International Journal of Industrial Engineering & Production Research March 2024 Vol. 35, No. 1: 1-23
DOI: 10.22068/ijiepr.35.1.1909

RESEARCH PAPER

Behavioral Finance Biases: A Comprehensive Review on Regret Approach Studies in Portfolio Optimization

Amir Mohammad Larni Fooeik[1], Hossein Ghanbari[2], Seyed Jafar Sadjadi[3*] & Emran Mohammadi[4]

Received 12 November 2023; Revised 3 February 2024; Accepted 20 February 2024;

ABSTRACT

In the ever-evolving realm of finance, investors have a myriad of strategies at their disposal to effectively and cleverly allocate their wealth in the expansive financial market. Among these strategies, portfolio optimization emerges as a prominent approach used by individuals seeking to mitigate the inherent risks that accompany investments. Portfolio optimization entails the selection of the optimal combination of securities and their proportions to achieve lower risk and higher return. To delve deeper into the decision-making process of investors and assess the impact of psychology on their choices, behavioral finance biases can be introduced into the portfolio optimization model. One such bias is regret, which refers to the feeling of remorse that can induce hesitation in making significant decisions and avoiding actions that may lead to unfavorable investment outcomes. It is not uncommon for investors to hold onto losing investments for extended periods, reluctant to acknowledge mistakes and accept losses due to this behavioral tendency. Interestingly, in their quest to sidestep regret, investors may inadvertently overlook potential opportunities. This research article aims to undertake an in-depth examination of 41 publications from the past two decades, providing a comprehensive review of the models and applications proposed for the regret approach in portfolio optimization. The study categorizes these methods into accurate and approximate models, scrutinizing their respective timeframes and exploring additional constraints that are considered. Utilizing this article will provide investors with insights into the latest research advancements in the realm of regret, familiarize them with influential authors in the field, and offer a glimpse into the future direction of this area of study. The extensive review findings indicate a growth in the adoption of the regret approach in the past few years and its advancements in portfolio optimization.

KEYWORDS: *Portfolio selection; Regret biases; Loss aversion; Behavioral finance; Market psychology; Bibliometrics.*

1. Introduction

Economic growth is strongly influenced by investment, one of the essential activities in the finance industry. A capital market investment allows investors to increase their profits while protecting their wealth from inflation [1], [2]. The capital market offers investors various strategies for allocating their wealth. The portfolio selection strategy, introduced by Markowitz [3], is a way to spread the risk of an investment. His framework provides a standard for finding optimal portfolios in logical cases [4], [5], [6]. Behavioral Finance has a long history going back decades. Financial sciences, which incorporate psychology and sociology to analyze financial markets, is a combined branch of the field of economic sciences. An approach to investing that looks at investors' decision-making process and reactions to financial market conditions. It emphasizes the impact of personality, culture, and judgment on

* **Corresponding author: Seyed Jafar Sadjadi**
Sjsadjadi@iust.ac.ir

1. *Master Student in Industrial Engineering, Faculty of Industrial Engineering, Iran University of Science and Technology, Tehran.*
2. *Ph.D. Student in Industrial Engineering, Faculty of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran.*
3. *Professor, Faculty of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran.*
4. *Assistant Professor, Faculty of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran.*

investment decisions [7]. This is a broad field with several branches, all of which consider a variety of distortions [8]. Several biases are used in portfolio optimization to improve the model's performance, with regret bias being the most common. To be understood as regret, it must be understood as an emotional consequence of the knowledge, ex-post, that a different decision would have had a more favorable outcome than what was done [9]. Avoiding regret means avoiding thinking about regret and avoiding taking actions that lead to investors staying in losing positions for an extended period. As a result, they have defined themselves as not accepting mistakes and not realizing losses [10].

Portfolio optimization plays a pivotal role in the realm of finance by aiming to maximize profits while minimizing risks for investors. Through the strategic distribution of assets within a portfolio, investors can strike a harmonious balance between risk and return that corresponds with their financial objectives and risk tolerance levels. Recently, there has been an increasing acknowledgment of the sway of investor conduct on financial decision-making, prompting the assimilation of behavioral finance methodologies into portfolio optimization strategies. These methodologies take into account the influences of psychological biases and cognitive fallacies on investment selections, aiding investors in making more well-informed and logical choices. By integrating insights from behavioral finance into portfolio optimization, investors can refine their decision-making processes and potentially attain superior outcomes in the management of their investments [11], [12], [13].

This paper analyzes the most relevant articles in the regret literature based on models and applications. As part of this Analysis, we classify the literature presenting solution techniques for solving regret portfolio optimization to answer the following research questions: Which models are primarily investigated in the regret area? What have finance constraints been introduced in regret portfolio optimization? To solve the optimization rate of the regret portfolio, which techniques have been used? For regret portfolio optimization, which period number has been used?

The remainder of this paper is organized as follows. In Section 2, the applied research methodology is clarified, and the bibliometric result is, while in Section 3, A literature review and table of those findings are presented after the explained discussion in Section 4, and finally, a conclusion and future research directions are discussed in Section 5.

2. Research Methodology

In four sections, the research methodology was summarized: material collection, Bibliometrics Analysis, category selection, and material evaluation [14], [15].

2.1. Material collection

The material for the literature review is detailed in this section. The study covered the relevant journal papers written in English and published from 2000 to 2023 in the Web of Science database.

The keywords were identified through several experiments and error attempts according to the prior experience of the purpose. A keyword structure reaches a wide range of searches for publications in Regret Aversion Studies (RAS) literature is carried out. Level 1 explains the main search context, while class introduces different alternative approaches. Level 3 focused on behavioral Finance and the regret approach. Main keywords utilizing the "title, abstract, keywords" search in the Web of Science database, which covers more relevance than the Google Scholar and Scopus databases, initially 171 publications are reached with the search. To obtain relevant publications about different models and applications of RAS from an operations research perspective, 40 articles are hand-selected, reviewed, classified, and saved in a spreadsheet for a deeper analysis and evaluation. A review of previous behavioral finance studies and their topics is presented in Table 1.

Tab. 1. Previous reviews on behavioral finance

Authors	subject
García [16]	Using information to make financial decisions: new insights
Gabrel et al. [17]	A review of robust optimization developments since 2007 is presented in this paper.
Sehgal and Vasishth [18]	An analysis of past price movements, trading volumes, and portfolio returns from selected emerging markets

Nigam et al. [19]	In this review, we examine behavioral variables in financial decision-making as examined in behavioral finance studies conducted in the past decade (2006-15)
Antony [20]	Theoretical and empirical studies on behavioral Finance and portfolio management
Wong [21]	Economic and financial reviews of behavioral economics

Tab. 2. The main keyword combination structure

Level	Search terms						
1	Portfolio						
	AND						
2	Optimization	OR	Selection	OR	Management	OR	Allocation
	AND						
3	Regret	OR	Behavioral				

2.1. Bibliometrics analysis

There are so many scientific contributions and publications nowadays that it is challenging to keep up with them all and review them all [22]. Using statistical measures, the bibliometric method can resolve the problem by evaluating the literature on specific research areas [23]. It helps measure the influence of publications in the scientific community by evaluating articles, books, or book chapters based on statistical data [24]. From engineering to sports science, bibliometric Analysis has become increasingly popular in recent years. Several good researchers have focused on portfolio optimization in recent years, although its application in Finance is relatively new. This paper uses bibliometric Analysis to assess emerging trends, identify outstanding publications, and identify articles, journals, authors, countries, and institutions that have significantly influenced a scientific field [25], [26], [27], [28].

A five-step Scientometrics analysis was conducted on the article query in fig2 using R's Bibliometric package, which analyzes (1) Data Set Analysis, (2) Countries Production Analysis, (3) Source Analysis, (4) Author Analysis, and (5) Trend Topics. The five Scientometrics techniques selected are employed to (i) Maintain a close eye on the frontiers of research knowledge, (ii) Find out about the principal researchers, institutions, countries, and critical areas of study, (iii) Clusters of co-citations and research keywords; and (v) Research topics that are emerging in the field [29], [30].

A search and selection of publications were conducted using the academic database Web of Science (WoS). It consisted of the following equation: portfolio" AND ("optimization" OR "Management" OR "Selection" OR "Allocation") AND ("Behavioral Finance" OR "Regret"). 378 studies were obtained from the Web of Science in December 2022. Table 2 illustrates the framework implementation of the current review.

2.1.1. Analysis of the sources

This section aims to examine and assess the findings related to the keywords. This part entails evaluating key authors, relevant studies, top countries involved in the subject area, citation trends within the field, and influential journals, and conducting a comparative analysis of the outcomes.

2.1.1.1. General information

It was determined that 856 authors contributed to the 378 documents selected for this study. Generally, academic papers receive 15.78 citations, which is highly regarded. Growth increased by 11.85% on an annual basis. The main document is an article (286). In total, 775 keywords were identified, along with 1152 keywords associated with authors. A summary of the general characteristics of the papers examined in this study can be found in Table 3.

Tab. 3. An overview of the descriptive information, compiled from authors' research in WoS databases and Bibliometrics

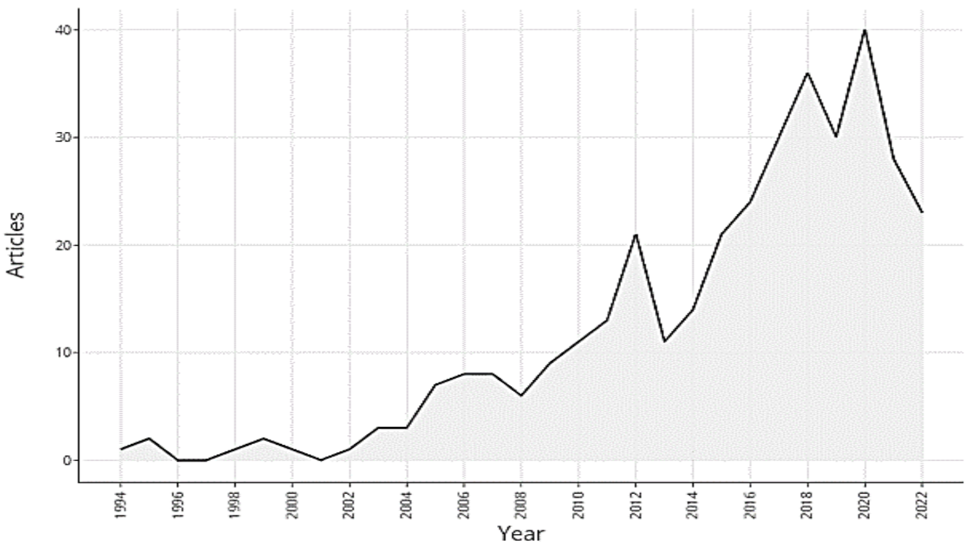
Description	Results	Description	Results
MAIN INFORMATION ABOUT THE DATA		Single-authored docs	70
Timespan	1994:2022	Co-Authors per Doc	2.57
Sources (Journals, Books, etc.)	188	International co-authorships %	29.63
Documents	378	DOCUMENT TYPES	
Annual Growth Rate %	11.85	article	286
Document Average Age	6.64	article; book chapter	4
Average citations per doc	15.78	article; early access	22
References	13332	article; proceedings paper	4
DOCUMENT CONTENTS		book	1
Keywords Plus (ID)	775	book review	1
Author's Keywords (DE)	1152	editorial material	1
AUTHORS		editorial material; book chapter	1
Authors	856	proceedings paper	42
Authors of single-authored docs	64	review	14
AUTHORS COLLABORATION		review; early access	2

After establishing the relevant keywords for this study, specified in Table 2, we conducted searches in the Web of Science database. The search yielded 378 documents, as illustrated in Table 3. Following a comprehensive review and analysis of these articles, we carefully selected 41 articles that best aligned with the research objectives. To ensure transparency in our study, we have included these explanatory notes in Table 3.

2.1.1.2. Publication output

As shown in Figure 1a, a significant increase in publications over the previous year indicates a growing interest among the academic community. As of 2020, the number of documents produced yearly has increased from 1 in 1994 to 40 in 2020. This trend is expected to continue as 22 studies were published in 2022 about this topic. Annual publication trends, however, can be divided into two categories. Up until 2013, research contributions were limited in the first one. In the second period, from 2013 to 2022, research contributions increased significantly due to advances in methodologies. Figure 4b shows the average number of citations per year, which indicates that the maximum number of sources was recorded in 2002 (13%).

Production of scientific research each year (a)



The average number of citations per year (b)

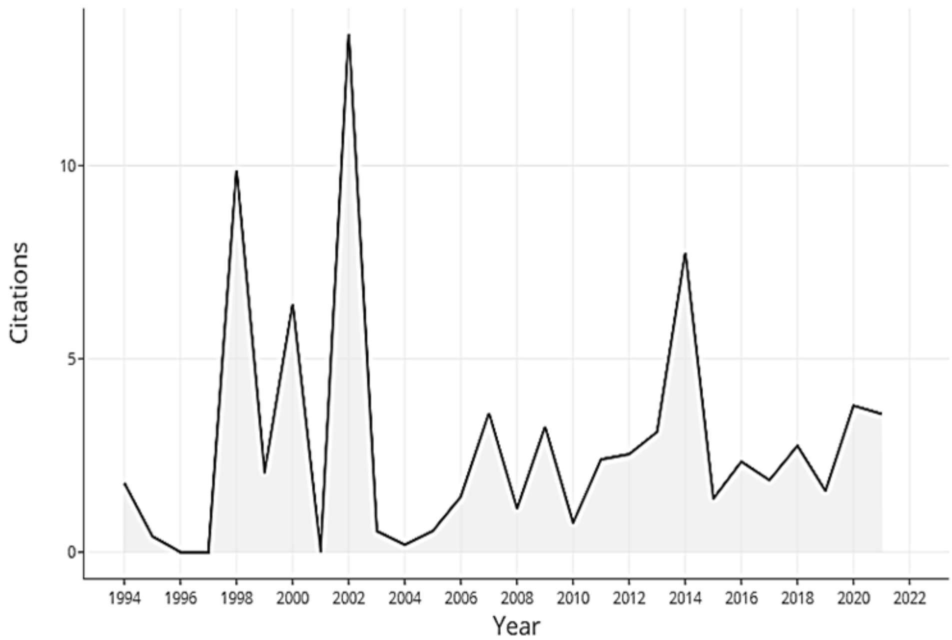


Fig. 1. An average number of citations per year (a) based on publication output and (b) based on publication output. The author conducted the research using bibliometric tools and the WoS database.

2.1.1.3. Discipline-wise analysis

Each source's articles are ranked in order of importance in researching dynamic co-movements between behavioral finance and regret biases in Figure 2. There has been extensive research on this topic, mainly in the Journal of Behavioral Finance (36). Review of Behavioral Finance was the second leading journal in occurrences (28). The European Journal of Operational Research (15) and financial market and portfolio management (14) were the third and fourth most relevant journals. Thus, these sources are crucial to the related research.

Most relevant source

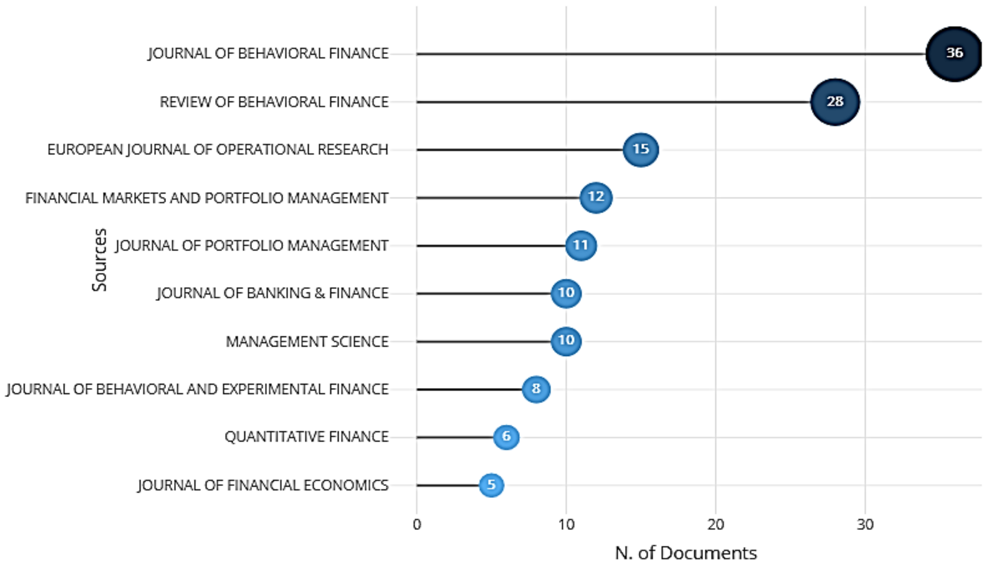
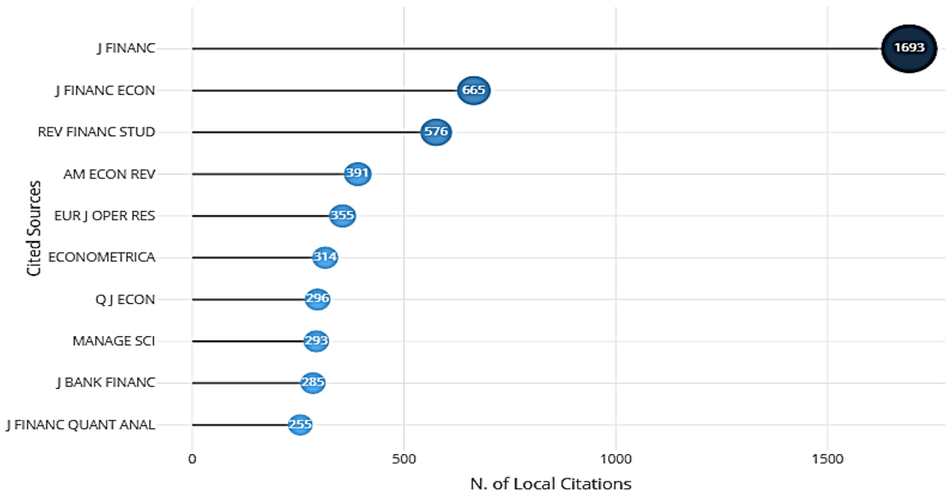


Fig. 2. Authors use bibliometrics tools and WoS databases to distribute documents across sources.

2.1.1.4. Most relevant sources

A discussion of the most influential and significant sources for research on behavioral Finance and portfolio optimization (such as regret biases and uncertain areas) is presented in this section. The distribution of the most cited sources is shown in Figure 3a. There are 1693 citations in the Journal of Behavioral Finance, 665 in the Journal of Financial Economics, and 576 in the Review of Behavioral Finance according to the number of citations. Figure 3b below illustrates the importance of the Journal of Behavioral Finance in our research area, which focuses on analyzing the relationship between behavioral Finance and portfolio optimization. The Bradford's Law [31] (Figure 3b) includes only ten journals in Zone 1, the core area where the most citations are found. According to this figure, the top three journals are the European Journal of Operational Research, the Journal of Behavioral Finance, and the Review of Behavioral Finance.

(3a)



(3b)

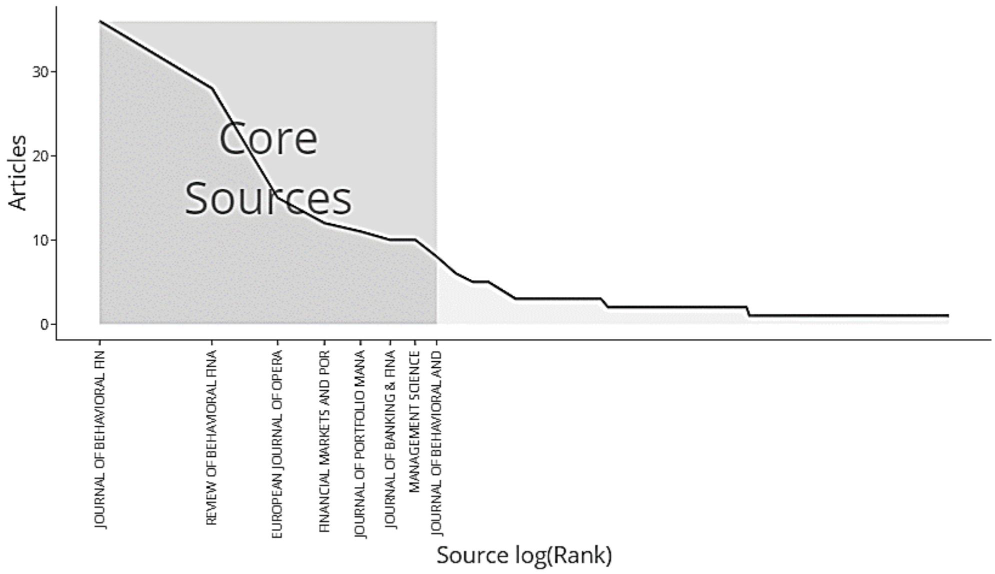


Fig. 3. Effect of the sources. (3a) most cited sources and (3b) source clustering through Bradford's law. source: bibliometrics tool and WoS databases were used by authors to conduct research.

2.1.1.5. Most relevant authors and authors' impacts

Figure 4 shows the authors who have published the most articles based on the number of articles: Statman, hens, Jiang, Baptista, and Fabozzi.

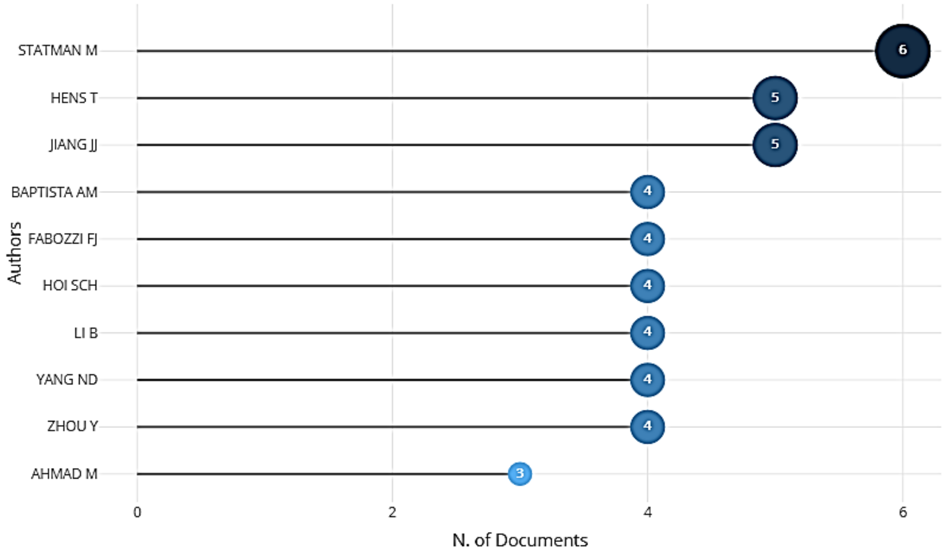


Fig. 4. Effect of the author's number of publications by authors. source: bibliometrics tool and WoS databases were used by authors to conduct research.

2.1.1.6. Authors' production over time

The top authors' documents over time on dynamic co-movements between regret biases and portfolio optimization are shown in Figure 5. A graph's colors indicate the year a publication was cited, and bubble dimensions indicate how many publications were produced by the author each year. For example, the first article about this topic was published by Statman in 1994. Later, the number of papers published in 2014 was four, and the number of papers published in 2018 was six.

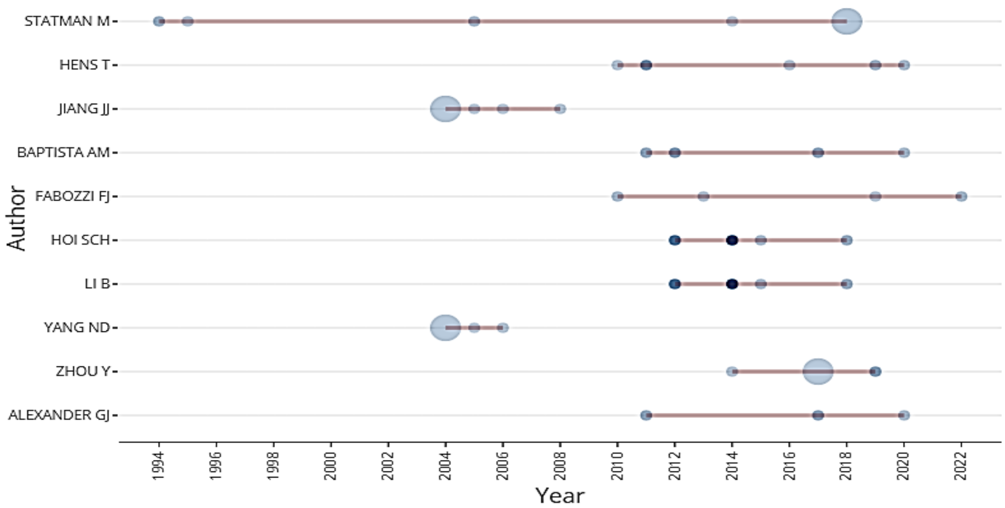


Fig. 5. A study of the dynamic co-movements between regret biases and portfolio optimization by the top authors from 1994 to 2022. source: the bibliometrics tool and WoS databases were used by authors to conduct research.

2.1.1.7. The leading countries and institutions

A study was conducted analyzing leading countries and institutions around the world. First and foremost, the USA is the most prolific country in terms of the number of publications on this topic, with 98 in total The second-placed country is CHINA (56), and the third-placed country is France (24). Table 4 presents a list of other top nations.

Tab. 3. The top 10 corresponding author countries

	Country	No of.Articles
1	USA	98
2	CHINA	56
3	FRANCE	24
4	GERMANY	24
5	UNITED KINGDOM	22
6	INDIA	16
7	NETHERLANDS	11
8	CANADA	10
9	SWITZERLAND	10
10	IRAN	9

2.1.1.8. Country scientific production

According to Figure 6, numbers are produced in different countries in different proportions. Blue represents countries that have worked in this area, and black shows countries that have not. This field has been studied more by the country shown in dark blue.

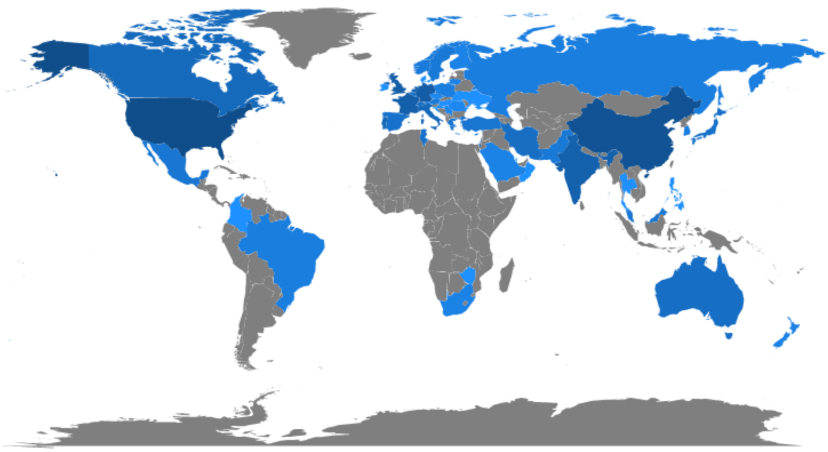


Fig. 6. Dispersion of the number production of every country. source: bibliometrics tool and WoS databases were used by authors to conduct research.

2.1.1.9. Trend topics over the years

In literature mapping, trending topic analyses are essential for demonstrating the literature's evolution. Based on keyword analysis and maintaining a minimum five-word frequency per article three times a year, the topics shown in Figure 7 were identified.

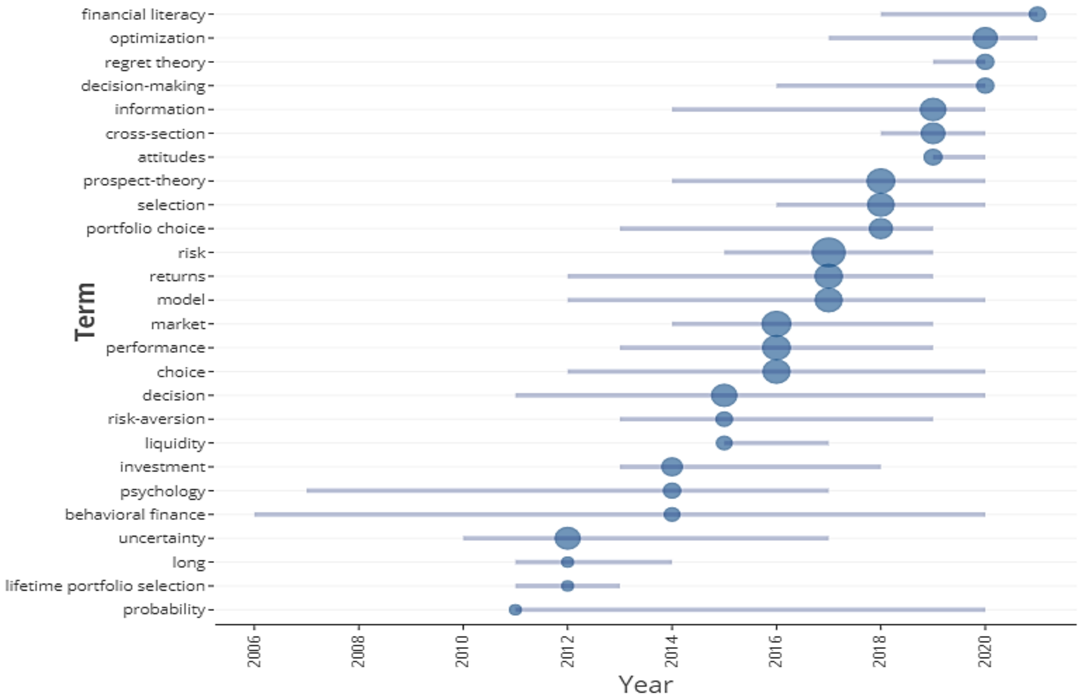


Fig. 7. Trend topics over the years. Source: Bibliometrics tool and WoS databases were used by authors to conduct research.

2.1.1.10. Three-field plot analysis

Figure 8 illustrates the most relevant topics researched by the most relevant authors.: Among his research topics, Jiang is most concerned with behavioral Finance and portfolio selection, and most of his papers have been published in China and the United States. An overview of the relationship between the top 10 authors, trend keywords, and researched countries is shown in Figure 8.

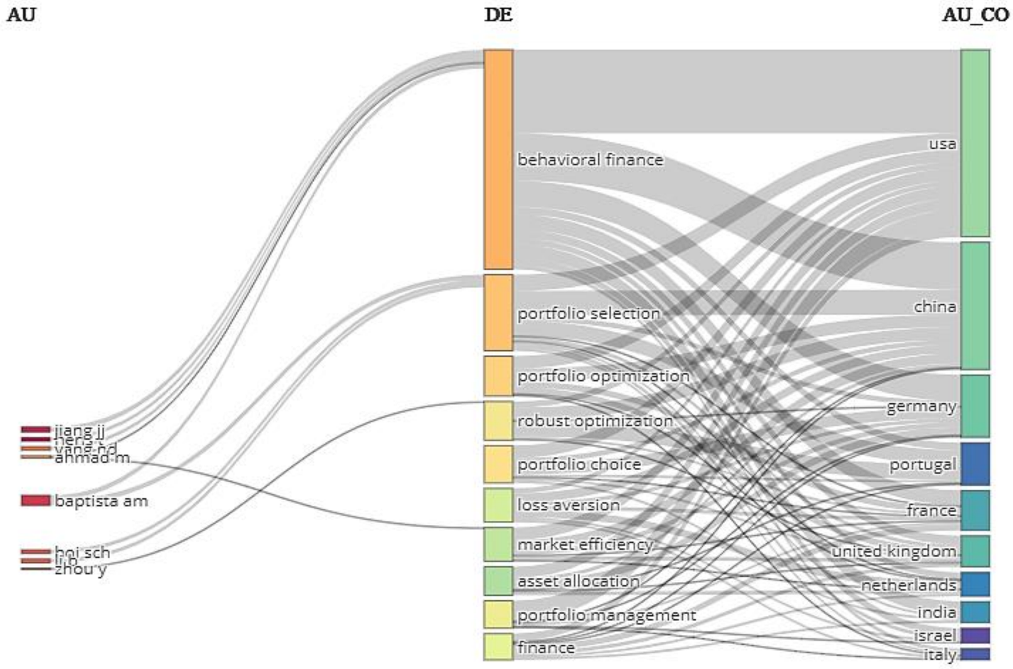


Fig. 8. Three-field plot.

2.2. Descriptive analysis

The article publishing trend using the number of article publications in a given year is shown in FIG 9. A total number of 40 articles are reviewed. The considerable growth in the number of articles is noticeable after 2017. The significance of this portfolio optimization method becomes apparent given that, despite the inception of research in this area dating back to 2003, it has consistently captured the attention of researchers. This is particularly noteworthy as the pace of research growth in this domain has markedly accelerated in recent years.

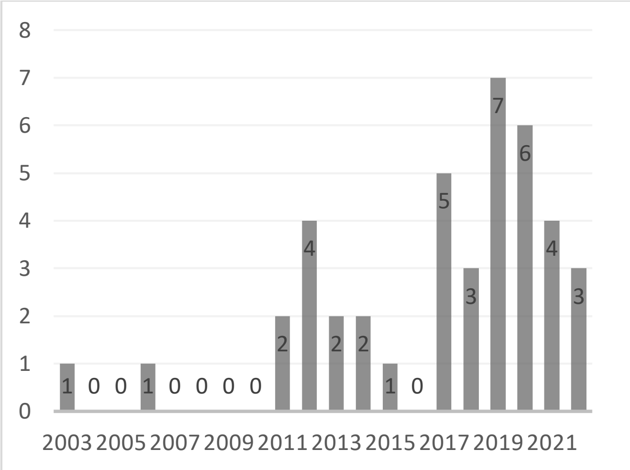


Fig. 9. Distribution of articles per year.

2.3. Category selection

The categorization used in this review is based on the different properties of various models and applications of RAS. The categories are formed according to the following criteria: solution techniques, period numbers, example types, model type, and uncertain branch. The significance of this section is highlighted when delving into the specifics of each of these articles, allowing for a deeper comprehension of the methodologies employed by authors in this field. This facilitates the establishment of a specific framework concerning the application of regret in portfolio optimization. The classes used to classify the articles are shown in Fig10. Furthermore, are described below:

2.4. Material evaluation

As part of the validation process, Mendeley reference manager software and Web of Science are also used to enhance credibility, analyze, and minimize errors during the validation stage. The study is also enhanced by adding papers not initially included in Google Scholar and Scopus. Considering the articles within the Web of Science database allows us the opportunity to explore studies that offer a broader perspective on utilizing regret in portfolio optimization compared to a singular focus.

3. Literature Review

A variety of research in the field of regret biases has been investigated over the past few decades, which is presented as follows:

Stoltz and Lugosi [32] developed sequential investment strategies to minimize internal regrets. Giove et al. [33] described that the prices of the securities are treated as interval variables in a portfolio selection problem, and the minimax regret approach based on a regret function is proposed for dealing with interval portfolio problems of this type. Gregory et al. [34] identified the robust counterpart of the maximum return portfolio optimization problem and evaluated its cost of robustness; a polyhedral uncertainty set models asset returns instead of the ellipsoidal uncertainty set proposed earlier. Lim et al. [35] explained an approach to finding robust portfolios when uncertainty in the model is introduced. Bean and Singer [36] expressed various insights from universal portfolio research to construct more sophisticated algorithms that take transaction costs into account. Li et al. [37] applied a model for expected regret minimization that minimizes the distance between the maximum return and the obtained return for each portfolio. Lourenço et al. [38] considered several types of uncertainty, multiple criteria, multiple project interactions, and limited resources in selecting and managing a compelling portfolio of projects. Rivaz and Yaghoobi [39] described A multiobjective linear programming problem with interval coefficients in their article. Ji et al. [40] used a regret portfolio optimization approach to minimize the weighted sum of the difference between the return and the sum of each portfolio. Nwogugu [41] has introduced the concepts of reducing return regret, accepting losses, and framing. Xidonas et al. [42] determined representative points on the efficient frontier by considering future returns and developing Minimax regret portfolios. Xidonas et al. [43] developed an optimization model that minimizes portfolio variance for a finite set of scenarios. Ahmadi and Davari-Ardakani [44] developed a multistage stochastic programming model that optimizes portfolios within a cardinality constraint over multiple periods. Rivaz and Yaghoobi [45] presented a multiobjective linear programming problem with interval objective function coefficients and an introduction to the weighted sum problem of maximum regrets and its properties. Simões et al. [46] improved portfolio performance analysis by considering benchmarks when analyzing portfolio optimization models. Baule et al. [47] explained how regret affects portfolio weights and what distributional characteristics make assets less or more attractive than in Markowitz's model. Ji et al. [48] reformulated the worst-case regret optimization problem using polyhedral and conic support sets. Tsionas [49] demonstrated robust solutions to the minimax regret problem can be found, and similar Monte Carlo posterior simulators have also been developed without any scenarios being set. Vohra and Fabozzi [50] inspected how foreign exchange options can be used in international portfolios as an active currency risk management tool in addition to forward risk. Li and Wang [51] extended robust multiobjective portfolio selection under ellipsoidal uncertainty sets using the minimax regret criterion. Filho and Silva Neiro [52]

Stoltz and Lugosi [32] developed sequential investment strategies to minimize internal regrets. Giove et al. [33] described that the prices of the securities are treated as interval variables in a portfolio selection problem, and the minimax regret approach based on a regret function is proposed for dealing with interval portfolio problems of this type. Gregory et al. [34] identified the robust counterpart of the maximum return portfolio optimization problem and evaluated its cost of robustness; a polyhedral uncertainty set models asset returns instead of the ellipsoidal uncertainty set proposed earlier. Lim et al. [35] explained an approach to finding robust portfolios when uncertainty in the model is introduced. Bean and Singer [36] expressed various insights from universal portfolio research to construct more sophisticated algorithms that take transaction costs into account. Li et al. [37] applied a model for expected regret minimization that minimizes the distance between the maximum return and the obtained return for each portfolio. Lourenço et al. [38] considered several types of uncertainty, multiple criteria, multiple project interactions, and limited resources in selecting and managing a compelling portfolio of projects. Rivaz and Yaghoobi [39] described A multiobjective linear programming problem with interval coefficients in their article. Ji et al. [40] used a regret portfolio optimization approach to minimize the weighted sum of the difference between the return and the sum of each portfolio. Nwogugu [41] has introduced the concepts of reducing return regret, accepting losses, and framing. Xidonas et al. [42] determined representative points on the efficient frontier by considering future returns and developing Minimax regret portfolios. Xidonas et al. [43] developed an optimization model that minimizes portfolio variance for a finite set of scenarios. Ahmadi and Davari-Ardakani [44] developed a multistage stochastic programming model that optimizes portfolios within a cardinality constraint over multiple periods. Rivaz and Yaghoobi [45] presented a multiobjective linear programming problem with interval objective function coefficients and an introduction to the weighted sum problem of maximum regrets and its properties. Simões et al. [46] improved portfolio performance analysis by considering benchmarks when analyzing portfolio optimization models. Baule et al. [47] explained how regret affects portfolio weights and what distributional characteristics make assets less or more attractive than in Markowitz's model. Ji et al. [48] reformulated the worst-case regret optimization problem using polyhedral and conic support sets. Tsionas [49] demonstrated robust solutions to the minimax regret problem can be found, and similar Monte Carlo posterior simulators have also been developed without any scenarios being set. Vohra and Fabozzi [50] inspected how foreign exchange options can be used in international portfolios as an active currency risk management tool in addition to forward risk. Li and Wang [51] extended robust multiobjective portfolio selection under ellipsoidal uncertainty sets using the minimax regret criterion. Filho and Silva Neiro [52] presented concepts from relative regret models and robust static optimization into robust optimization. Caçador et al. [53] proposed a method for computing relative-robust portfolios using minimax regret. Gong et al. [54] spread the fuzzy mean-variance-skewness model to incorporate portfolio efficiency as another decision objective. Benati and Conde [55] considered a portfolio model with a hybrid optimization objective function oriented toward average returns and constraints in which the worst-case CVaR is the upper bound when included in the set of scenarios. Groetzner and Werner [56] robustly defined regret by extending it from a single-objective to a multiobjective frame of reference. Ding and Uryasev [57] created a new risk measure for portfolio performance called expected regret of drawdown based on a threshold of drawdowns above which a negative return was expected. Figure 10 presents the categorization used in this review and the literature table.

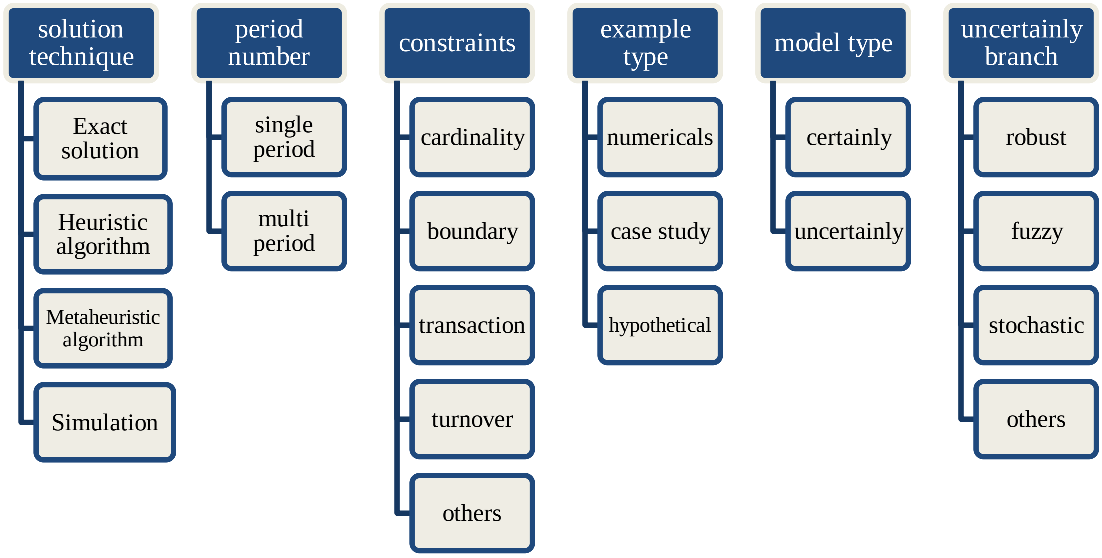


Fig. 10. The categorization used in this review.

Tab. 5. Review of the most relevant documents

	Authors	Year	Solution Technique: Exact solution	Solution Technique: Heuristic algorithm	Solution Technique: Metaheuristic algorithm	Solution Technique: Simulation	Period Number: Single period	Period Number: Multi-period	Constraints: Cardinality	Constraints: Boundary	Constraints: Transaction	Constraints: Turnover	Constraints: Others	Example Type: Numerical	Example Type: Case Study	Example Type: Hypothetical	Model type	Data type: Certainly	Data type: Uncertainly: Robust	Data type: Uncertainly: Fuzzy	Data type: Uncertainly: Stochastic	Data type: Uncertainly: Others	Reference
1	Kagrecha et al	2023			bandit			✓		✓			✓	✓			NLP				✓		[58]
1	Ding and Uryasev	2022	✓					✓		✓				✓				✓					[57]
2	Groetzner and Werner	2022	✓				✓		✓	✓				✓			MOLP		✓				[56]
3	Benati and Conde	2022	✓				✓		✓	✓	✓	✓	✓	✓			LP		✓				[55]
4	Caçador et al.	2022			GA		✓		✓	✓					✓		LP		✓				[59]
5	Filho and Silva Neiro	2022				MC	✓						✓	✓			LP and NLP		✓		✓		[52]
6	Zhang et al.	2021	✓					✓		✓	✓			✓			LP		✓				[60]
7	Gong et al.	2021	✓				✓		✓	✓					✓		LP			✓			[54]
8	Chakrabarti	2021	✓				✓				✓				✓		LP		✓				[61]
9	Caçador et al.	2021	✓				✓		✓	✓	✓		✓		✓		LP		✓				[53]
10	Won and Kim	2020	✓				✓			✓	✓	✓		✓			LP		✓				[62]
11	Li and Wang	2020	✓					✓	✓	✓				✓			LP		✓				[51]
12	Hernandez and al Janabi	2020	✓				✓			✓				✓			LP and NLP	✓					[63]
13	Caçador et al	2020	✓				✓		✓	✓		✓			✓		LP		✓				[64]
14	Vohra and Fabozzi	2019	✓				✓			✓					✓		LP	✓					[50]
15	Tsionas	2019				MC		✓		✓					✓		MOLP				✓		[49]
16	Ngerng and Ngerng	2019	✓				✓			✓	✓				✓		MILP	✓					[65]

	Authors	Year	Solution Technique				Period Number		Constraints					Example Type			Model type	Data type					Reference
																			Uncertainly				
			Exact solution	Heuristic algorithm	Metaheuristic algorithm	Simulation	Single period	Multi-period	Cardinality	Boundary	Transaction	Turnover	Others	Numerical	Case Study	Hypothetical		Certainly	Robust	Fuzzy	Stochastic	Others	
17	Lu et al.	2019			MFA -SCA			✓		✓				✓			MINLP					✓	[66]
18	Ji et al.	2019	✓					✓		✓				✓			LP		✓				[48]
19	Baule et al.	2019	✓			✓	✓							✓			LP	✓					[47]
20	Huang et al.	2018						✓		✓	✓	✓			✓		LP		✓				[67]
21	Van den Broeke et al.	2018	✓				✓			✓					✓		MILP	✓					[68]
22	Simões et al.	2018	✓				✓			✓					✓		LP		✓				[46]
23	Rivaz and Yaghoobi	2018	✓				✓			✓			✓	✓			MOLP	✓					[45]
24	Ahmadi and Davari-Ardakani	2017	✓					✓	✓	✓	✓				✓		MOLP				✓		[44]
25	Xidonas, et al.(b)	2017	✓				✓		✓	✓					✓		MINLP		✓				[43]
26	Xidonas , et al.(a)	2017	✓					✓		✓					✓		MILP		✓				[42]
27	Mohr and Dochow	2017	✓					✓		✓			✓		✓		MILP	✓					[69]
28	Grechuk and Zabarankin	2017	✓				✓							✓			LP		✓				[70]
29	Ji et al.	2014	✓				✓			✓				✓			LP		✓		✓		[40]
30	Gupta et al.	2014	✓				✓			✓				✓			LP			✓	✓		[71]
31	Fernandez et al.	2013			GA			✓	✓						✓		NLP		✓	✓			[72]
32	Lourenço et al.	2012						✓		✓					✓		MILP		✓				[38]
33	Lim et al.	2012	✓				✓			✓				✓			LP		✓				[73]

	Authors	Year	Solution Technique				Period Number		Constraints					Example Type			Model type	Data type					Reference
																			Uncertainly				
			Exact solution	Heuristic algorithm	Metaheuristic algorithm	Simulation	Single period	Multi-period	Cardinality	Boundary	Transaction	Turnover	Others	Numerical	Case Study	Hypothetical		Certainly	Robust	Fuzzy	Stochastic	Others	
34	Li et al.	2012	✓				✓							✓			LP and NLP			✓			[37]
35	Bean and Singer	2012		✓		✓		✓		✓	✓					✓	MILP	✓					[36]
36	Lim et al.	2011	✓				✓			✓				✓			LP		✓		✓		[35]
37	Gregory et al.	2011	✓					✓	✓	✓				✓			MILP	✓					[34]
38	Giove et al.	2006	✓				✓			✓				✓			LP			✓			[33]
39	Nwogugu	2006	✓				✓			✓				✓			NLP	✓					[41]
40	Stoltz and Lugosi	2003	✓							✓	✓					✓	LP				✓		[32]

Genetic Algorithm (GA), Mont Carlo (MC), Multiobjective Firefly Algorithm and Sine Cosine Algorithm (MFA-SCA), Linear Programming (LP), Multiobjective Linear Programming (MOLP), Non-Linear Programming (NLP), Mix Integer Linear Programming (MILP), Mix Integer Non-Linear Programming (MINLP)

3.1. Document analysis

According to Figure 11, 81 percent of articles used exact algorithms for solving models, whereas 10 percent used just simulation, 7 percent used metaheuristic algorithms, and 2 percent used heuristic algorithms. Based on Figure 12, most studies use multi-period periods, whereas a few utilize single-period studies. According to Figure 13, boundary constraints comprise 53 percent of most articles, followed by cardinality, transactions, others, and turnover constraints.

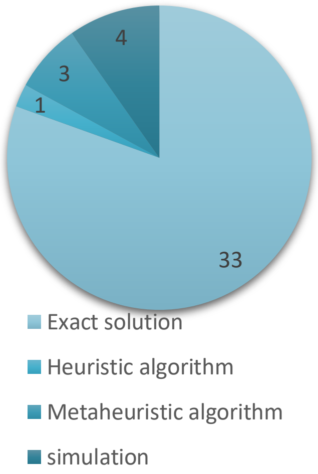


Fig. 11. Category of solution technique

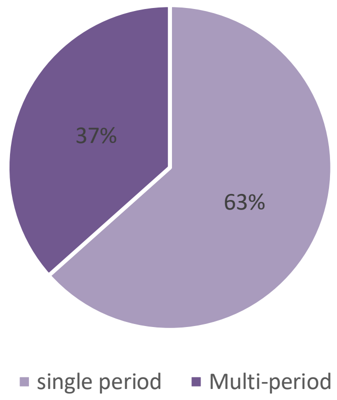


Fig. 12. Category of period number

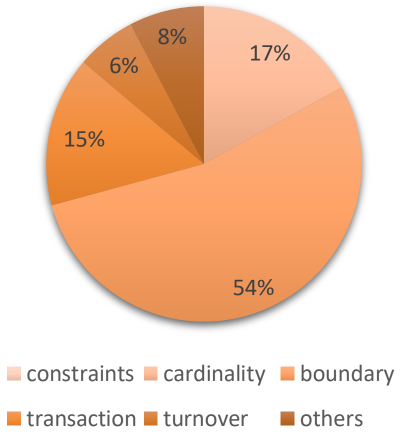


Fig. 13. Category of constraints

As depicted in Figure 14, 54 percent of articles use numerical data, 41 percent use case studies, and 5 percent use examples. Figure 15 shows that 71 percent of articles used specific dates, while 29 percent used uncertain dates. In contrast, figure 16 shows the details of uncertain dates, showing that most articles used robust uncertain dates and stochastic, fuzzy, and others ranked next.

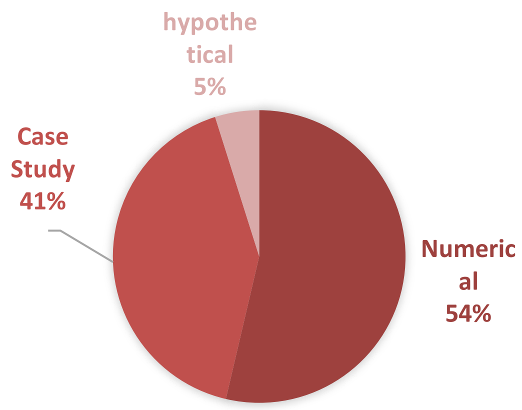


Fig. 14. Category of example type

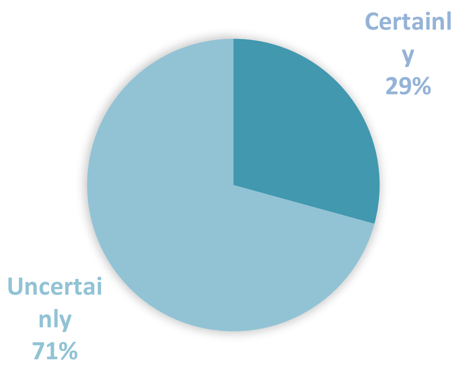


Fig. 15. Category data type

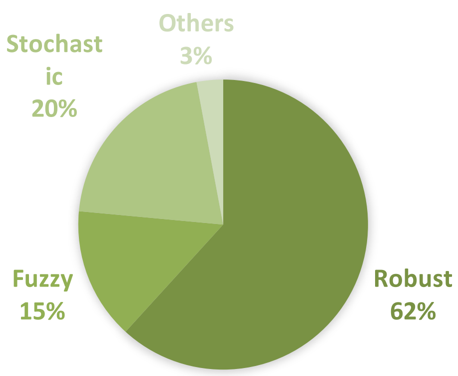


Fig. 16. Category of uncertainly

3.2. Finding results of this section

After assessing relevant literature in this field, the findings suggest that regret's utilization in portfolio optimization holds significance, manifesting in diverse approaches and models across linear and non-linear programming. This underscores the assurance in data accuracy and acknowledgment of practical constraints. Such prevalence of regret underscores its status as a prominent trend in stock portfolio optimization strategies.

4. Discussion and Managerial Implications

Extensive discussions have revolved around the inferences and implications drawn from bibliometric and content analyses, shedding light on the topic. The field of RAS has witnessed a remarkable surge in scholarly works, indicating a growing interest within the academic community. Notably, there has been a dramatic increase in the number of publications in 2023. However, the scarcity of studies specifically focusing on bibliometric data analysis in the context of RAS is worth mentioning. Such studies are significant as they provide insights into research quantity, directions, and academic interactions. This research adopts a scientific mapping approach to examine the structural and dynamic aspects of RAS research. The analysis of conceptual structures reveals crucial themes and intellectual contributions, aiding in comprehending the prevailing trends. Moreover, this approach enables the tracking of concept development over time. By highlighting prominent publications within theme clusters, researchers can effectively concentrate their investigations. The resulting thematic map offers valuable insights into the significance of topics, facilitating predictions regarding the future expansion of themes within the field.

In this research article, an in-depth bibliometric analysis using the Web of Science database is conducted to explore the extensive landscape of publications on RAS. The findings shed light on important aspects of this field, beginning with the significant attention it has received from prominent sources such as the Journal of Behavioral Finance, Review of Behavioral Finance, and European Journal of Operational Research. These sources serve as crucial references for researchers interested in RAS due to their substantial publication output. To enhance our understanding, the study ranks the top sources based on their h-index, providing valuable insights into their overall impact. The examination of highly cited sources emphasizes the dominant position of the Journal of Behavioral Finance with 1693 citations, followed by the Journal of Financial Economics with 665 citations. In addition to source analysis, the study identifies influential authors in the domain of RAS, including Statman, Hens, and Jiang. Furthermore, a comprehensive bibliometric analysis delves into the geographical dimension, uncovering the leading countries contributing to RAS research, namely the United States, China, France, Germany, and the United Kingdom.

The regret approach in portfolio optimization poses substantial implications for investors. This phenomenon entails investors making decisions aimed at avoiding regret rather than optimizing potential gains.

For investors, practical implications of the regret approach in portfolio optimization include:

1. **Tendency Towards Conservative Investment Strategies**: Investors may opt for less volatile assets to steer clear of regret from significant losses, favoring stability over potentially higher returns.
2. **Herding Behavior Influence**: Regret-averse investors may tend to follow popular trends in investments, potentially sacrificing optimal portfolio diversification to prevent regret over underperforming compared to peers.
3. **Underinvestment in High-Risk Assets**: The fear of regret can prompt investors to avoid riskier assets with higher potential returns, leading to missed opportunities in assets like emerging markets or innovative industries.
4. **Short-Term Focus and Decision-making**: Regret can drive investors to frequently adjust their portfolios in response to short-term market fluctuations, potentially deviating from a well-thought-out long-term investment strategy.
5. **Challenges in Risk Management**: Investors driven by regret aversion may be hesitant to adopt risk-management techniques like hedging or derivatives due to the uncertainty involved and the fear of regret over unexpected outcomes.
6. **Cognitive Biases Awareness**: The regret approach represents one of several cognitive biases influencing investment decisions. Recognizing these biases and their impact is crucial for investors to make rational and well-informed portfolio decisions.

Understanding the implications of the regret approach enables investors to acknowledge the influence of emotional biases on investment decisions and portfolio performance, guiding them toward more objective and effective investment strategies.

This research article specifically concentrated on publications related to RAS that were indexed in the Web of Science database. Although the study did not explore the comparison of datasets from different databases, it is crucial to acknowledge that such comparisons may result in different sets of entries, which can consequently lead to variations in the analysis results.

5. Conclusions

In this research article, a thorough examination of RAS has been conducted utilizing bibliometric analysis, aiming to identify significant contributions from articles, journals, authors, countries, and institutions in the field. The findings demonstrate a continuous rise in the number of RAS articles starting from 2012. Additionally, the analysis reveals that the top three countries contributing to RAS research are the United States, China, and France, while specific institutions from these countries have also made notable contributions.

To advance the current understanding of RAS, several promising directions for future research should be considered. One potential avenue is to delve into other behavioral finance biases, such as loss aversion, which holds widespread relevance. Investigating the origins and impacts of behavioral finance in portfolio optimization has the potential to enhance the precision and dependability of risk management strategies in this domain. Another area that warrants attention is the analysis of selection optimization risk, which involves assessing the risks associated with the asset selection process for portfolio construction. Conventional portfolio optimization methods often assume that historical data accurately reflects future market behavior; however, this assumption can introduce selection biases and overlook crucial risk factors. Tackling selection optimization risk may involve exploring alternative approaches that account for the inherent uncertainties and biases in asset selection processes.

6. Declaration of Competing Interest

The authors confirm that they do not have any apparent competing financial interests or personal relationships that could have influenced the findings presented in this paper.

References

[1] A. Larni Fooeik, H. Ghanbari, M. Bagheriyan, and E. Mohammadi, Analyzing the effects of global oil, gold and palladium markets: Evidence from the Nasdaq com-posite index, Journal of Future Sustainability, Vol. 2, (2022), pp. 105-112.

[2] H. Ghanbari, A. Larni Fooeik, A. Eskorouchi, and E. Mohammadi, Investigating the effect of US dollar, gold and oil prices on the stock market, Journal of Future Sustainability, Vol. 2, (2022), pp. 97-104.

[3] H. Markowitz, PORTFOLIO SELECTION*, J Finance, Vol. 7, No. 1, (1952), pp. 77-91.

[4] Z. Zhang, Intelligent Optimization of the Financial Sharing Path Based on Accounting Big Data, Math Probl Eng, (2022).

[5] L. Gu and G. Liang, The Effect of Bank Financing under Supply Chain-to-Chain Competition, Math Probl Eng, (2022).

[6] A. Eskorouchi, E. Mohammadi, and S. J. Sajadi, Robust Portfolio Optimization based on Evidence Theory, (2022).

[7] A. Tversky and D. Kahneman, Availability: A Heuristic for Judging Frequency and Probability122, (1973).

[8] M. A. Azouzi and S. Bacha, Do Behavioral Biases Affect Credit Risk Assessment Methods?, Iranian Journal of Management Studies (IJMS), Vol. 16, No. 2, (2023), p. 2023.

[9] D. E. Bell, RISK PREMIUMS FOR DECISION REGRET, Manage Sci, Vol. 39, No. 10, (1983), pp. 1156-1166.

[10] H. Shefrin and M. Statman, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, J Finance, Vol. 40, No. 3, (1985), pp. 777-790.

[11] R. S. G. R. Casado, M. H. Alencar, and A. T. de Almeida, Portfolio-based decision model for enhancing the mitigation of multidimensional risks in hydrogen pipeline sections, Process Safety and Environmental Protection, Vol. 175, (2023), pp. 700-714.

[12] X. Deng and F. Geng, Portfolio model with a novel two-parameter coherent fuzzy number based on regret theory, Soft comput, (2023).

[13] T. Cui, N. Du, X. Yang, and S. Ding, Multi-period portfolio optimization using a deep reinforcement learning hyper-heuristic approach, Technol Forecast Soc Change, Vol. 198, (2024).

[14] K. Govindan, H. Soleimani, and D. Kannan, Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future, European Journal of Operational Research, Vol. 240, No. 3, (2015), pp. 603-626.

[15] C. B. Kalayci, O. Ertenlice, and M. A. Akbay, A comprehensive review of deterministic models and applications for mean-variance portfolio optimization, Expert Systems with Applications, Vol. 125, (2019), pp. 345-368.

[16] M. J. R. García, Financial education and behavioral finance: New insights into the role of information in financial decisions," J Econ Surv, Vol. 27, No. 2, (2013), pp. 297-315.

[17] V. Gabrel, C. Murat, and A. Thiele, Recent advances in robust optimization: An overview, European Journal of Operational Research, Vol. 235, No. 3, (2014), pp. 471-483.

[18] S. Sehgal and V. Vasishth, Past price changes, trading volume and prediction of portfolio returns: Evidence from select emerging markets, Journal of Advances in Management Research, Vol. 12, No. 3, (2015), pp. 330-356.

[19] R. M. Nigam, S. Srivastava, and D. K. Banwet, Behavioral mediators of financial decision making – a state-of-art literature review, Review of Behavioral Finance, Vol. 10, No. 1, (2018), pp. 2-41.

[20] A. Antony, Behavioral finance and portfolio management: Review of theory and literature, J Public Aff, Vol. 20, No. 2, (2020).

[21] W. K. Wong, Review on behavioral economics and behavioral finance, Studies in Economics and Finance, Vol. 37, No. 4, (2020), pp. 625-672.

[22] D. Zabavnik and M. Verbič, Relationship between the financial and the real economy: A bibliometric analysis, International Review of Economics and Finance, Vol. 75, (2021), pp. 55-75.

[23] M. Aria and C. Cuccurullo, bibliometrix: An R-tool for comprehensive science mapping analysis, J Informetr, Vol. 11, No. 4, (2017), pp. 959-975.

[24] R. N. Broadus, Toward a definition of 'bibliometrics, Scientometrics, Vol. 12, Nos. 5-6, (1987), pp. 373-379.

[25] L. C. Ampese, W. G. Sganzerla, H. di Domenico Ziero, A. Mudhoo, G. Martins, and T. Forster-Carneiro, Research progress, trends, and updates on anaerobic digestion technology: A bibliometric analysis, Journal of Cleaner Production, Vol. 331. Elsevier Ltd, (2022).

[26] H. Ghanbari, M. Safari, R. Ghousi, E. Mohammadi, and N. Nakharutai, Bibliometric analysis of risk measures for portfolio optimization, Accounting, Vol. 9, No. 2, (2023), pp. 95-108.

[27] R. Duan and L. Guo, Application of Blockchain for Internet of Things: A Bibliometric Analysis, Math Probl Eng, (2021).

[28] W. Zhou, Q. Gu, and D. Yu, Knowledge Framework and Evolution of Fuzzy

Portfolio Research: A Bibliometric Analysis, Math Probl Eng, (2020).

[29] P. Peykani, F. Hosseinzadeh Lotfi, S. J. Sadjadi, A. Ebrahimnejad, and E. Mohammadi, Fuzzy chance-constrained data envelopment analysis: a structured literature review, current trends, and future directions, Fuzzy Optimization and Decision Making, Vol. 21, No. 2, (2022), pp. 197-261.

[30] N. J. Marín-Rodríguez, J. D. González-Ruiz, and S. Botero Botero, Dynamic Co-Movements among Oil Prices and Financial Assets: A Scientometric Analysis, Sustainability (Switzerland), Vol. 14, No. 19, (2022).

[31] B. C. Brookes, Sources of information on specific subjects' by S.C. Bradford, J Inf Sci, Vol. 10, No. 4, (1985), pp. 173-175.

[32] G. Stoltz and G. Lugosi, Internal regret in on-line portfolio selection, Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science), Vol. 2777, (2003), pp. 403-417.

[33] S. Giove, S. Funari, and C. Nardelli, An interval portfolio selection problem based on regret function, Eur J Oper Res, Vol. 170, No. 1,(2006), pp. 253-264.

[34] C. Gregory, K. Darby-Dowman, and G. Mitra, Robust optimization and portfolio selection: The cost of robustness, Eur J Oper Res, Vol. 212, No. 2, (2011), pp. 417-428.

[35] A. E. B. Lim, J. G. Shanthikumar, and T. Watewai, Robust asset allocation with benchmarked objectives, Math Financ, Vol. 21, No. 4, (2011), pp. 643-679.

[36] A. J. Bean and A. C. Singer, Universal switching and side information portfolios under transaction costs using factor graphs, IEEE Journal on Selected Topics in Signal Processing, Vol. 6, No. 4, (2012), pp. 351-365.

[37] X. Li, B. Shou, and Z. Qin, An expected regret minimization portfolio selection model, Eur J Oper Res, Vol. 218, No. 2, (2012), pp. 484-492.

[38] J. C. Lourenço, A. Morton, and C. A. Bana E Costa, PROBE - A multicriteria decision support system for portfolio robustness evaluation, Decis Support Syst, Vol. 54, No. 1, (2012), pp. 534-550.

[39] S. Rivaz and M. A. Yaghoobi, Minimax regret solution to multiobjective linear programming problems with interval objective functions coefficients, Cent Eur J Oper Res, Vol. 21, No. 3, (2013), pp. 625-649.

[40] Y. Ji, T. Wang, M. Goh, Y. Zhou, and B. Zou, The worst-case discounted regret portfolio optimization problem, Appl Math Comput, Vol. 239, (2014), pp. 310-319.

[41] M. Nwogugu, Regret minimization, willingness-to-accept-losses and framing, Appl Math Comput, Vol. 179, No. 2, (2006), pp. 440-450.

[42] P. Xidonas, G. Mavrotas, C. Hassapis, and C. Zopounidis, Robust multiobjective portfolio optimization: A minimax regret approach, Eur J Oper Res, Vol. 262, No. 1, (2017), pp. 299-305.

[43] P. Xidonas, C. Hassapis, J. Soulis, and A. Samitas, Robust minimum variance portfolio optimization modelling under scenario uncertainty, Econ Model, Vol. 64, (2017), pp. 60-71.

[44] A. Ahmadi and H. Davari-Ardakani, A multistage stochastic programming framework for cardinality constrained portfolio optimization, Numerical Algebra, Control and Optimization, Vol. 7, No. 3, (2017), pp. 359-377.

[45] S. Rivaz and M. A. Yaghoobi, Weighted sum of maximum regrets in an interval MOLP problem, International Transactions in Operational Research, Vol. 25, No. 5, (2018), pp. 1659-1676.

[46] G. Simões, M. McDonald, S. Williams, D. Fenn, and R. Hauser, "Relative Robust

Portfolio Optimization with benchmark regret," *Quant Finance*, Vol. 18, No. 12, (2018), pp. 1991-2003.

[47] R. Baule, O. Korn, and L. C. Kuntz, "Markowitz with regret," *J Econ Dyn Control*, Vol. 103, (2019), pp. 1-24.

[48] Y. Ji, S. Qu, and Y. Dai, "A new approach for worst-case regret portfolio optimization problem," *Discrete and Continuous Dynamical Systems - Series S*, Vol. 12, No. 45, (2019), pp. 761-770.

[49] M. G. Tsionas, "Multi-objective optimization using statistical models," *Eur J Oper Res*, Vol. 276, No. 1, (2019), pp. 364-378.

[50] S. Vohra and F. J. Fabozzi, "Effectiveness of developed and emerging market FX options in active currency risk management," *J Int Money Finance*, Vol. 96, (2019), pp. 130-146.

[51] J. Li and L. Wang, "A minimax regret approach for robust multi-objective portfolio selection problems with ellipsoidal uncertainty sets," *Comput Ind Eng*, Vol. 147, (2020).

[52] A. C. B. B. Filho and S. M. da Silva Neiro, "Fine-tuned robust optimization: Attaining robustness and targeting ideality," *Comput Ind Eng*, Vol. 165, (2022).

[53] S. Caçador, J. M. Dias, and P. Godinho, "Portfolio selection under uncertainty: a new methodology for computing relative-robust solutions," *International Transactions in Operational Research*, Vol. 28, No. 3, (2021), pp. 1296-1329.

[54] X. Gong, C. Yu, L. Min, and Z. Ge, "Regret theory-based fuzzy multi-objective portfolio selection model involving DEA cross-efficiency and higher moments," *Appl Soft Comput*, Vol. 100, (2021).

[55] S. Benati and E. Conde, "A relative robust approach on expected returns with bounded CVaR for portfolio selection," *Eur J Oper Res*, Vol. 296, No. 1, (2022), pp. 332-352.

[56] P. Groetzner and R. Werner, "Multiobjective optimization under uncertainty: A multiobjective robust (relative) regret approach," *Eur J Oper Res*, Vol. 296, No. 1, (2022), pp. 101-115.

[57] R. Ding and S. Uryasev, "Drawdown beta and portfolio optimization," *Quant Finance*, (2022).

[58] A. Kagrecha, J. Nair, and K. Jagannathan, "Constrained regret minimization for multi-criterion multi-armed bandits," *Mach Learn*, Vol. 112, No. 2, (2023), pp. 431-458.

[59] S. C. Caçador, P. M. C. Godinho, and J. M. P. C. M. Dias, "A minimax regret portfolio model based on the investor's utility loss," *Operational Research*, Vol. 22, No. 1, (2022), pp. 449-484.

[60] Y. Zhang, H. Lin, X. Yang, and W. Long, "Combining expert weights for online portfolio selection based on the gradient descent algorithm," *Knowl Based Syst*, Vol. 234, (2021).

[61] D. Chakrabarti, "Parameter-free robust optimization for the maximum-Sharpe portfolio problem," *Eur J Oper Res*, Vol. 293, No. 1, (2021), pp. 388-399.

[62] J. H. Won and S. J. Kim, "Robust trade-off portfolio selection," *Optimization and Engineering*, Vol. 21, No. 3, (2020), pp. 867-904.

[63] J. A. Hernandez and M. A. M. al Janabi, "Forecasting of dependence, market, and investment risks of a global index portfolio," *J Forecast*, Vol. 39, No. 3, (2020), pp. 512-532.

[64] S. Caçador, J. M. Dias, and P. Godinho, "Global minimum variance portfolios under uncertainty: a robust optimization approach," *Journal of Global*

Optimization, Vol. 76, No. 2, (2020), pp. 267-293.

[65] M. H. Ngerng and S. S. F. Ngerng, "Portfolio selection algorithm under financial crisis: a case study with Bursa Malaysia," *Commun Stat Simul Comput*, (2019).

[66] S. Lu, N. Zhang, Y. Qiu, and Y. Gao, "A multi-period regret minimization model for uncertain portfolio selection with bankruptcy constraint," *Journal of Intelligent and Fuzzy Systems*, Vol. 37, No. 6, (2019), pp. 8417-8439.

[67] D. Huang, S. Yu, B. Li, S. C. H. Hoi, and S. Zhou, "Combination forecasting reversion strategy for online portfolio selection," *ACM Trans Intell Syst Technol*, Vol. 9, No. 5, (2018).

[68] M. M. van den Broeke, R. N. Boute, and J. A. van Mieghem, "Platform flexibility strategies: R&D investment versus production customization tradeoff," *Eur J Oper Res*, Vol. 270, No. 2, (2018), pp. 475-486.

[69] E. Mohr and R. Dochow, "Risk management strategies for finding universal portfolios," *Ann Oper Res*, Vol. 256, No. 1, (2017), pp. 129-147.

[70] B. Grechuk and M. Zabarankin, "Sensitivity analysis in applications with deviation, risk, regret, and error measures," *SIAM Journal on Optimization*, Vol. 27, No. 4, (2017), pp. 2481-2507.

[71] "Possibilistic programming approaches to portfolio optimization," *Studies in Fuzziness and Soft Computing*, Vol. 316, (2014), pp. 81-125.

[72] E. Fernandez, E. Lopez, G. Mazcorro, R. Olmedo, and C. A. Coello Coello, "Application of the non-outranked sorting genetic algorithm to public project portfolio selection," Inf Sci (N Y), Vol. 228, (2013), pp. 131-149.

[73] A. E. B. Lim, J. G. Shanthikumar, and G. Y. Vahn, "Robust portfolio choice with learning in the framework of regret: Single-period case," Manage Sci, Vol. 58, No. 9, (2012), pp. 1732-1746.

Follow this article at the following site:

Amir Mohammad Larni Fooeik, Hossein Ghanbari, Seyed Jafar Sadjadi & Emran Mohammadi. Behavioral Finance Biases: A Comprehensive Review on Regret Approach Studies in Portfolio Optimization. IJIEPR 2024; 35 (1) :1-23
URL: http://ijiepr.iust.ac.ir/article-1-1909-en.html