only synthesizes past research but also identifies emerging trends and gaps, providing a foundation for future explorations in this dynamic field.

Keywords: *Portfolio Optimization; Bibliometric Analysis; Systematic Review; Modern Portfolio Theory; Artificial Intelligence; Financial Modeling.*

1. Introduction

Portfolio optimisation is a financial strategy to construct a portfolio to maximise return with minimal risk (Mangram, 2013) after considering assets such as stocks, bonds, mutual funds, gold, ETFs, and fixed deposits (Pandey, 2012). The critical principle is diversifying across different asset classes to make an optimal portfolio (Reddy Irala et al., n.d.). Mathematical models like modern portfolio theory (Markowitz, 1952) and capital asset pricing model(Karp, 2017) can be employed in selecting and allocating assets while taking into consideration constraints like budget and risk tolerance of investors (Bartram et al., n.d.). The efficient frontier is a collection of ideal portfolios that provides the maximum return for a specified level of risk (H. Markowitz, 1952). Regular rebalancing is essential as the market changes to maintain the desired level of asset allocation (Kent Baker, n.d.).
Markowitz (1952) quantified risk-return trade-offs by diversifying assets, thus making an ideal portfolio but unable to comprehend investors' subjective views and beliefs. To deal with this problem, a new theory was developed by (Black & Litterman) in 1990, which added investors' viewpoints into account while determining portfolio weights and asset allocation, enacting the beginning of both quantitative and qualitative analysis. However, it fails to promise the best portfolio because it was based on the assumption that investors' views are independent of one another (Idzorek, 2004). To meet this expectation, the factor model came into existence, where more than one factor was analysed to see the impact on the prices of assets. In this, the factor model developed by (Fama & French, 1993), which was built upon the Capital asset pricing model (Karp, 2017), focuses on factors like risk, risk size, and value risk of investment(Kilsgård & Wittorf, n.d.). They believed that value stocks would perform better than growth stocks. Again, in 2014, they incorporated momentum, quality, and low volatility to size risk and value risk, thus making it to the Five Factor model (Fama & French, n.d.), setting a pivotal shift in optimisation. In recent years, the incorporation of artificial intelligence(Santos et al., 2022) has revolutionised the optimisation process through a significant advancement in algorithms which enables investors to process vast amounts of data and identify complex patterns(Gustavo Carvalho Santos, n.d.) which ultimately help in making informed decisions. Incorporating Machine learning techniques (Mazraeh et al., 2022) can potentially address non-linear relationships and changing market conditions.

So, the evolution of portfolio optimisation (Thein Lwin, 2015) is ongoing, and many new theories remain to be developed to deal with the dynamic nature of financial markets. This study aims to develop an understanding of current literature by employing both systematic and bibliometric analyses that other researchers have not previously explored. The scope of this study is to meticulously analyse and identify critical insights, keywords, Significant authors, leading countries publishing papers on it as well as highly cited articles along with the respective countries, most journals publishing articles in this area, Key authors whose contributions are significantly getting mentioned, and leading organisations from all over the world from the last three decades. This study will be helpful for a deeper understanding of the theory portfolio optimisation and will guide researchers and practitioners in the future.
The rest of the paper is structured as follows: Section 2 gives the methodology for this study, Section 3 describes bibliographic analysis results to address Portfolio optimisation, and Section 4 describes the conclusion and suggestions for further research.

2. Methodology

2.1. Data collection strategy

The study aimed to systematically evaluate the literature on portfolio optimization from 1989 to 2023. We employed a comprehensive literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The data was extracted from the Web of Science (WoS) database, chosen for its extensive coverage of high-quality peer-reviewed journals across finance, management, and related disciplines.
Search Strategy: We utilized a combination of keywords related to portfolio optimization, including "Portfolio Optimization," "Portfolio Selection," "Investment Management," and "Financial Market." The search was restricted to articles published in English, given the language limitations, and focused on finance and management subject areas to ensure relevance to the research topic.
Inclusion and Exclusion Criteria: The initial search yielded 7,500 articles. After screening for relevance, 6,500 articles were excluded based on the following criteria:

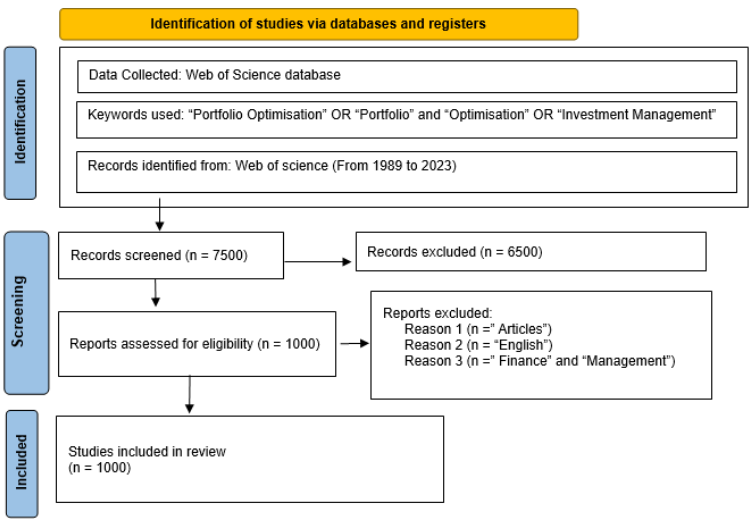
- Non-English language: Articles not published in English were excluded.
- Irrelevant subject areas: Papers unrelated to finance and management were removed.
- Non-academic publications: Only peer-reviewed journal articles were included.

This rigorous filtering resulted in a final dataset of 1,000 articles, which formed the basis for the subsequent bibliometric analysis.

2.2. Bibliometric analysis

The bibliometric analysis was conducted using VOSviewer software, a robust tool for constructing and visualizing bibliometric networks. This software was selected for its capability to handle large datasets and its ability to generate clear visualizations of relationships among authors, journals, and key terms.
Key Bibliometric Techniques:

- Citation Analysis: To identify the most influential papers, authors, and journals in the field.
- Co-occurrence Analysis: To map the relationships between key terms and concepts within the portfolio optimization literature.
- Bibliographic Coupling: To determine connections between articles based on shared references, helping to identify research clusters.
- Co-authorship Analysis: To uncover collaborative networks among researchers, highlighting influential author groups and their contributions to the field.



PRISMA 2020 flow diagram (Milhomem & Dantas, 2020a; Page et al., 2021) for identifying and selecting manuscripts for systematic and bibliometric analysis study.

This paper attempts to present a thorough knowledge of portfolio optimisation theory after including ideas from a wide range of literature. More than 7500 articles on Portfolio optimisation were published between 1989 and 2022 in one of the largest bibliographic digital databases, WOS (Dzikowski, 2018), using keywords such as "Portfolio", "Optimisation", "Portfolio Selection", "Financial Market", and "Optimisation Problem". A total of 1000 articles are included in this study after applying inclusion criteria for papers related to finance and in the English language only due to the language barrier and after excluding other papers unrelated to our topic. These articles were distributed in subject areas such as finance, management, machine learning, and algorithms. Figure 1 shows the articles published throughout the year, with their citation details, and Figure 2 displays the distribution publication types in those years.

2.3. Research questions

The research questions related to Portfolio Optimisation are shown in Table 1(Rojas-Sánchez et al., 2023).
Four key research questions guided this study:

- RQ1: What are the most prominent journals and authors in the field of portfolio optimization?
- RQ2: What are the main topics and keywords used in portfolio optimization research?
- RQ3: What are the most influential research papers in portfolio optimization?
- RQ4: What are the trends and patterns in the bibliometric data on portfolio optimization?

2.4. Data analysis and visualization

The results were synthesized into visual networks and tables to depict the evolution of research in portfolio optimization. Figures such as network diagrams and density maps were employed to provide a clear visual representation of the most frequently occurring keywords, the interconnectedness of authors, and the distribution of publications across different journals and countries.

3. Bibliographic analysis results

The summary table of previous related Literature Reviews in Portfolio Optimisation is shown in Table 2 (Ghanbari et al., 2023b)

Table 2: Summary of Related Literature Reviews in Portfolio Optimisation

Sl. No.	Articles Name	Objective	Findings
1	Overview of Portfolio Optimisation Models (Zanjirdar, 2020)	To review portfolio optimisation models and theories to introduce a comprehensive model for optimal portfolio selection.	After carefully comparing various methods and techniques, mathematical modelling impacts the selection procedure and refining theory.
2	A comprehensive review of deterministic models and applications for mean-variance portfolio optimisation (Kalayci et al., 2019)	To review deterministic models in mean-variance optimisation and to extract a solution technique for the same.	This paper found that multi-objective methods are more realistic than single-objective methods.
3	Analysis of new approaches used in portfolio optimisation: a systematic literature review (Milhomem & Dantas, 2020b)	Identify the leading tools, methods, and techniques used in portfolio optimisation.	They found that heuristic methods focused on multi-period and multi-objective problems.

After careful analysis of previous works in this area, this study provides a comprehensive review, as given in Table 2, that helps consolidate fragmented research and offers a cohesive understanding of the field by employing advanced bibliometric techniques such as citation analysis, co-occurrence analysis, bibliographic coupling, and author-citation analysis, the paper goes beyond traditional review methods. These techniques provide a more detailed and structured literature analysis, highlighting influential works, key authors, and leading journals. Beyond synthesizing existing research, this review identifies critical gaps in the literature, particularly in the integration of artificial intelligence and machine learning techniques in portfolio optimization. By highlighting these gaps, the study provides a roadmap for future research, encouraging scholars to explore under-researched areas and develop innovative methodologies

3.1. Year-wise and publication types

The details of Publication of Articles over the years with citations shown in Figure 1 (Ghanbari et al., 2023b; Xu et al., 2020).

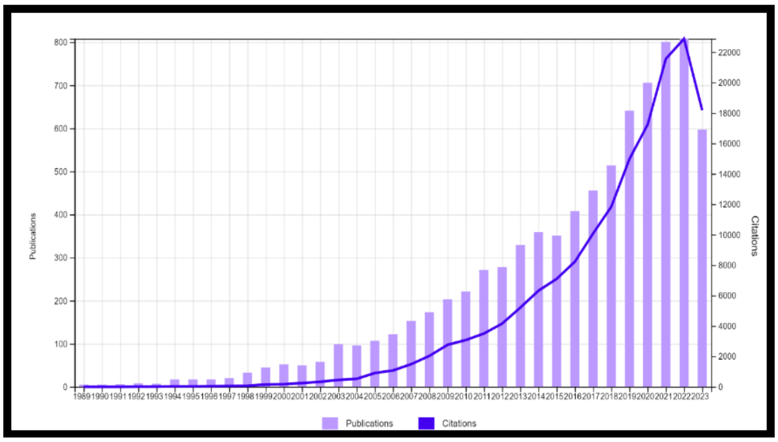


Fig. 1: Publication Papers Source: Web of Science.

Figure 1 depicts the number of research studies published over the years and citation details on Portfolio optimisation (Statman, 1987). The first research work was published in 1989. As evident from the graph, the number of publications shows an upward trend after an initial stagnation (1889-97), but it reached its highest level in 2022 with more than 760 publications.

3.2. All Keywords

The most frequently used keywords are depicted in Figure 2 (Xu et al., 2020).

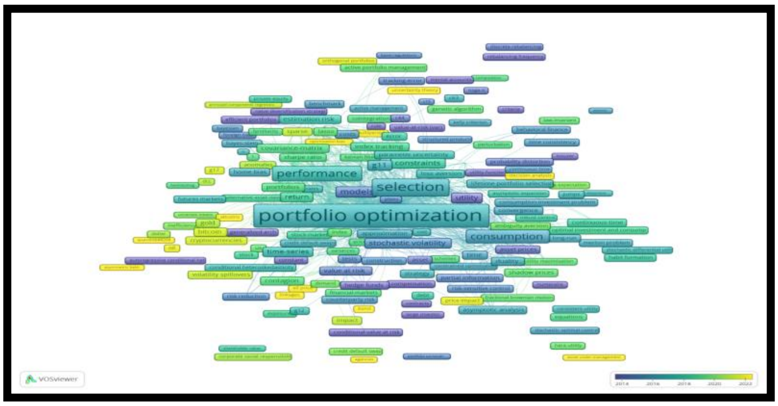


Fig. 2: All Keywords Published and Searched Most Frequently in Portfolio Optimization.

Figure 2 represents a network diagram of keywords for Portfolio optimisation. The keywords are represented as nodes in the graph, and the edges show their co-occurrence in articles. The thickness of the edges reflects the number of papers in which the two keywords co-occur, while the size of the nodes reflects the number of papers in which the term appears. In the diagram, the centre has the largest cluster of terms. Keywords like "Portfolio optimization"(Resta, 2012), "Selection"(Roman & Mitra, 2009), "Performance"(Oberoi et al., 2019), and "Mean-variance"(H. M. Markowitz, 1989) are included in this cluster. These terms imply that the Portfolio optimisation study's main goal is to comprehend investors' actions in financial markets. Many smaller term clusters representing different subfields within the Portfolio optimisation study form around the major cluster. However, a cluster of keywords related to "Correlation"(Markowitz, 1952) "investment"(Siaw et al., 2015), "Dynamic portfolio optimisation"(Zhou et al., 2022), and "Asymptotic risk" (Yang et al., n.d.) are found among them. In summary, the diagram offers a useful visual aid for understanding the connections among keywords associated with studies on Portfolio optimisation.

3.3. Authors keyword

The most frequently used keywords by Authors are presented in Figure 3 (Colapinto & Mejri, 2024).

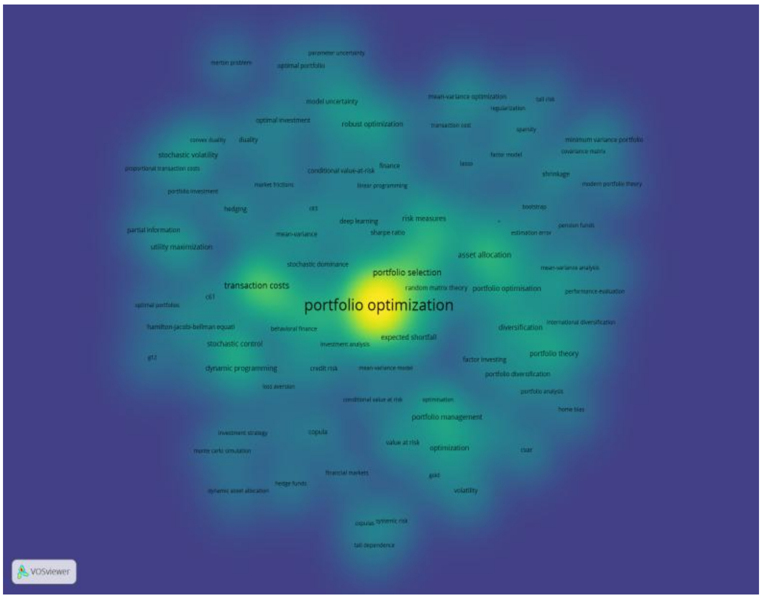


Fig. 3: All The Keywords Used by the Authors In Portfolio Optimisation.

Figure 3 depicts a density network diagram of the most frequent keywords related to Portfolio optimisation research, with nodes representing keywords and edges denoting co-occurrence in research articles. The diagram centre has the largest cluster of terms. Keywords like "Portfolio selection", "transaction cost"(Mellal et al., 2020), "Investment analysis"(Hayes, 2021), and "Behavioural finance"(Molina et al., 2020) are included in this cluster. However, a cluster of keywords " Montecarlo simulation"(Ghodrati & Zahiri, 2014), "copulas"(Deng et al., 2011), "conditional value at risk"(Pinar, 2013), "mean-variance"(Alexander & Baptista, 2002) and "value at risk" (Pinar, 2013) are found among them. The diagram offers a functional visual network diagram for understanding the connections among keywords on Portfolio optimisation.

3.4. Journal distributions

The topmost strongly related to Portfolio optimisation in the complete counting bibliographic coupling network is shown in Table 3 (Perianes-Rodriguez et al., 2016).

Table 3: Top Ten Active Journalsthst Published Articles on Portfolio Optimisation from 1989 to 2023

Rank	Journal Name	Total Count	Percentage (%)
1	European journal of operational research	349	4.58%
2	Annals of operations research	214	2.81%
3	Expert systems with applications	170	2.23%
4	Quantitative Finance	168	2.21%
5	Insurance mathematics economics	114	1.50%
6	Journal of Portfolio Management	97	1.27%
7	Applied energy	95	1.25%
8	Journal of Banking Finance	92	1.21%
9	Mathematical finance	83	1.09%
10	Energy	77	1.01%

Table 3 represents the top ten journals contributing to portfolio optimisation theory by publication count. The European Journal of Operational Research leads with 349 publications, constituting 4.58% of the total records, followed by the Annals of Operations Research with 214 publications (2.81%) with other significant contributors.

3.5. Top authors that published articles in portfolio optimisation from 1989 to 2023

Most influential authors and co-authors are organised in clusters in Figure 4 (Xu et al., 2020; Zaimovic et al., 2021).

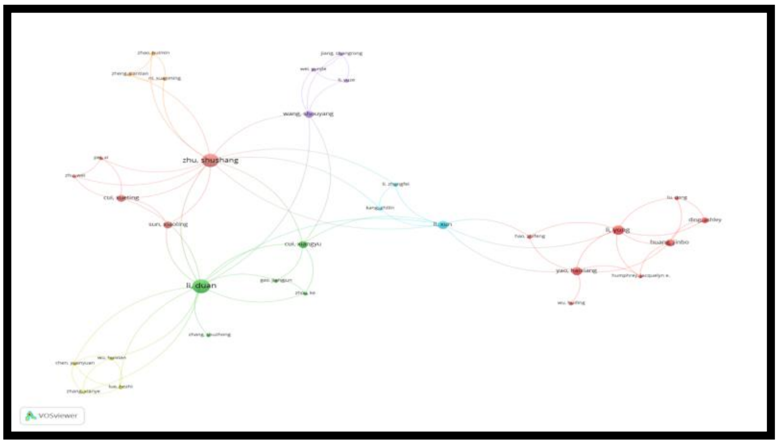


Fig. 4: Top Authors and Co-Authorship in Portfolio Optimisation from 1989 to 2023.

Figure 4 shows a network of influential authors who published papers on portfolio optimisation from 1989 to 2023 taken from VOS viewer. The nodes in the network represent authors, and the edges represent co-authorship relationships. As evident from the diagram, the network is divided into several clusters, represented by different colours like red, orange, green, and purple, with more prominent authors at the centre connecting with other authors. As depicted in the picture, Li Duan has worked chiefly with Cui, Li Yong with Yao, Huan, and Ding, whereas Zhu has coauthored mostly with Cui.

3.6. Country-wise

The most productive and influential countries and their network with other countries are depicted in Figure 5 (Colapinto & Mejri, 2024).

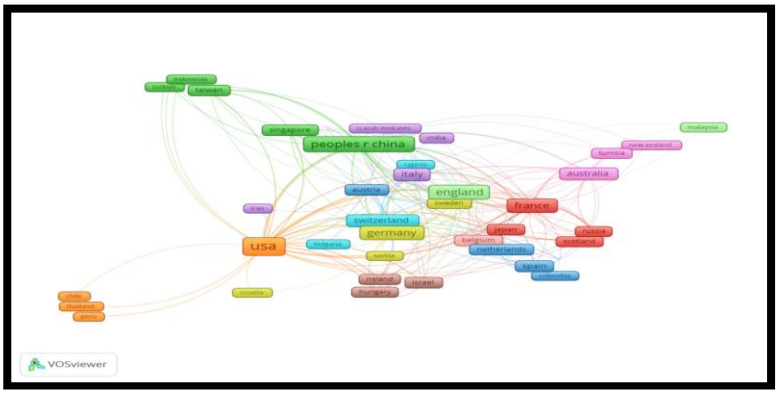


Fig. 5: Country-Wise in Portfolio Optimisation from 1989 to 2023.

Figure 5 represents the network diagram of the top countries with the highest publications and connections shown in nodes. They connected with other countries, as shown in the edge of the connection nod, dividing the data into various clusters. As shown in the picture, the USA, China, France, and England are mostly connected countries publishing papers on portfolio optimisation. Other significant participants in the network are Germany, India, Australia, France, and Italy, which are highly connected to other countries in the network and have a sizable number of publications. Canada and Spain are less connected to the other countries in the network, but they still have many articles and citations.
The geographical distribution of the papers is shown in Table 4 (Colapinto & Mejri, 2024; Dzikowski, 2018).

Table 4: List of Countries of Publication and Citation in Decreasing Order from 1989 to 2023

Ordered according to Highest to Lowest article published		Ordered according to Highest to Lowest citation	
Country	Articles	Country	Citations
USA	291	USA	6303
People's republic of china	143	England	4059
England	121	France	1773
France	99	People's republic of china	1753
Germany	95	Germany	1573
Canada	72	Switzerland	1378
Italy	61	Italy	1033
Australia	51	Spain	892

The data in Table 4 outlines the top countries that contribute to portfolio optimisation ranked according to publication and citation. The United States tops the list with an extensive 291 publications, and citation-wise, 6303 in total are well represented in the research. China comes second with 143 documents, which also indicates significant research activity. Other notable contributing countries are England, Germany, France etc. India, with nine publications and 53 citations, has a great scope of research in this area. The dataset highlights the global nature of research in portfolio optimisation, with several countries actively participating in academics and contributing to the body of knowledge.

3.7. Top organisations that published articles in portfolio optimisation from 1989 to 2023

The top organisation's network is based on publications in Figure 6 (Xu et al., 2020).

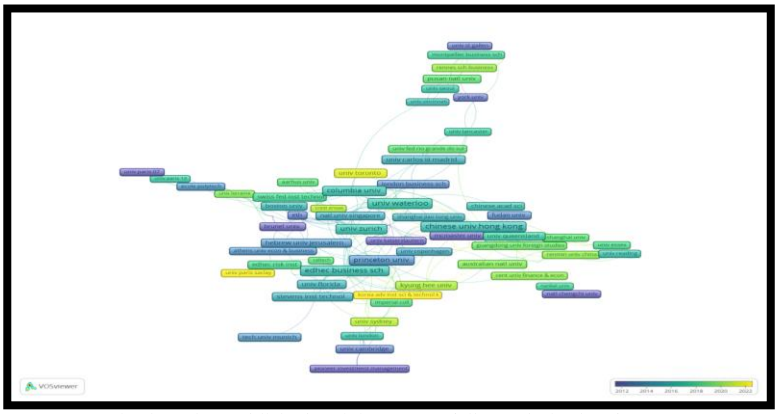


Fig. 6: Organisation That Published Articles on Portfolio Optimisation from 1989 to 2023.

The map shows that the University of California, Berkeley (Teplova et al., 2023) is the most connected university, with connections to 23 other universities. The University of Toronto is the second most connected university, connecting to 21 universities. Other highly connected universities include Stanford, Harvard, and the Massachusetts Institute of Technology. The map also shows strong connections between universities in the United States, Canada, and Europe. However, there are also connections between universities in Asia and Australia (Xidonas et al., 2020).
Top ten organisations based on the citation of publications are shown in Table 5(Xu et al., 2020).

Table 5: Top Organisations Publishing Articles on Portfolio Optimisation with the Highest Citation from 1989 to 2023

Organisation	Documents	Citations
London business school	6	1692
University Texas Austin	7	1522
Columbia univ	17	521
Univ oxford	14	517
Stevens inst technol	9	500
Chinese univ hong Kong	23	481
Univ Washington	8	445
Univ Florida	10	431
Univ Paris 09	7	416
Univ Vienna	5	363

Table 5 provides an overview of research output and citation impact across various academic and research organisations (Santos et al., 2022). The London Business School stands out with six documents, yet a remarkable citation councount1692, showcasing substantial influence in the field. Other institutions with notable citation impact include the University of Texas at Austin (1522 citations), Columbia University (521 citations), the University of Oxford (517 citations), and Stevens Institute of Technology (500 citations) etc.

3.8. Top cited references

Most influencing authors and co-authors' network layout in Figure7 (Colapinto & Mejri, 2024).

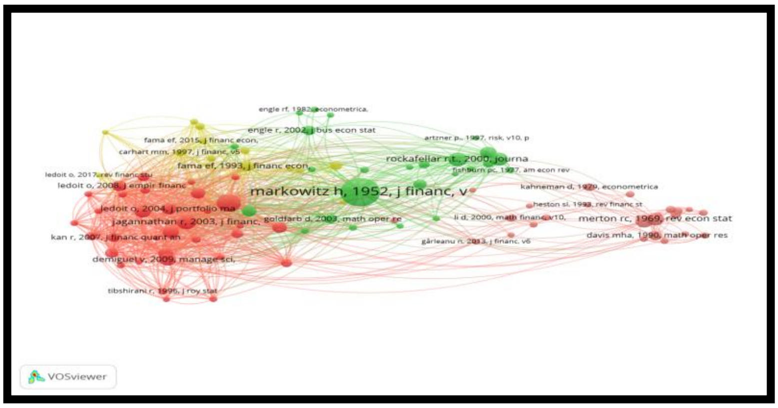


Fig. 7: Top Cited References on Portfolio Optimisation from 1989 to 2023.

The top-cited publications and influential authors are shown in Table 6 (Perianes-Rodriguez et al., 2016).

Table 6: Top cited Referenced that Published in Portfolio Optimization from 1989 to 2023

Name	Year	Source	Volume	Page	DOI	Cita- tions
Markowitz, H.	1952	Journal of Finance	7	77	10.1111/j.1540-6261. 1952.tb01525.x	412
DeMiguel, V.	2009	Review of Financial Studies	22	1915	10.1093/RFS/hhm075	175
Jagannathan, R.	2003	Journal of Finance	58	1651	10.1111/1540-6261.00580	123
Rockafellar, R.T.	2000	Journal of Risk	2	21	10.21314/jor.2000.038, doi 10.21314/jor.2000.038	119
Artzner, P.	1999	Mathematical Finance	9	203	10.1111/1467-9965.00068	109
Merton, R.C.	1969	Review of Economics and Statistics	51	247	10.2307/1926560	103
Merton, R.C.	1971	Journal of Economic The- ory	3	373	10.1016/0022-0531(71)90038-x	102
DeMiguel, V.	2009	Management Science	55	798	10.1287/mnsc.1080.0986	90
Ledoit, O.	2003	Journal of Empirical Fi- nance	10	603	10.1016/s0927-5398(03)00007-0	88
Rockafellar, R.T.	2002	Journal of Banking & Fi- nance	26	1443	10.1016/s0378-4266(02)00271-6	86
Michaud, R.	1989	Financial Analysts Journal	45	31	10.2469/faj.v45.n1.31	85
Ledoit, O.	2004	Journal of Portfolio Man- agement	30	110	10.3905/jpm.2004.110	78
Black, F.	1992	Financial Analysts Journal	48	28	10.2469/faj.v48.n5.28	75
Fama, E.F.	1993	Journal of Financial Eco- nomics	33	3	10.1016/0304-405x(93)90023-5	74
Chopra, V.K.	1993	Journal of Portfolio Man- agement	19	6	10.3905/jpm.1993.409440	72
Best, M.J.	1991	Review of Financial Studies	4	315	10.1093/rfs/4.2.315	71
Ledoit, O.	2008	Journal of Empirical Fi- nance	15	850	10.1016/j.jempfin.2008.03.002	71

Figure 7 depicts a network diagram of the most cited reference works taken from Vos viewer software over the years. As mentioned in Table 6, (H. Markowitz, 1952) introduced the mean-variance framework for portfolio optimisation, which is still the foundation for most modern portfolio theory getting the highest citations. Janc (2004) proposed a robust optimisation approach(Gunjan & Bhattacharyya, 2023) to portfolio optimisation, which can handle uncertainty in the model parameters. (ENGLE & NG, 1993) and (Engle, 2001)developed models for estimating time-varying volatility, which can be used to improve the accuracy of risk calculations in portfolio optimisation. (Kilsgård & Wittorf, n.d.) proposed a three-factor model for asset pricing, which can be used to construct more efficient portfolios. (Artzner et al., 1999) introduced the concept of coherent risk measures, which are desirable properties for risk measures in portfolio optimisation. (Trimech & Kortas, 2009) proposed a four-factor asset pricing model which includes a momentum factor. Rockafellar (2000) developed a risk measure called CVaR(Deng et al., 2011), which is more robust to outliers than traditional risk measures. Ledoit and Wolf (2003) proposed a shrinkage estimator for the covariance matrix (Albuquerque et al., 2023), which can improve the accuracy of portfolio optimisation models. Fama and French (1993) proposed a three-factor asset pricing model, including size and value factors. Fishburn (1977) introduced the concept of mean-semivariance analysis (Rigamonti & Lučivjanská, 2022), which is a more robust alternative to mean-variance analysis(Alexander & Baptista, 2002). Ledoit and Wolf (2004) proposed a shrinkage estimator for the covariance matrix that is more robust than the estimator proposed in their 2003 paper. Heston (1993) developed a stochastic volatility model (Lin & SenGupta, 2023), which can be used to model the time-varying volatility of asset prices. Jagannathan and Wang (2003) (Jagannathan & Ma, 2003) proposed a four-factor asset pricing model, which includes a liquidity factor. Goldfarb and Iyengar (2003) developed an algorithm for robust portfolio optimisation (Xidonas et al., 2020). LID (2000) and Merton (1969) developed models for pricing options, which can be used to construct portfolios that are hedged against risk.

4. Conclusion and future suggestion

This systematic and bibliographic literature review stands out by integrating advanced bibliometric methods, including network visualization and bibliographic coupling, which offer a more nuanced understanding of the intellectual structure and research trends in portfolio optimization. These techniques allow for the identification of key research clusters and emerging themes that have not been thoroughly explored in previous reviewsCovering over three decades of research, this review provides a comprehensive temporal analysis that traces the evolution of portfolio optimization. By examining shifts in research focus and methodology, the study uncovers trends that highlight the field's dynamic nature and its adaptation to emerging financial challenges. The foundation of Modern Portfolio Theory(Elton & Gruber, n.d.) established by Markowitz emphasised risk-return(Mangram, 2013; H. Markowitz, 1952; Pandey, 2012) and diversification remains the basis for portfolio construction. Meanwhile, the construction of efficient portfolios that can outperform market benchmarks highlights the importance of the asset pricing model by Sharpe in 1964(Sharpe, 1964) That leads to further advancements like robust optimisation (García et al., 2012; Ghahtarani et al., 2022; Oberoi et al., 2019; Xidonas et al., 2020), multi-asset class integration, and machine learning(Mazraeh et al., 2022; Pattnaik & Pattnaik, n.d.) algorithms(Kumar et al., 2023; Sharma et al., 2023; H. Zhou, 2017) to meet the dynamic and contemporary market. Still, risk management (Ghanbari et al., 2023a; Jagannathan & Ma, 2003; Risk Management in Indian Stock Market, n.d.; Yang et al., n.d.)will mitigate risk with advanced models with multimodal risk measures.

Ts field anticipates further integration of artificial intelligence, complex data, and machine learning for personalisation that can deal with dynamics portfolio construction and asset allocation(Milhomem & Dantas, 2020b; Resta, 2012).

The insights generated from this review offer a valuable foundation for future researchers, particularly those new to the field. By identifying key studies and methodological trends, the review equips scholars with the necessary background to advance the field of portfolio optimization, fostering the development of new models and approaches. For practitioners, the findings of this review underscore the increasing relevance of AI-driven methodologies in portfolio optimization. As the field continues to evolve, these insights can inform the adoption of cutting-edge techniques, enabling portfolio managers to enhance decision-making processes and optimize investment outcomes in increasingly complex financial markets. he review's comprehensive analysis of portfolio optimization literature has the potential to influence educational curricula and policy-making in finance. By integrating the latest research trends and methodologies into academic programs, educators can better prepare students for the challenges of modern financial management, while policymakers can leverage these insights to promote more informed investment strategies. (Fabretti & Herzel, 2012).

References

[1] Albuquerque, P. H. M., de Moraes Souza, J. G., & Kimura, H. (2023). Artificial intelligence in portfolio formation and forecast: Using different variance-covariance matrices. Communications in Statistics - Theory and Methods, 52(12), 4229–4246. https://doi.org/10.1080/03610926.2021.1987472.

[2] Alexander, G. J., & Baptista, A. M. (2002a). Economic implications of using a mean-VaR model for portfolio selection: A comparison with mean-variance analysis. In Journal of Economic Dynamics & Control (Vol. 26). www.elsevier.com/locate/econbase. https://doi.org/10.1016/S0165-1889(01)00041-0.

[3] Alexander, G. J., & Baptista, A. M. (2002b). Economic implications of using a mean-VaR model for portfolio selection: A comparison with mean-variance analysis. In Journal of Economic Dynamics & Control (Vol. 26). www.elsevier.com/locate/econbase. https://doi.org/10.1016/S0165-1889(01)00041-0.

[4] Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. Mathematical Finance, 9(3), 203–228. https://doi.org/10.1111/1467-9965.00068.

[5] Bartram, S. M., Branke, J., & Motahari, M. (n.d.). CFA INSTITUTE RESEARCH FOUNDATION / LITERATURE REVIEW ARTIFICIAL INTELLIGENCE IN ASSET MANAGEMENT.

[6] Black, F., & Litterman, R. (n.d.). Global Portfolio Optimization. In Source: Financial Analysts Journal (Vol. 48, Issue 5). https://doi.org/10.2469/faj.v48.n5.28.

[7] Colapinto, C., & Mejri, I. (2024). The relevance of goal programming for financial portfolio management: a bibliometric and systematic literature review. Annals of Operations Research. https://doi.org/10.1007/s10479-024-05911-y.

[8] Deng, L., Ma, C., & Yang, W. (2011). Portfolio Optimisation via Pair Copula-GARCH-EVT-CVaR Model. Systems Engineering Procedia, 2, 171–181. https://doi.org/10.1016/j.sepro.2011.10.020.

[9] Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070.

[10] Dzikowski, P. (2018). A bibliometric analysis of born global firms. Journal of Business Research, 85, 281–294. https://doi.org/10.1016/j.jbusres.2017.12.054.

[11] Elton, E. J., & Gruber, M. J. (n.d.). Modern portfolio theory, 1950 to date.

[12] Engle, R. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. In Journal of Economic Perspectives (Vol. 15, Issue 4). https://doi.org/10.1257/jep.15.4.157.

[13] ENGLE, R. F., & NG, V. K. (1993). Measuring and Testing the Impact of News on Volatility. The Journal of Finance, 48(5), 1749–1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x.

[14] Fabretti, A., & Herzel, S. (2012). Delegated portfolio management with socially responsible investment constraints. European Journal of Finance, 18(3–4), 293–309. https://doi.org/10.1080/1351847X.2011.579746.

[15] Fama, E. F., & French, K. R. (n.d.). A Five-Factor Asset Pricing Model. http://ssrn.com/abstract=2287202Electroniccopyavailableat:https://ssrn.com/abstract=2287202Electroniccopyavailableat:https://ssrn.com/abstract=2287202

[16] Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds*. In Journal of Financial Economics (Vol. 33). https://doi.org/10.1016/0304-405X(93)90023-5.

[17] García, S., Quintana, D., Galván, I. M., & Isasi, P. (2012). Time-stamped resampling for robust evolutionary portfolio optimisation. Expert Systems with Applications, 39(12), 10722–10730. https://doi.org/10.1016/j.eswa.2012.02.195.

[18] Ghahtarani, A., Saif, A., & Ghasemi, A. (2022). Robust portfolio selection problems: a comprehensive review. In Operational Research (Vol. 22, Issue 4, pp. 3203–3264). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s12351-022-00690-5.

[19] Ghanbari, H., Safari, M., Ghousi, R., Mohammadi, E., & Nakharutai, N. (2023a). Bibliometric analysis of risk measures for portfolio optimisation. Accounting, 9(2), 95–108. https://doi.org/10.5267/j.ac.2022.12.003.

[20] Ghanbari, H., Safari, M., Ghousi, R., Mohammadi, E., & Nakharutai, N. (2023b). Bibliometric analysis of risk measures for portfolio optimisation. Accounting, 9(2), 95–108. https://doi.org/10.5267/j.ac.2022.12.003.

[21] Ghodrati, H., & Zahiri, Z. (2014). A Monte Carlo simulation technique to determine the optimal portfolio. Management Science Letters, 465–474. https://doi.org/10.5267/j.msl.2014.1.023.

[22] Gunjan, A., & Bhattacharyya, S. (2023a). A brief review of portfolio optimisation techniques. Artificial Intelligence Review, 56(5), 3847–3886. https://doi.org/10.1007/s10462-022-10273-7.

[23] Gunjan, A., & Bhattacharyya, S. (2023b). A brief review of portfolio optimisation techniques. Artificial Intelligence Review, 56(5), 3847–3886. https://doi.org/10.1007/s10462-022-10273-7.

[24] Gustavo Carvalho Santos, F. B. A. C. P. V. (n.d.). Portfolio Optimisation using Artificial Intelligence: A Systematic Literature Review. Retrieved 6 January 2024, from https://www.researchgate.net/publication/362660222_Portfolio_Optimization_using_Artificial_Intelligence_A_Systematic_Literature_Review.

[25] H. Kent Baker, J. R. N. A. C. S. (n.d.). DESIGNING YOUR PORTFOLIO: THE ROLE OF ASSET ALLOCATION, DIVERSIFICATION, AND REBALANCING. Retrieved 6 January 2024, from https://www.emerald.com/insight/content/doi/10.1108/978-1-83909-608-220201005/full/html.

[26] Hayes, A. S. (2021). The active construction of passive investors: Robo-advisors and algorithmic "low-finance." Socio-Economic Review, 19(1), 83–110. https://doi.org/10.1093/ser/mwz046.
[27] Idzorek, T. M. (2004). A STEP-BY-STEP GUIDE TO THE BLACK-LITTERMAN MODEL Incorporating user-specified confidence levels.
[28] Jagannathan, R., & Ma, T. (2003). Risk Reduction in Large Portfolios: Why Imposing the Wrong Constraints Helps. In Source: The Journal of Finance (Vol. 58, Issue 4). https://doi.org/10.1111/1540-6261.00580.
[29] Jahan, N., Naveed, S., Zeshan, M., & Tahir, M. A. (2016). How to Conduct a Systematic Review: A Narrative Literature Review. Cureus. https://doi.org/10.7759/cureus.864.
[30] Kalayci, C. B., Ertenlice, O., & Akbay, M. A. (2019). A comprehensive review of deterministic models and applications for mean-variance portfolio optimisation. In Expert Systems with Applications (Vol. 125, pp. 345–368). Elsevier Ltd. https://doi.org/10.1016/j.eswa.2019.02.011.
[31] Karp, A. (2017). The Capital Asset Pricing Model and Fama-French Three Factor Model in An Emerging Market Environment. In International Business & Economics Research Journal-Third Quarter (Vol. 16, Issue 3). https://doi.org/10.19030/iber.v16i4.10040.
[32] Kilsgård, D., & Wittorf, F. (n.d.). The Fama and French Three-Factor Model-Evidence from the Swedish Stock Market.
[33] Kolm, P. N., Tütüncü, R., & Fabozzi, F. J. (2014). 60 Years of portfolio optimisation: Practical challenges and current trends. European Journal of Operational Research, 234(2), 356–371. https://doi.org/10.1016/j.ejor.2013.10.060.
[34] Kumar, A., Nadeem, M., & Banka, H. (2023). Nature inspired optimisation algorithms: a comprehensive overview. In Evolving Systems (Vol. 14, Issue 1, pp. 141–156). Institute for Ionics. https://doi.org/10.1007/s12530-022-09432-6.
[35] Lin, M., & SenGupta, I. (2023). Analysis of optimal portfolio on finite and small-time horizons for a stochastic volatility model with multiple correlated assets. http://arxiv.org/abs/2302.06778. https://doi.org/10.1142/S0219024924500237.
[36] Mangram, M. E. (2013). A SIMPLIFIED PERSPECTIVE OF THE MARKOWITZ PORTFOLIO THEORY (Vol. 7). http://ssrn.com/abstract=2147880
[37] Markowitz, H. (1952). PORTFOLIO SELECTION*. The Journal of Finance, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x.
[38] Markowitz, H. M. (1989). Review Reviewed Work(s): Mean-Variance Analysis in Portfolio Choice and Capital Markets by The Journal of Finance (Vol. 44, Issue 2). https://doi.org/10.2307/2328607.
[39] Mazraeh, N. B., Daneshvar, A., Madanchi Zaj, M., & Roodposhti, F. R. (2022). Stock Portfolio Optimization Using a Combined Approach of Multiobjective Grey Wolf Optimizer and Machine Learning Preselection Methods. Computational Intelligence and Neuroscience, 2022. https://doi.org/10.1155/2022/5974842.
[40] Mellal, M. A., Zio, E., & Williams, E. J. (2020). Cost minimisation of repairable systems subject to availability constraints using an efficient cuckoo optimisation algorithm. Quality and Reliability Engineering International, 36(3), 1098–1110. https://doi.org/10.1002/qre.2617.
[41] Milhomem, D. A., & Dantas, M. J. P. (2020a). Analysis of New Approaches Used in Portfolio Optimisation: a Systematic Literature Review. Production, 30, 1–16. https://doi.org/10.1590/0103-6513.20190144.
[42] Milhomem, D. A., & Dantas, M. J. P. (2020b). Analysis of New Approaches Used in Portfolio Optimisation: a Systematic Literature Review. Production, 30, 1–16. https://doi.org/10.1590/0103-6513.20190144.
[43] Molina, D., Poyatos, J., Ser, J. Del, García, S., Hussain, A., & Herrera, F. (2020). Comprehensive Taxonomies of Nature- and Bio-inspired Optimisation: Inspiration Versus Algorithmic Behavior, Critical Analysis Recommendations. Cognitive Computation, 12(5), 897–939. https://doi.org/10.1007/s12559-020-09730-8.
[44] Oberoi, S., Girach, M. B., & Chakrabarty, S. P. (2019). Can robust optimisation offer improved portfolio performance?: An empirical study of the Indian market. http://arxiv.org/abs/1908.04962
[45] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. In The BMJ (Vol. 372). BMJ Publishing Group. https://doi.org/10.1136/bmj.n71.
[46] Pandey, M. (2012). APPLICATION OF MARKOWITZ MODEL IN ANALYSING RISK AND RETURN A CASE STUDY OF BSE STOCK. In Risk governance & control: financial markets & institutions (Vol. 2, Issue 1). https://doi.org/10.22495/rgcv2i1art1.
[47] Pattnaik, M., & Pattnaik, A. (n.d.). Machine Learning Algorithms to Fight the COVID-19 Pandemic. https://doi.org/10.1101/2022.12.31.22284091.
[48] Perianes-Rodriguez, A., Waltman, L., & van Eck, N. J. (2016). Constructing bibliometric networks: A comparison between full and fractional counting. Journal of Informetrics, 10(4), 1178–1195. https://doi.org/10.1016/j.joi.2016.10.006.
[49] Pinar, M. Ç. (2013). Static and dynamic VaR-constrained portfolios with application to delegated portfolio management. Optimisation, 62(11), 1419–1432. https://doi.org/10.1080/02331934.2013.854785.
[50] Reddy Irala, L., Patil, P., & Patil, P. (n.d.). Portfolio Size and Diversification. In SCMS Journal of Indian Management (Vol. 4, Issue 1). http://ssrn.com/abstract=977763.
[51] Resta, M. (2012). Portfolio Optimisation: New Challenges and Perspectives. In Recent Patents on Computer Science (Vol. 5). https://doi.org/10.2174/1874479611205010059.
[52] Rigamonti, A., & Lučivjanská, K. (2022). Mean-semivariance portfolio optimisation using minimum average partial. Annals of Operations Research. https://doi.org/10.1007/s10479-022-04736-x.
[53] Risk management in the Indian stock market. (n.d.).
[54] Rojas-Sánchez, M. A., Palos-Sánchez, P. R., & Folgado-Fernández, J. A. (2023). Systematic literature review and bibliometric analysis on virtual reality and education. Education and Information Technologies, 28(1), 155–192. https://doi.org/10.1007/s10639-022-11167-5.
[55] Roman, D., & Mitra, G. (2009). Portfolio selection models: a review and new directions. Wilmott Journal, 1(2), 69–85. https://doi.org/10.1002/wilj.4.
[56] Santos, G. C., Barboza, F., Veiga, A. C. P., & Gomes, K. (2022). Portfolio Optimisation using Artificial Intelligence: A Systematic Literature Review. Exacta. https://doi.org/10.5585/exactaep.2022.21882.
[57] Sharma, L., Chellapilla, V. L., & Chellapilla, P. (2023). Socio-inspired evolutionary algorithms: a unified framework and survey. Soft Computing, 27(19), 14127–14156. https://doi.org/10.1007/s00500-023-07929-z.
[58] Sharpe, W. F. (1964). CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK. The Journal of Finance, 19(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x.
[59] Siaw, R. O., Dei Ofosu-Hene, E., & Evans, T. (2015). ELK ASIA PACIFIC JOURNAL OF FINANCE AND RISK MANAGEMENT INVESTMENT PORTFOLIO OPTIMISATION WITH GARCH MODELS. 8. https://doi.org/10.16962/EAPJFRM/issn
[60] Statman, M. (1987). How Many Stocks Make a Diversified Portfolio? In Source: The Journal of Financial and Quantitative Analysis (Vol. 22, Issue 3). https://doi.org/10.2307/2330969.
[61] Teplova, T., Evgeniia, M., Munir, Q., & Pivnitskaya, N. (2023). Black-Litterman model with copula-based views in mean-CVaR portfolio optimisation framework with weight constraints. Economic Change and Restructuring, 56(1), 515–535. https://doi.org/10.1007/s10644-022-09435-y.
[62] Thein Lwin, K. (2015). Evolutionary Approaches for Portfolio Optimization.
[63] Trimech, A., & Kortas, H. (2009). 61 Multiscale Carhart Four-Factor Pricing Model: Application to the French Market Multiscale Carhart Four-Factor Pricing Model: Application to the French Market. https://doi.org/10.1108/15265940910938251.
[64] Xidonas, P., Steuer, R., & Hassapis, C. (2020). Robust portfolio optimisation: a categorised bibliographic review. Annals of Operations Research, 292(1), 533–552. https://doi.org/10.1007/s10479-020-03630-8.
[65] Xu, S., Zhang, X., Feng, L., & Yang, W. (2020). Disruption risks in supply chain management: a literature review based on bibliometric analysis. In International Journal of Production Research (Vol. 58, Issue 11, pp. 3508–3526). Taylor and Francis Ltd. https://doi.org/10.1080/00207543.2020.1717011.
[66] Yang, Y., Zhao, L., Chen, L., Wang, C., & Han, J. (n.d.). Portfolio optimisation with idiosyncratic and systemic risks for financial networks.

[67] Zaimovic, A., Omanovic, A., & Arnaut-Berilo, A. (2021). How Many Stocks Are Sufficient for Equity Portfolio Diversification? A Review of the Literature. In Journal of Risk and Financial Management (Vol. 14, Issue 11). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/jrfm14110551.

[68] Zanjirdar, M. (2020). Overview of Portfolio Optimization Models. Advances in Mathematical Finance & Applications, 5(4), 419–435. https://doi.org/10.22034/amfa.2020.1897346.1407

[69] Zhou, H. (2017). Algorithmic Trading and High Frequency Trading.

[70] Zhou, W., Zhu, W., Chen, Y., & Chen, J. (2022). Dynamic changes and multi-dimensional evolution of portfolio optimisation. Economic Research-Ekonomska Istrazivanja , 35(1), 1431–1456. https://doi.org/10.1080/1331677X.2021.1968308.