

Bibliometric analysis of risk measures for portfolio optimization**Hossein Ghanbari^a, Mojtaba Safari^b, Rouzbeh Ghousi^{a*}, Emran Mohammadi^a and Nawapon Nakharutai^b**^a*Department of Industrial Engineering, Iran University of Science & Technology, Tehran, 13114-16846, Iran*^b*Department of Statistics, Faculty of Science, Chiang Mai University, Thailand, Mai 50200 Thailand***CHRONICLE****ABSTRACT***Article history:*

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Portfolio optimization aims to minimize risk and maximize return on investment by determining the best combination of securities and proportions. The variance in portfolio optimization models is typically used for a measure of risk. Over the last few decades, portfolio optimization utilizing a variety of risk measures has grown significantly, and many studies have been conducted. Therefore, this paper provides a systematic review of risk measures for portfolio optimization using bibliometric analysis and maps to analyze the evolution and trends of 682 articles published between 2000 and 2022. Throughout this analysis, communication networks among articles, authors, sources, countries, and keywords are explored. Furthermore, a classification of risks and risk measures were presented to demonstrate a comprehensive overview of the field, and the top 50 papers were analyzed to determine which risk measures were most often used in recent studies.

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1. Introduction

Capital markets are among the most significant economic sectors in a country, so their activity and prosperity are an indication of a country's development on the international scene (Ghanbari et al., 2022). One of the key levers in achieving the economic development of society is investment, which is so crucial for economic and social growth (Orlowski, 2020). Over the last few decades, the investment industry has grown significantly in theory and practice (Foeik et al., 2022). This can be attributed to the development of capital markets and the introduction of various financial instruments. The impact of this growth is clearly visible in financial markets (William Sharpe, Gordon J. Alexander, 1998). Individual Investors, brokers, and fund managers invest billions of dollars each year in various sectors. The most common investment strategy is to create an investment portfolio to spread the risk (Kalayci et al., 2019). Portfolio optimization is the process of selecting the best and the most suitable number of stocks among various types of stocks to purchase and hold for a period to maximize returns (Shadabfar & Cheng, 2020). The problem of selecting the optimal stock portfolio is a classic problem in the financial management literature that was founded by Markowitz (1952). By conducting an analysis of the impact of risk in 1952, Harry Markowitz introduced a revolutionary paradigm for portfolio theory called the mean-variance model, ushering in the era of modern portfolio theory. Previously, investors understood the concepts of return and risk, and diversification was intuitively recognized as a good way of managing portfolios, but Markowitz introduced a quantitative approach to estimating risk and return. For his pioneering works in financial theory, Markowitz received the Nobel Prize in economics in 1991. Technology advancements, as well as the rise of computing power, have significantly increased the number of

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researchers interested in this field, as evidenced by the high number of articles published in scientific journals (Beyhaghi & Hawley, 2013; Hallin & Trucios, 2021; Le, 2021; Sass & Thös, 2021; Wang et al., 2022). During their research, researchers have attempted to improve the original Markowitz model by providing a new solution that would cover its weaknesses (Konno & Yamazaki, 1991). When making investment decisions, investors consider risk to be one of the most important factors, and they seek to achieve the highest return with the least amount of risk acceptance, so in response to this problem, after Markowitz, many researchers focused on this area and created new risk measures. In recent decades, researchers have analyzed the current trends and future research directions of risk measures for portfolio optimization (Table 1).

Table 1
The Risk Measures for Portfolio Optimization - A Selection of Previous Reviews

Year	Authors	Focus	Key Contribution
2004	Byrne and Lee	Mean-Variance, Semi-Variance, Lower Partial Moments, Minimax, Mean Absolute Deviation	Considered a new approach that compares portfolio assets generated by different risk measures
2007	Mausser and Rosen	Value at Risk, Expected Shortfall	Discussed the advantages and disadvantages of various risk measures and models, the interpretation of various allocation strategies as well as the numerical issues associated with this task
2011	Ortobelli et al.	Minimax, Mean Absolute Deviation, Standard Deviation, Safety-Risk Measures and Dispersion Measures	Discussed and analyzed risk measure properties in order to see how a risk measure has to be used to optimize the investor's portfolio choices
2014	Hong et al.	Value at Risk, Conditional Value at Risk	Reviewed some of the developments in Monte Carlo methods, provide a unified framework to understand them, and discuss their applications in financial risk management
2015	Targino et al.	Standard Deviation, Value at Risk, Expected Shortfall	Focused on studying the problem of capital allocation, with particular focus on operational risk capital
2016	Postek et al.	Mean-Variance, Mean Absolute Deviation, Standard Deviation, Value at Risk, Conditional Value at Risk, Entropic Value at Risk, Coherent Risk Measures	Reviewed the literature on the problem of reformulating such constraints into tractable forms. As their contribution, they have provided a unified framework for tackling this issue
2017	Masmoudi Abdelaziz and	Mean-Variance, Mean Absolute Deviation, Semi-Variance, Value at Risk	Provided a comprehensive literature review of multiple objective deterministic and stochastic programming models for the portfolio selection problem
2019	Kalayci et al.	Mean-Variance	Focused on analyzing the publications based on deterministic models and applications in the Mean-Variance portfolio optimization literature

The main purpose of this paper is to review and analyze the literature regarding risk measure models. The study categorizes risk measures to answer the following questions: (i) What are the different types of risks and risk measures? (ii) Which risk measure models are investigated most often? (iii) Which solution techniques have been applied to risk measure models? Besides, this paper presents a comprehensive bibliometric and network analysis, which provides insights that have not been fully explored or analyzed by other studies. The remainder of this paper is organized as follows. Section 2 presents the data and methodology used in this review. This is followed by the results of bibliometrics analysis which highlights the recent trends of the investigated research area and provides an overview of the most influential authors, journals, and affiliations as well as documents. Section 4 introduces risk measures and reviews the articles to determine which risk measures have been used most often in the articles and finally, section 5 concludes the article and discusses future research orientations.

2. Data and Methodology

Since the scientific community is practicing an era called "big science", it is difficult to stay current with all contributions and review all scientific publications (Zabavnik & Verbič, 2021). To overcome the problem, Bibliometrics can be used to evaluate the literature via statistical measures on the subject of a particular research area (Aria & Cuccurullo, 2017). Bibliometric analysis is a statistical evaluation of published articles, books, or book chapters, and it is a useful way to measure the influence of publications in the scientific community (Broadus, 1987). In recent years, there has been a surge

in interest in bibliometric analysis, which is being used in a variety of scientific fields, from engineering to sports science (Ampese et al., 2022; Donthu, Kumar, Mukherjee, et al., 2021; Donthu, Kumar, Pandey, et al., 2021; Goyal & Kumar, 2021; Kumar et al., 2020; Safari et al., 2022). However, its application in Finance is relatively new, in particular portfolio optimization, whereas a few good researchers have focused on this subject in recent years (Figure 1). The bibliometric analysis of this paper primarily focuses on finding out about emerging trends, determining outstanding publications, identifying articles, journals, authors, countries, and institutions that have had a major influence on the development of a scientific subject.

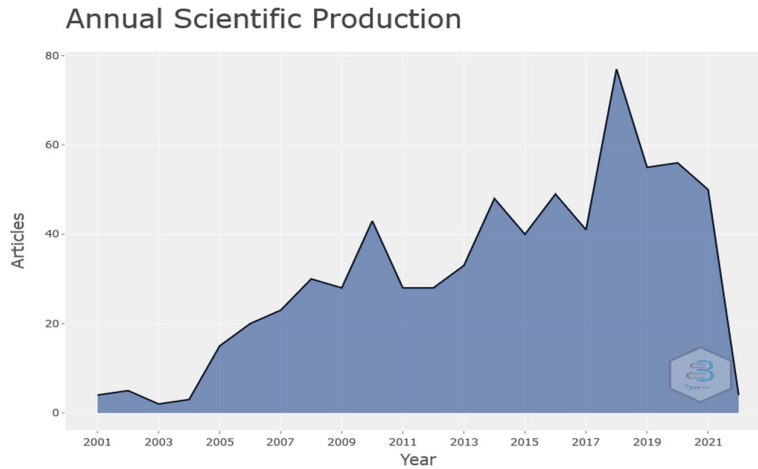


Fig. 1. Published Papers

The first step in bibliometric analysis is to collect data to create a database of relevant documents. Therefore, defining appropriate search terms in databases such as Web of Science and Scopus is necessary to provide the database of relevant papers. The search terms must be defined in such a way that they provide documents relevant to the dedicated field, while also being big enough to permit bibliometric analysis (Kilani et al., 2016; Xiang, 2014). So, a two-step methodology for finding final keywords is used. Initially, we reviewed the literature in order to identify relevant search terms (Table 1), and then we brainstorm among ourselves as well as subject matter experts to determine the final keywords. A list of keywords, including "Portfolio Optimization", "Portfolio Selection", "Portfolio Management", and "Risk Measures" are provided. According to Table 2, With the help of conjunctions "AND" and "OR" and the extracted list of keywords, 682 documents from 2000 to 2022 are obtained on the Web of Science, which is one of the largest bibliographic databases that contain scholarly literature from almost any field of study (Dzikowski, 2018). Following that document titles and abstracts were scrutinized to exclude irrelevant documents. 21 articles were removed and finally, 661 articles were reviewed with the help of Scientometrics. Fig. 2 illustrates detailed information about the document types. Finally, the bibliometric data included Titles, Abstracts, Keywords, full text of publications, and references were collected to analyze. Figure 3 illustrates the bibliometric analysis procedure to better understand readers. It should be noted that prior to running the bibliometric analysis; collected data had been cleaned from duplicates and erroneous entries. In a case, for instance, there were two institutions for a single author.

Table 2
The Proposed Keyword Combination Structure

Level	Search Terms
1	Portfolio AND
2	Optimization OR Selection OR Management AND
3	Risk Measure OR Risk Measures

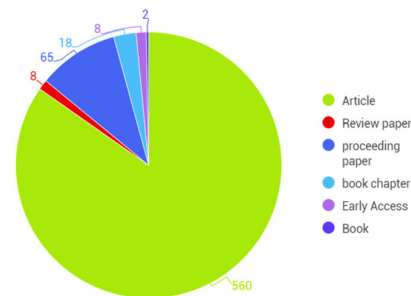


Fig. 2. Details of Search Results

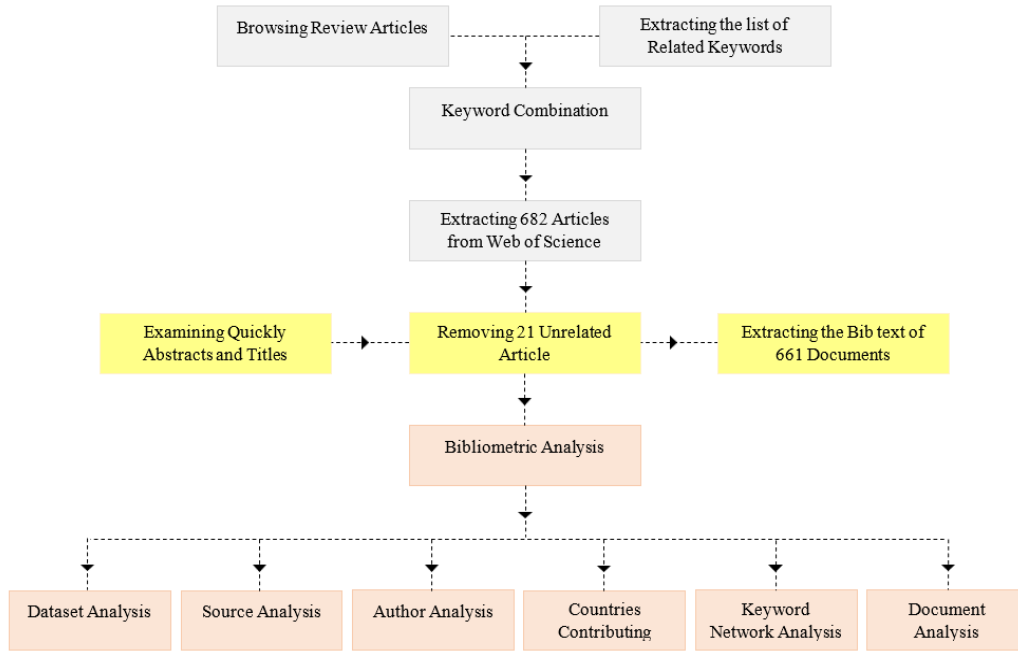


Fig. 3. Steps of Bibliometric Analysis

3. Results of Bibliometrics Analysis

The results are divided into six subsections, including dataset analysis, source analysis, authors and country of productions analysis, keywords network analysis, and document analysis, summarizes a wide range of bibliometric data.

3.1. Dataset Analysis

According to Fig. 1, there is a gradual increase in the number of articles on risk measures for portfolio optimization between 2001 and 2022. Additionally; it peaked at almost 80 articles in 2019. According to the initial statistics, it was found that 315 sources have contributed to the publication of 661 documents. Moreover, the average number of citations per year per document is around 1.601, while the average number of citations per document is around 16.99. To illustrate the most researched topics by the most relevant authors, a three-field plot is shown in Figure 4; For example, Zhiping Chen's research area has focused on portfolio optimization and value at risk as well as conditional value at risk, as two important risk measures, and his most articles in recent years have been published by journal of Quantitative Finance.

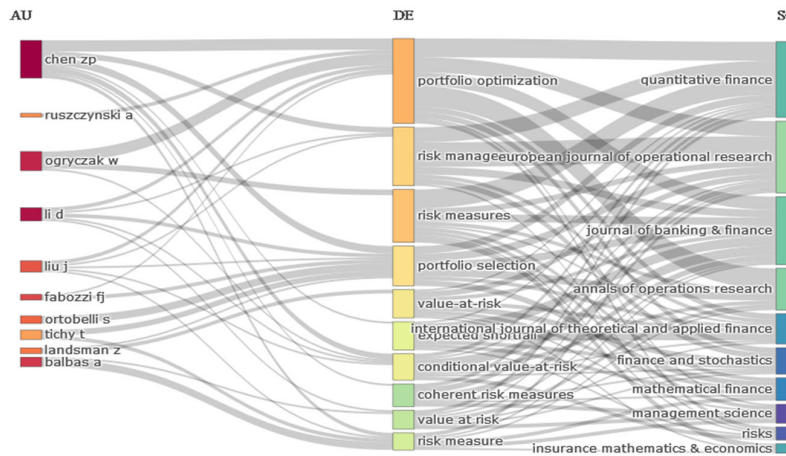


Fig. 4. Three-Field Plot

3.2. Source Analysis and H-Index

The 10 top sources were sorted according to their h-index. H-index has been introduced as a quantitative metric to estimate the overall effective performance of researchers, journals, countries, and institutions since 2005 (Hirsch, 2005). The Journal of Banking and Finance is the most-cited journal by other journals, while the European Journal of Operation Research, which appears at the top of the table in terms of the h-index, has the most self-citations.

Table 3
Top Sources

Rank	Source	Number of Documents	H-Index	Total Citation	Start Year
1	EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	41	17	1199	2001
2	JOURNAL OF BANKING & FINANCE	24	16	2626	2002
3	QUANTITATIVE FINANCE	24	11	572	2007
4	ANNALS OF OPERATIONS RESEARCH	24	10	473	2007
5	INSURANCE MATHEMATICS & ECONOMICS	18	8	207	2001
6	MATHEMATICAL FINANCE	11	7	378	2005
7	OPERATIONS RESEARCH	7	6	362	2009
8	FINANCE AND STOCHASTICS	10	5	378	2006
9	INTERNATIONAL JOURNAL OF THEORETICAL AND APPLIED FINANCE	11	5	235	2005
10	JOURNAL OF ECONOMIC DYNAMICS & CONTROL	5	5	172	2004

3.3. Author Influence

The top 10 authors are sorted according to the number of their publications in table 4. As can be seen in this table Chen as well as Li has the most publications in the topic area. It should be noted that Figure 5 shows that Chen has coauthored a considerable portion of his productions with Liu, and there has been a great cooperation between Li and Zhu in contributing the articles.

Table 4
Top 10 Authors

Rank	Authors	Number of Documents	H-Index	Total Citation	Start Year
1	Chen, Zp	18	7	157	2007
2	Li, D	11	8	146	2009
3	Ogryczak, W	9	7	586	2002
4	Fabozzy, Fj	8	7	292	2005
5	Liu, J	7	5	38	2014
6	Ortobelli, S	7	5	125	2005
7	Uryasev, S	7	6	2324	2001
8	Zabaranki, M	7	6	489	2005
9	Balbas, A	6	5	59	2007
10	Landsman, Z	6	3	31	2011

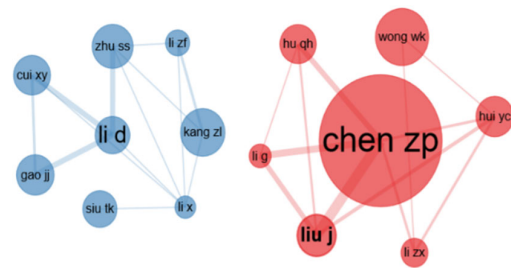


Fig. 5. Co-Authors

3.4. Top Countries Affiliations

Fig. 6 depicts the top countries contributing to portfolio optimization based on risk measures. As a result, CHINA, the United States, ITALY, GERMANY, the UK, and FRANCE have the most participants in the field with 224, 207, 109, 96, 74, and 73 articles, respectively. However, the ranking of countries according to citation per year was depicted in table 5. For instance, although the United States has published the majority of documents on the topic, the Netherlands is the most cited country with 353 publications. Besides, Xi'an Jiaotong University, National University of Singapore, the Chinese

University of Hong Kong, and University of Bergamo have been leading universities in their respective fields.

Table 5
Top Countries

Rank	Country	Total Citation	Average Article citation
1	Netherlands	353	58.83
2	USA	4101	45.57
3	Singapore	301	37.62
4	Norway	138	34.50
5	Ireland	64	32.00
6	Poland	529	29.39
7	Hungary	118	23.60

Country Scientific Production

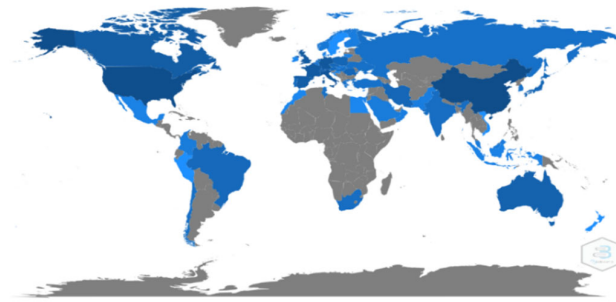


Fig. 6. Top Contributing Countries

3.5. Keywords Network Analysis

Table 6 shows the most frequently used keywords in Author's keywords. The following keywords were drawn from 661 papers and collected from a pool of 2646. Besides, 6 keywords that appeared at least 10 times and were sorted according to their occurrences over time (Figure 7). This figure can be used to identify topics, which have continuously been used in scientific production in the field's portfolio optimization and risk measures. As an example, robustness has recently been considered, while keywords such as conditional value-at-risk and portfolio optimization have been continuously studied by researchers since 2010.

Table 6
The Most Frequency Used Keywords

Rank	Keywords	Frequency
1	Portfolio Optimization	119
2	Risk Measures	112
3	Value at Risk	89
4	Risk Management	70
5	Portfolio Selection	69
6	Conditional Value at Risk	69
7	Expected Shortfall	35
8	Coherent Risk Measures	42
9	Downside Risk	20
10	Stochastic Programming	17

Trend Topics

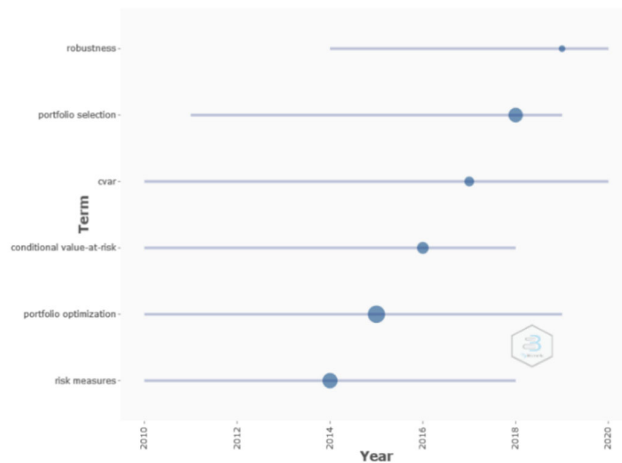


Figure 7: Trend Topics

3.6. Document Analysis

Table 7 lists the most cited articles each year. As a result of Table 7, Figure 8 depicts 84 percent of articles used exact algorithms to solve models, whereas 14 percent of articles used just approximation algorithms, including heuristics and meta-heuristics as the solution techniques. Mansini et al. (2014) compared exact algorithms with approximation algorithms.

According to Figure 9, the parameters used in modeling were mostly uncertain, and certain parameters were only used in a few studies. The following section introduces risk measures before determining what risk measures were used in the listed articles.

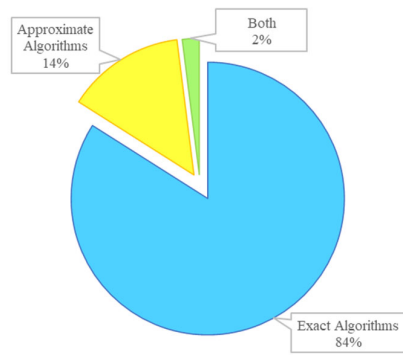


Fig. 8. Category of Solution Technique

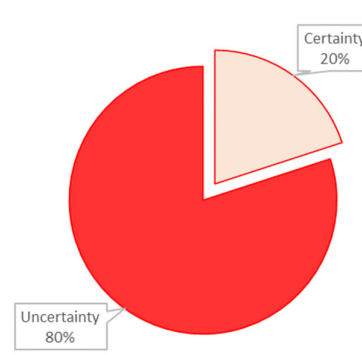


Fig. 9. Category of Parameters Type

Table 7
Review of the Most Cited Documents

Rank	Year	Authors	Solution Techniques			Parameters	
			Exact Algorithm	Approximate Algorithm Heuristic	Meta Heuristic	Certainty	Uncertainty
1	2002	Rockafellar and Uryasev	√				√
2	2018	Mohajerin Esfabani and Kuhn	√				√
3	2004	Rockafellar et al.	√				√
4	2006	Ogryczak and Ruszczyński	√				√
5	2018	Mensi et al.	√			√	
6	2010	Cont et al.	√			√	
7	2014	Mansini et al.	√	√	√		√
8	2009	Fabozzi et al.	√				√
9	2019	Buehler et al.	√			√	
10	2009	Chang et al.	√		√	√	
11	2009	Bali et al.	√			√	
12	2012	Glasserman and Xu	√				√
13	2007	Vercher et al.	√				√
14	2014	Soleimani et al.	√				√
15	2007	Mansini et al.	√				√
16	2005	Kalkbrener	√			√	
17	2012	Pflug et al.	√				√
18	2009	Natarajan et al.	√				√
19	2015	Embrechts et al.	√				√
20	2006	Alexander et al.	√				√
21	2011	Chekhlov et al.	√				√
22	2016	Tietjen et al.	√				√
23	2010	Ben-Tal et al.	√				√
24	2004	Bertsimas et al.	√				√
25	2013	Zymler et al.	√				√
26	2016	Hemmati et al.	√				√
27	2011	He and Zhou	√				√
28	2007	Calafiore	√				√
29	2008	Natarajan et al.	√	√			√
30	2008	Quaranta and Zaffaroni	√				√
31	2011	Chen et al.	√				√
32	2019	Liagkouras	√		√		√
33	2017	Cui et al.	√			√	
34	2015	Najafi and Mushakhian	√		√		√
35	2010	Natarajan et al.	√	√			√
36	2018	Gotoh et al.	√				√
37	2007	Kondor et al.	√				√
38	2019	Kaucic et al.	√		√		√
39	2020	Mensi et al.	√			√	
40	2012	Bertsimas et al.	√				√
41	2015	Branda	√				√
42	2015	Bernard and Vanduffel	√	√			√
43	2017	Ahmadi-Javid and Fallah-Tafti	√				√
44	2018	Masmoudi and Abdelaziz	√				√
45	2019	Trucios Maza et al.	√			√	
46	2007	Roman et al.	√			√	
47	2015	Bekiros et al.	√				√
48	2006	Bäuerle and Müller	√				√
49	2009	Brown and Sim	√				√
50	2014	Hong et al.	√				√

4. Identifying Risk and Risk Measures

As mentioned in the first section, every investment decision is influenced by two factors: return and risk. Investors must understand the nature of risk and how to manage it in order to make informed decisions (Xidonas et al., 2012). The purpose of this section is to explain the theoretical basis of risk in the financial literature.

4.1. Risk

Defining risk is the first step to understanding it. Each researcher provided their own interpretation of risk by presenting a variety of reasons and topics. There are several different and considerable definitions of risk according to time and degree of risk evolution. The risk is the uncertainty of what will occur as the result of an action. In other words, risk occurs when multiple events are likely to occur. Also, the risk is defined as the undesirable deviation between what actually occurs and what was expected. An even more precise definition of risk would be a deviation from events that occurs during a specific period and in a specific situation. Although there are many variations in the way risk is defined, it can still be argued that risky situations have three factors in common (Capiński & Kopp, 2015; Chong, 2004; Peterson, 2012).

1. More than one result is produced by an action.
2. Results are not definitely known until they are tangible.
3. At least one of the possible outcomes has relatively undesirable consequences.

As a result, risk does not always constitute a negative phenomenon, but there is risk with every opportunity, and in principle, not all risks can be eliminated because all opportunities have been lost (Capiński & Kopp, 2015; Chong, 2004; Peterson, 2012).

4.2. Risk Management

The purpose of risk management is to control the adverse consequences of risk imposition and to ensure that the benefits of risk acceptance are realized. Risk management is the process of identifying potential sources of loss and providing solutions to reduce damage and compensation. In financial markets, financial risk management refers to methods that reduce the risk of financial activity. In these methods, the first step is identifying the source of risk, followed by measuring and analyzing it, and then providing a solution to reduce it (Baker & Filbeck, 2015; Bessis, 2011; Hubbard, 2012; Malz, 2011).

1. Identify the source of risk: the first step in risk management is to identify the source from which the risk originates.
2. Risk measurement: once the sources of risk are identified, their severity and degree need to be measured. It is necessary to identify those sources that present a high risk percentage in order to give priority to each for dealing with in the following step based on its importance. Various tools have been made available to investors in this way. Three general categories of risk measures have been introduced for the assessment of risks: volatility risk measures, sensitivity risk measures and downside risk measures.
3. Risk treatment: after identifying the types of risks and measuring them, the next step is to apply strategies to reduce them. There are four strategies we can use here: risk transference, risk avoidance, risk mitigation, and risk acceptance (Baker & Filbeck, 2015; Bessis, 2011; Hubbard, 2012; Malz, 2011).

4.3. Types of Risks

Identifying the different types of risks is the first step in risk assessment. Depending on the nature and consequences of the risks, experts in the financial and economic fields have categorized them in different ways. Here we introduce two perspectives of risks categorization below: a fundamental perspective and a modern portfolio theory perspective (Connor et al., 2010; Parlinska & Panchenko, 2014).

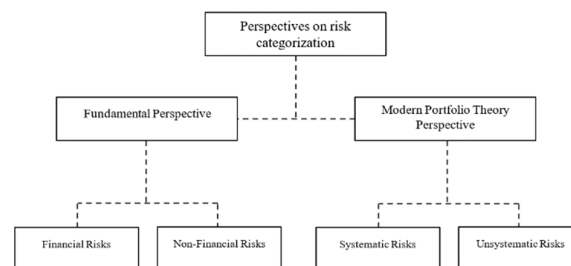


Fig. 10. Perspectives on risk categorization

4.3.1. Fundamental perspective

- Financial risks: financial risks are associated with financial markets and may occur as a result of movements in stock prices or interest rates. Some of them include: exchange rate risk, inflation risk, interest rate risk, liquidity risk, market risk.
- Non-financial risks: unlike financial risks, non-financial risks originate from outside the financial market environment and are influenced by factors other than financial and economic variables, such as processes, environmental consequences, and external events. Some of them include: political risk, industrial risk, operational risk.

Non-financial risks have a large impact on financial risks, meaning each of these non-financial risks eventually causes changes in financial variables. For example, political risks easily cause exchange rate fluctuations. Therefore, changes occur in a complex environment that is hard to evaluate and analyze (Banks, 2012; Saunders & Cornett, 2021; Sironi & Resti, 2007; Skoglund & Chen, 2015).

4.3.2. Modern Portfolio Theory Perspective

The previous perspective to risk is known as the fundamental perspective. According to modern portfolio theory, portfolio risks are divided into two categories: systematic and unsystematic (Brentani, 2004; Brownlees & Engle, 2017; Hill, 2010).

- Systematic risks: systematic risk refers to the part of the total risk of an asset that is affected by the volatility of macro factors. Risks of this nature affect all market securities, diversifying financial assets does not reduce this type of risk. Some of them include: political risk, interest rate risk, and inflation risk.
- Unsystematic risk: unsystematic risk is the part of asset risk that is not influenced by changes in macro factors and is a function of the circumstances of the company and type of industry. Diversification and portfolio building can reduce this type of risk. Some of them include: business risk and liquidity risk.

Investment risk can be described as follows: Total Stock Risk = Systematic Risk + Unsystematic Risk (Brentani, 2004; Brownlees & Engle, 2017; Hill, 2010).

4.4. Risk Measures

So far, several criteria for assessing risk have been proposed by experts, each of them referring to a different aspect of the uncertainty debate, and some of them complementing each other. Dispersion measures were initially used to calculate risk, and then downside risk measures and sensitivity measures were introduced. Thus, risk measures can be divided into volatility risk measures, sensitivity risk measures, and downside risk measures (Bacon, 2008; Catania & Luati, 2021; Chapados, 2011; Hult, 2012; Rachev et al., 2008).

- Volatility risk measures: refers to the fluctuation of a variable around a mean or another random parameter. Variance and standard deviation are examples of volatility risk measures.
- Downside risk measures: contrary to volatility measures, these measures only examine the destructive part of the risk. In fact, they focus on harmful fluctuations. There are two types of downside risk measures: semi-risk measures and quantile-based risk measures. Measures such as semi-variance and semi-standard deviation are in the group of semi-risk measures and measures such as value at risk and expected shortfall are in the group of quantile-based measures.
- Sensitivity risk measures: these risk measures examine the change in a dependent variable resulting from a change in an independent variable. The duration, convexity, and beta coefficient are among the measures of sensitivity (Bacon, 2008; Chapados, 2011; Hult, 2012; Rachev et al., 2008).

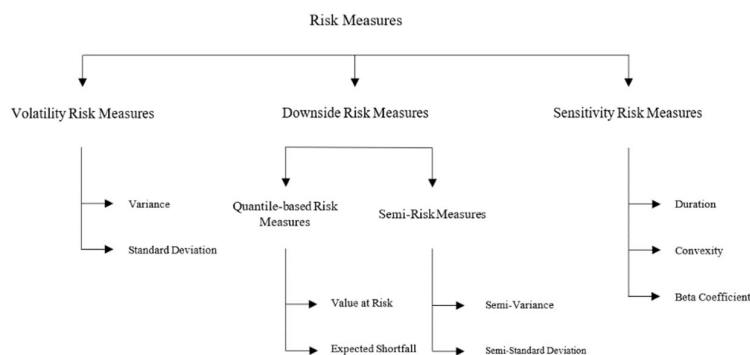


Fig. 11. Risk Measures

As mentioned before the following table introduces the risk measures used in the articles listed in Table 7, section 3.

Table 8
Review of the Most Cited Documents

Rank	year	Authors	Risk Measures
1	2002	Rockafellar and Uryasev	Value at Risk, Conditional Value at Risk
2	2018	Mohajerin Esfahani and Kuhn	Conditional Value at Risk
3	2004	Rockafellar et al.	Value at Risk, Conditional Value at Risk, Deviation Measures, Coherent Risk Measures
4	2006	Ogryczak and Ruszczyński	Quantile Risk Measures
5	2018	Mensi et al.	Conditional Value at Risk
6	2010	Cont et al.	Value at Risk, Conditional Value at Risk, Coherent Risk Measures
7	2014	Mansini et al.	Mean-Safety Models, Mean-Variance, Expected Shortfall
8	2009	Fabozzi et al.	Mean-Variance, Value at Risk, Conditional Value at Risk
9	2019	Buehler et al.	Convex Risk Measures
10	2009	Chang et al.	Mean-Variance, Semi-Variance, Mean Absolute Deviation, Variance with Skewness
11	2009	Bali et al.	Value at Risk, Expected Shortfall, Tail Risk
12	2012	Glasserman and Xu	Mean-Variance, Conditional Value at Risk
13	2007	Vercher et al.	Downside Risk Measures, Semi Absolute Deviation
14	2014	Soleimani et al.	Value at Risk, Conditional Value at Risk, Mean Absolute Deviation
15	2007	Mansini et al.	Conditional Value at Risk, Gini's Mean Difference
16	2005	Kalkbrenner	Standard Deviation, Value at Risk, Expected Shortfall
17	2012	Pflug et al.	Mean-Variance, Conditional Value at Risk
18	2009	Natarajan et al.	Mean-Variance, Value at Risk, Conditional Value at Risk, Coherent risk measures
19	2015	Embrechts et al.	Value at Risk, Expected Shortfall
20	2006	Alexander et al.	Value at Risk, Conditional Value at Risk
21	2011	Chekhlov et al.	Conditional Drawdown, Conditional Value at Risk
22	2016	Tietjen et al.	Conditional Value at Risk
23	2010	Ben-Tal et al.	Entropic Risk Measure, Conditional Value at Risk, Convex Risk Measures, Coherent Risk Measures
24	2004	Bertsimas et al.	Shortfall, Standard Deviation, Value at Risk, Lower Partial Moments, Coherent Risk Measures
25	2013	Zymler et al.	Value at Risk, Worst-case Polyhedral Value at Risk, Worst-case Quadratic Value at Risk
26	2016	Hemmati et al.	Conditional Value at Risk
27	2011	He and Zhou	Mean-Variance, Value at Risk, Conditional Value at Risk
28	2007	Calafiore	Mean-Variance, Mean Absolute Deviation
29	2008	Natarajan et al.	Value at Risk, Coherent Risk Measures
30	2008	Quaranta and Zaffaroni	Value at Risk, Conditional Value at Risk, Coherent Risk Measures
31	2011	Chen et al.	Lower Partial Moments, Value at Risk, Conditional Value at Risk
32	2019	Liagkouras	Mean-Variance, Semi-Variance, Mean Absolute Deviation
33	2017	Cui et al.	Mean-Variance
34	2015	Najafi and Mushakhian	Semi-Variance, Conditional Value at Risk
35	2010	Natarajan et al.	Optimized Certainty Equivalent
36	2018	Gotoh et al.	Mean-Variance, Value at Risk, Conditional Value at Risk
37	2007	Kondor et al.	Mean-Variance, Mean Absolute Deviation, Expected Shortfall, Maximal Loss
38	2019	Kaucic et al.	Mean-Variance, Conditional Value at Risk
39	2020	Mensi et al.	Semi-Variance, Value at Risk, Regret Risk
40	2012	Bertsimas et al.	Mean-Variance, Value at Risk, Conditional Value at Risk, Coherent Risk Measures
41	2015	Branda	Value at Risk, Conditional Value at Risk
42	2015	Bernard and Vanduffel	Value at Risk, Tail Value at Risk
43	2017	Ahmadi-Javid and Fallah-Tafti	Conditional Value at Risk, Entropic Value at Risk, Coherent Risk Measures
44	2018	Masmoudi and Abdelaziz	Mean-Variance, Mean Absolute Deviation, Semi-Variance, Value at Risk
45	2019	Trucíos Maza et al.	Value at Risk, Expected Shortfall
46	2007	Roman et al.	Mean-Variance, Conditional Value at Risk
47	2015	Bekiros et al.	Mean-Variance, Mean Absolute Deviation, Minimizing Regret, Value at Risk, Conditional
48	2006	Bäuerle and Müller	Convex Risk Measures, Coherent Risk Measures
49	2009	Brown and Sim	Value at Risk, Conditional Value at Risk, Convex Risk Measures, Coherent Risk Measures
50	2014	Hong et al.	Value at Risk, Conditional Value at Risk

5. Conclusion

This paper has provided a comprehensive review of risk measures for portfolio optimization using bibliometric analysis to identify articles, journals, authors, countries, and institutions that have contributed significantly to the field. Results indicate that the number of articles on risk measures for portfolio optimization has steadily increased since 2001. Furthermore, regarding contributing countries and institutions, China, the United States, and Italy are the top three countries, and Xi'an Jiaotong University, the National University of Singapore, and the Chinese University of Hong Kong are the top three universities in the field of risk measures for portfolio optimization. In this article, 50 of the most cited papers in this field have been reviewed to determine which risk measure models have been investigated most often and which solution techniques have been applied to risk measure models. As a result of this paper, Value at Risk, Conditional Value at Risk, Mean-Variance, and Semi-Variance are the most commonly used risk measures that are usually calculated using exact algorithms. In addition, there are a few articles in that review that use certainty parameters, whereas most models are based on uncertainty parameters.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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