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A comparative scientometric analysis of investor sentiment and trading behaviour research

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Abstract

The purpose of this study is to conduct a comparative analysis of investor sentiment and trading behavior in the field of behavioral finance. This study analyzes and compares the research evolution within these two domains using various scientometric analysis methods. The analysis reveals that the number of publications in the field of investor sentiment has grown exponentially while research activity in trading behavior has slowed down in recent years. Investor sentiment research has attracted more attention and generated more publications despite a relatively late start. The USA and China are the major countries conducting research in these two fields and the research output is primarily derived from economically developed regions. Investor sentiment and trading behavior research shows a convergence trend with common research hotspots including COVID-19, Bitcoin and machine learning. Both fields are concentrated in financial market research and have emerging research frontiers such as financial crises, social media and cryptocurrencies. Highly cited articles indicate a degree of overlap between the two fields wherein the domain of trading behavior is predominantly linked to investor sentiment. This study provides valuable insights into the research progress on investor sentiment and trading behavior.

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1. Introduction

Investor sentiment and trading behaviour have acquired significance in the field of behavioural finance during the last two decades. Numerous studies have established the substantial influence of investor sentiment and trading behavior on asset pricing or stock returns (French, 2017;Hao, Chou, Ko, & Yang, 2018; Kaniel, Saar, & Titman, 2008). Shiller (2014) highlights the importance of considering people's genuine thoughts and actions in research that encompasses actual human behavior. Investor sentiment and trading behavior are particularly indicative of people's real thoughts and acts when investing in stocks.

The concept of "investor sentiment" originated from the closed-end fund puzzle where Charles, Andrei, and Thaler (1991) introduced it by examining the discount rate of those funds. Barberis, Shleifer, and Vishny (1998) introduced an investor sentiment model that assesses how investors develop views that cause stock prices to underreact and overreact. Researchers have proposed various indicators to evaluate investor sentiment such as stock trading data and news curiosity (Vicari & Gaspari, 2021; Xu & Zhao, 2022), mutual fund flow (Ben-Rephael, Kandel, & Wohl, 2012), Google search data (Brochado, 2020) and Twitter data (Indra & Husodo, 2020) etc.

Investor trading behavior, similar to investor sentiment is also driven by a combination of preferences and beliefs. Research on investors' trading behavior can be traced back to the study of tax-motivated securities trading behavior (Badrinath & Lewellen, 1991). Existing research has focused on various types of investor trading behavior such as the disposition effect (Weber & Camerer, 1998), herding behavior (Hsieh, Chan, & Wang, 2020) and the Chinese lunar calendar effect (Huang, Chiu, & Lin, 2022). Numerous studies have been conducted in these two research fields but there is still much debate regarding their definitions and interplay. For example, the same measuring methods are used to measure these two research objects, including Google searches (Brochado, 2020; Preis, Moat, & Stanley, 2013) and relevant stock trading data (Kim, Kim, & Seo, 2017; Yang & Zhou, 2015). Some researchers (Choi & Yoon, 2020; Dai & Yang, 2018; Kim & Ryu, 2021) assert that investor sentiment influences their trading behavior, others hold that it is investor trading behavior that shapes their sentiment (Chowdhury, Uddin, & Anderson, 2021). A thorough and extensive literature evaluation might possibly resolve this issue because differentiating between these two entities may be difficult.

Currently, there are limited studies on investor sentiment and trading behaviour. For instance, Koutmos (2014) performed a literature review specifically focusing on positive feedback trading and identified research limitations in this area. Aggarwal (2022) reviewed 81 articles focusing on the definition and measurement methods of market sentiment. Janková (2023) critically reviewed 49 articles on text mining and sentiment analysis in the context of stock market forecasting. These studies provided extensive evaluations of a limited or specific area of literature which may not provide a full understanding of broad improvements in the disciplines of investor sentiment or trading behaviour. Thus, there is currently a lack of systematic, comprehensive and data-driven literature reviews that compare and analyze these two domains.

An emerging approach for obtaining systematic high-level insights is scientometric analysis techniques. Scientometric methods have played a crucial role in numerous academic disciplines, offering valuable insights into research productivity, scholarly impact, collaboration networks and emerging trends (Goerlandt, Li, & Reniers, 2020). Their application has enhanced the understanding and advancement of knowledge across diverse fields of study (Južnič et al., 2010; Su, Zhang, & Wu, 2021; Zakka, Lim, & Khun, 2021). Some researchers have also conducted literature reviews using bibliometric methods to investigate relevant issues such as indicators of investor sentiment (Prasad, Mohapatra, Rahman, & Puniyani, 2022), the interplay between stock markets and oil prices (Lin & Su, 2020), sentiment analysis (Ángeles, Pérez-Pico, & López, 2020; Piryani, Madhavi, & Singh, 2017) and the behavior of investors in cryptocurrency markets (Almeida & Gonçalves, 2023). However, these systematic literature reviews have frequently been limited to individual issues, making it difficult to provide an entire overview of the study landscape concerning investor attitude and trading behaviour. As a result, they have fallen short of enabling in-depth comparative study of these two sectors.

The aim of this paper is to use various scientometric analysis techniques to gain a systematic understanding of the research domains of investor sentiment and trading behaviour as well as to conduct a comparative study of these two fields covering aspects such as annual output, geographic distribution, prolific journals, institutions, authors and their collaborative networks. It also sheds light on important research themes and trends in focus topics. Clustering partitions facilitate the identification of key contributions within these clusters. Moreover, the comparative analysis of this paper offers a macro perspective on the correlation between these two fields. This systematic knowledge, including key themes and documents enhance understanding of progress in fields, guide course instructors or self-study and identifies new research directions.

The subsequent sections of this paper are organized as follows: Section 2 outlines the research questions, the search strategy and the corresponding dataset of retrieved papers accompanied by a concise overview of the research methodology used in this paper. Section 3 applies these methods to analyze the research questions raised in section 2 and interprets the findings. Section 4 delves deeper into the results obtained highlighting the limitations of this study and proposing potential directions for future research. Finally, section 5 concludes the paper with the research findings.

2. Research Questions, Data and Methodology

2.1. Research Process and Research Questions

The research process in this paper is depicted in Figure 1, encompassing four main steps: formulating research questions (RQ), retrieving data, applying scientometric methods and tools and presenting and interpreting the results.

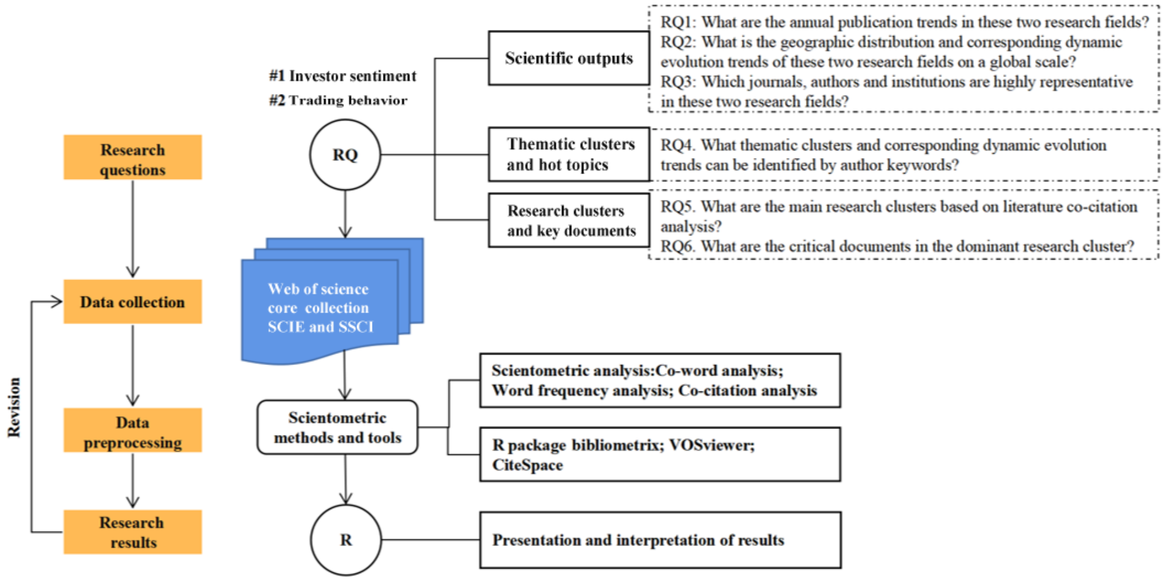


Figure 1. Research process applied in this paper.

2.2. Data Retrieval Strategy and Resulting Dataset

The data for this study was obtained from articles indexed in the "Science Citation Index Expanded (SCIE)" and "Social Sciences Citation Index (SSCI)" databases in the Web of Science Core Collections (WOSCC), with document types including "articles" and "reviews" as shown in the second step in Figure 1. This paper applied the topic-based search strategy on February 12, 2023. The first search term is "investor sentiment" and the second search term is "trading behavior". The study of literature spans from 1900 to 2022. The collection includes 1955 and 719 papers on investor sentiment and trading behaviour. In addition, 64 papers address both areas.

The dataset obtained from the WOSCC database is considered a fundamental collection of scientific knowledge on investor sentiment and trading behavior. Exploratory searches using titles as search fields result in the absence of many highly relevant articles and target knowledge areas. A topic-based search strategy can effectively prevent this problem. Original research articles and review articles represent the primary sources of significant scientific advancements or comprehensive summaries of specific topics that hold potential influence in the respective field.

Table 1 provides essential descriptive information about the dataset using the bibliometric package of R (Aria & Cuccurullo, 2017). The high average citation rate of 26.39 per paper suggests that investor sentiment research has a significant impact on academic literature. Various references and keywords demonstrate the broad scope of research in this field. 313 different journals have contributed to the literature in this area indicating a relatively concentrated distribution. The participation of 3,622 authors with 212 papers written by a single person illustrates the prevailing tendency towards collaborative authorship in the majority of publications. The average number of authors per paper is 2.75 and the international cooperation rate is 32.63% indicating a relatively high degree of collaboration among authors globally.

Table 1. Main information of the datasets on investor sentiment and trading behavior research

Description	Results	
	Investor sentiment	Trading behavior
Period covered	1991-2022	1992-2022
Number of documents	1955	719
Average citations per document	26.39	20.63
Keywords plus	2094	1317
Author's keywords	4014	1821
Sources (Journals, books, etc.)	313	239
References	43791	19927
Number of authors	3622	1634
Authors of single-authored documents	212	105
Single-authored documents	250	108
Co-Authors per document	2.75	2.75
International co-authorships %	32.63	30.46
Article	1936	715
Review	19	4

The study of trading behaviour began in 1992 close to the commencement of investor sentiment research and 719 articles were published by 2022 in comparison to investor sentiment research. The average number of citations per paper is 20.63 and 239 different journals and 1634 authors have contributed to the research literature in this field. The research on trading behavior has also made fruitful achievements with a relatively high influence in academic literature and relatively close collaboration among authors.

2.3. Scientometric Methods and Tools

This study uses specific bibliometric methodologies to accomplish the aforementioned research aims as illustrated in step 3 of Figure 1. According to Nalimov and Mulchenko (1971), scientometrics is defined as the utilization of quantitative methods to examine the progression of science as an information-based phenomenon. The combination of scientometric methods and visualization techniques is frequently employed to quantitatively analyze research documents, facilitating the interpretation of findings (Mingers & Leydesdorff, 2015). The following section briefly explains the scientometric tools and methods used to achieve the research objectives mentioned in section 2.1.

2.3.1. Research Outputs: RQ1 to RQ3

Research output is a crucial scientometric index that reflects research activities and performance in various aspects. This study determines the annual publication count in the fields of investor sentiment and trading behaviour research with the goal of observing dynamic changes in these two fields and deriving developmental patterns using regression analysis to address RQ1. The visualization tool VOS viewer which is suitable for mapping diagrams (Van Eck & Waltman, 2010) was used to uncover the authors' cooperation networks in these two research fields. To achieve RQ2, this study evaluates the impact of studies from different countries or regions using information from VOS viewer and generated Google Earth maps on CiteSpace (Goerlandt et al., 2020; Li, Goerlandt, & Reniers, 2021). This section also identifies the significant institutions in these fields. To address RQ3, this study analyzes the top productive journals and the authors' cooperation networks in these two research fields using VOS viewer.

2.3.2. Thematic Clusters and Hot Topics Comparison Analysis: RQ4

Co-word analysis or co-occurrence analysis has been employed to create a scientific dynamic map. Combining keyword co-word analysis with frequency analysis reveals both the thematic structure of topics in the study field and the growth of these thematic clusters (Li et al., 2021). The primary topic of an article can often be identified through the publication's keywords. This study conducted an annual analysis of keyword co-occurrence and frequency within the research fields of investor sentiment and trading behavior providing insights not only into thematic clusters but also into the current important topics in these fields. VOS viewer was used to visualize the resulting keyword networks (Van Eck & Waltman, 2010) which were then partitioned into distinct groups based on the strength of keyword co-occurrence. Thematic groups were also formed by examining the average year of occurrence of frequently occurring terms. These clusters of topics were superimposed to describe the temporal evolution of academic concerns regarding these topics.

2.3.3. Research Clusters and Key Documents: RQ5 and RQ6

Cited references are commonly used as an indicator of the intellectual foundations of a particular field in scientometric research (Hammarfelt, 2011). Co-citation analysis has been widely used to illuminate the structure and knowledge base of various research fields (Culnan, 1987; García-Lillo, Claver-Cortés, Marco-Lajara, & Úbeda-García, 2019; Köseoglu, Okumus, Dogan, & Law, 2019). One can gain insights into this intellectual underpinning by analysing the co-citation patterns of referenced sources (Persson, 1994). Co-citation information can be used to delineate research clusters and intellectual structure within a specific field. The greater the frequency of citation within a particular cluster, the more a paper is deemed to be key literature in the cluster making an important scientific contribution to that development (Li et al., 2021). This section used CiteSpace to conduct a co-citation analysis of the literature. Meanwhile, CiteSpace is leveraged to identify the pivotal documents within the top five ranked clusters and designate them as the primary knowledge base of these clusters. The clusters are assigned labels derived from the terms and extracted from the titles of the cited papers predominantly consisting of terms relevant to the articles within each respective cluster. The log-likelihood ratio (LLR) is employed for labeling. The dynamic evolution paths of knowledge structures in these two fields are revealed by identifying and comparing the average publication time of literature within these clusters. These frequently cited papers can be deemed the research frontier of the research field in the cluster (Chen, Ibekwe-SanJuan, & Hou, 2010).

3. Research Results

This section of the paper shows and interprets the results of scientometric analyses. First, RQ1 to RQ3 focus on the scientific outputs. Second, RQ4 presents the findings of keyword-based clustering as well as current topics. Finally, RQ5 and RQ6 were used to analyze knowledge clusters and key literature found by co-citation analysis.

3.1. Research Outputs

3.1.1. Overall Publication Trends Analysis (RQ1)

As mentioned in section 2.2, after more than 30 years of development, the literature on investor sentiment and trading behavior has been fruitful. According to Figure 2 (a), the number of publications in investor sentiment and trading behavior research fields has increased every year and the gap between them is also gradually widening indicating that in recent years scholars have paid more attention to investor sentiment. Figure 2 (b) shows the cumulative publication trends of investor sentiment and trading behavior research. According to Figure 2 (b), the year 2012 is an important time node. Prior to 2012, research in these two domains progressed at a modest pace. Subsequently, the quantity of cumulative records in these two fields continued to quickly expand. In addition, before 2012, even more scholars studied trading behavior but after 2012, cumulative documents on investor sentiment began to exceed trading behavior and the cumulative number of investor sentiment publications has grown faster which shows exponential growth and the gap between the two began to widen gradually. In addition, it is worth mentioning that the number of published documents containing both of these terms at the same time experienced an overall exponential growth trend in Figure 2(c) which suggests that there is a growing intersection between these two research fields.

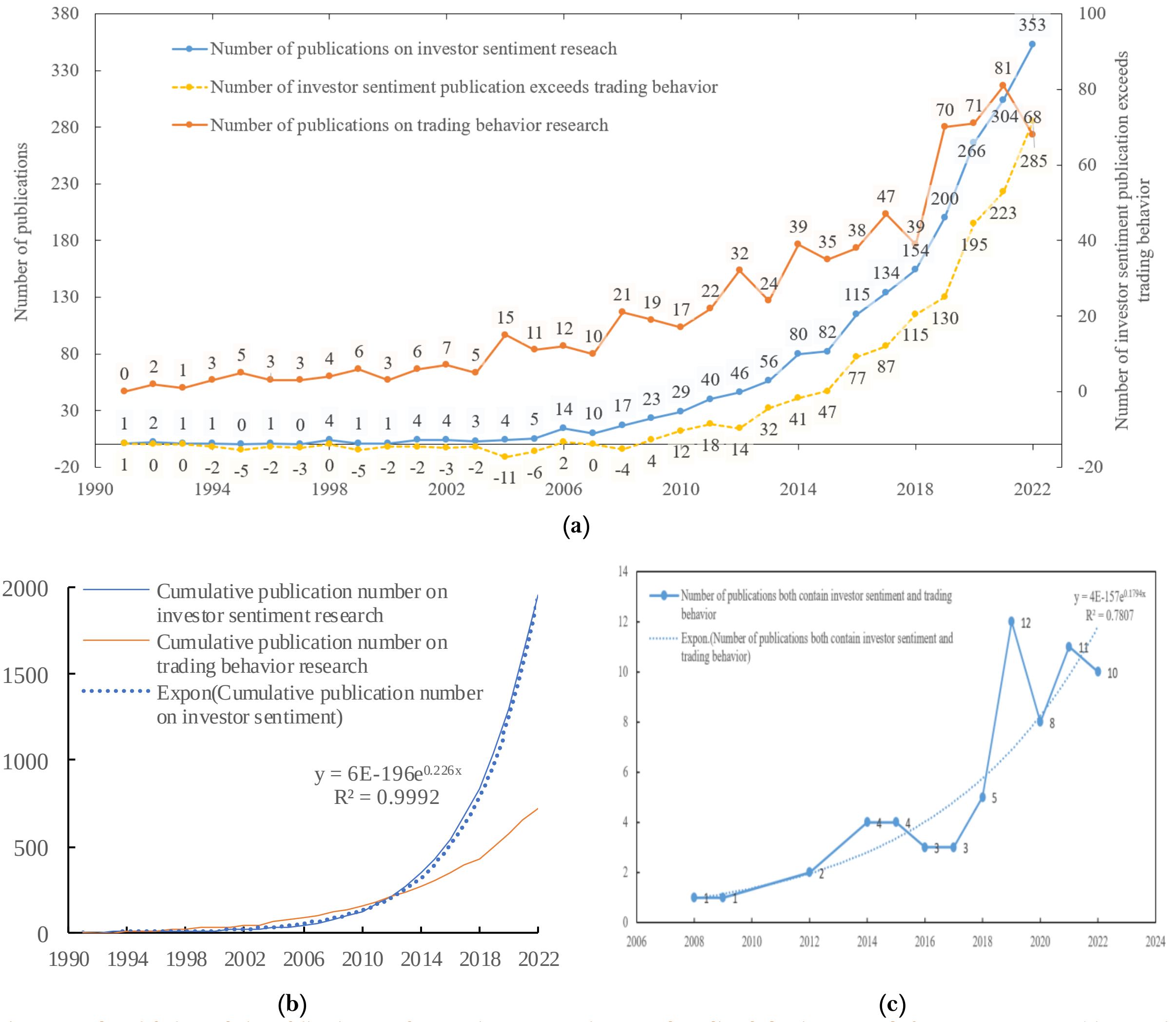


Figure 2. The global trends in publication numbers on investor sentiment and trading behavior research from 1991 to 2022. (a) Annual trends of the investor sentiment and trading behavior publications and the gap trends between them. (b) Cumulative publication trends of investor sentiment and trading behavior research. (c) Annual trends in publication number on research both contain investor sentiment and trading behavior (2008-2022).

3.1.2. Geographic Distribution (RQ2)

Table 2 lists the top 10 most productive countries or regions in investor sentiment and trading behavior research determined by using VOS viewer. In addition, "average citations (AC)" is an indicator to measure the average influence of a paper in each country or region and "average publication year (APY)" represents the time period and order in which a country has been active in the field.

According to Table 2, the top six production countries and regions in investor sentiment and trading behaviour are China, the United States, England, Austria, Taiwan and South Korea. Singapore, Ireland, Malaysia, and Israel have relatively high research output in the investor sentiment research field whereas Finland, Austria, Belgium, Scotland and Japan have relatively high research output in the trading behaviour research field.

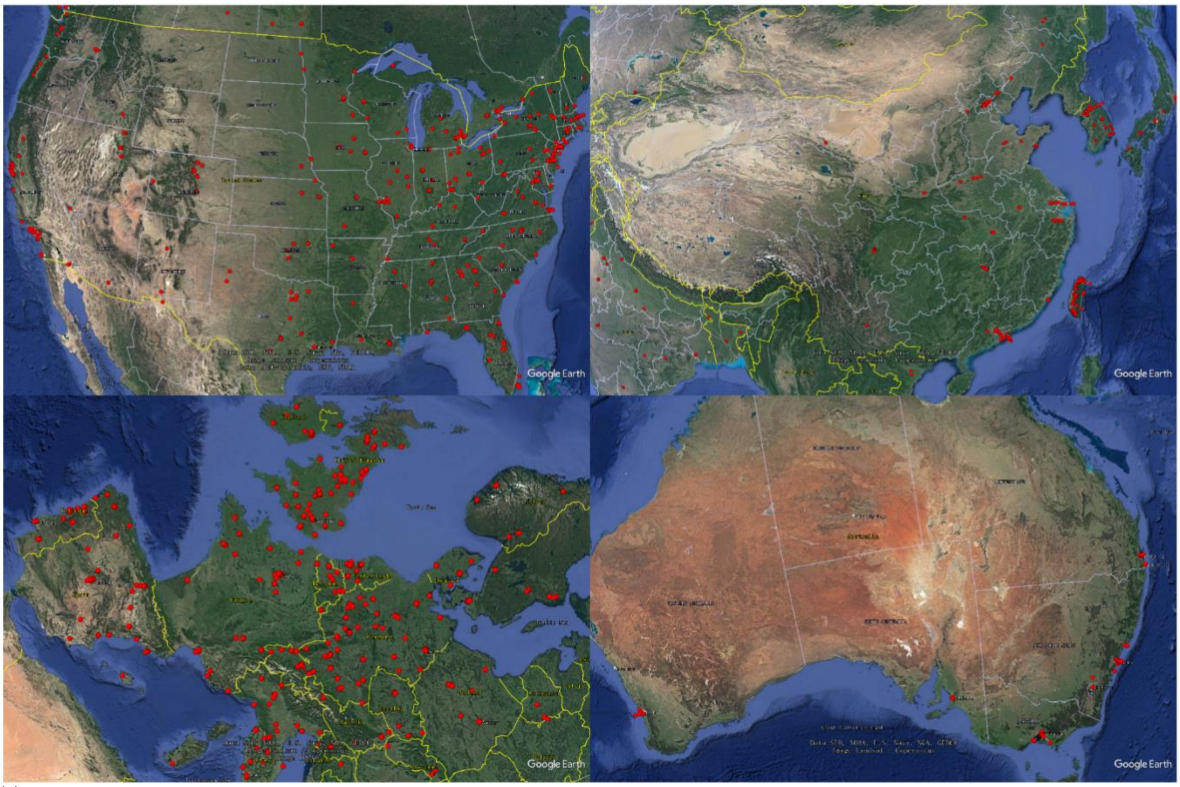
In terms of publishing time, the first countries or regions in the field of investor sentiment research were the United States, the Netherlands, and Singapore while the most recent were India, Italy, and Malaysia. In the research field of trading behavior, the early countries or regions are the USA, Netherlands and Finland and the recent countries or regions are India, China and Turkey. Table 2 shows that research on trading behaviour in these countries or regions is often earlier than research on investor attitude similar to the aforementioned study results in section 3.1.1.

The most cited countries and regions in the two research fields are the USA when analyzing the average influence of these papers. In comparison, the average citation of China is relatively lower. In terms of the number of published articles and the average citation count, the countries and regions with the most authority in the field of investor sentiment research are the USA, Germany and Canada (publication count exceeding 50 and average citation count surpassing 20) and the countries or regions with more authority in the field of trading behavior research include the USA, England and the Netherlands (publication count and average citation count both exceeding 20).

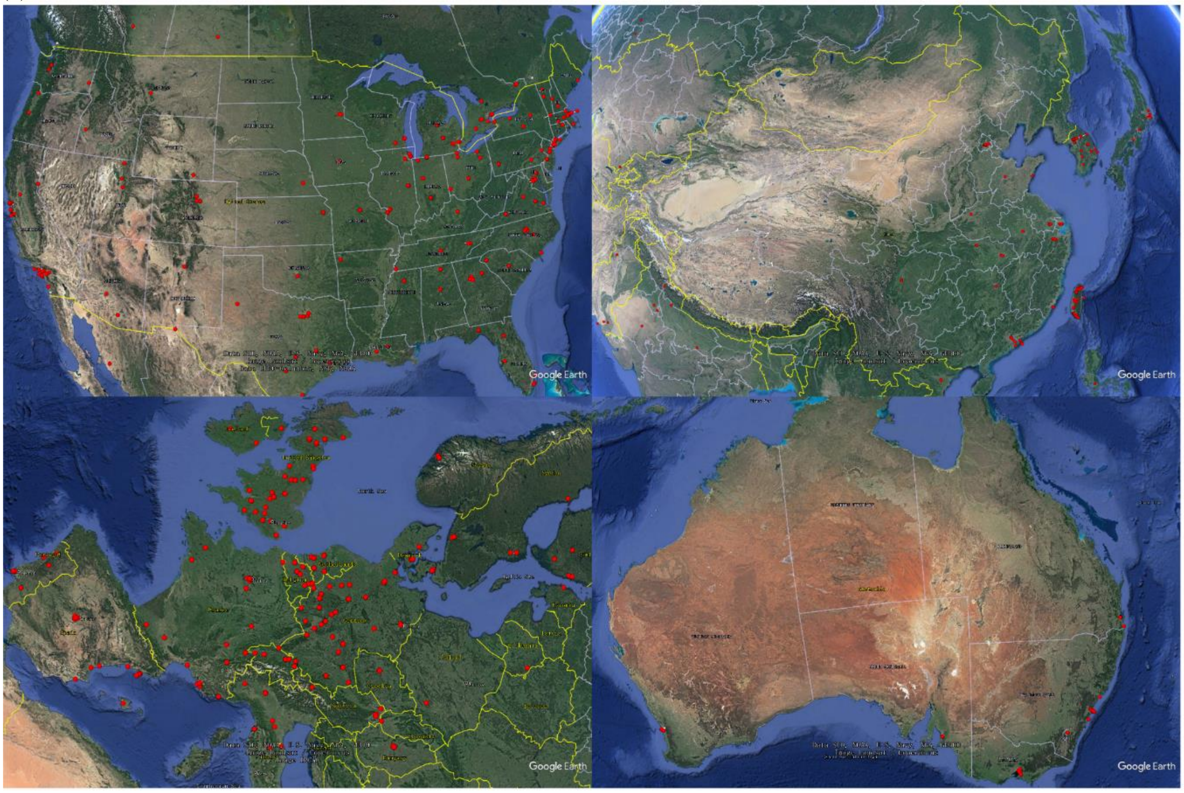
Table 2. Top 20 most productive countries or regions in investor sentiment and trading behavior research

Investor sentiment					Trading behavior			
No.	**Country/Region**	**Records**	**APY**	**AC**	**Country/Region**	**Records**	**APY**	**AC**
1	China	667	2019.4	12.97	USA	218	2012.14	42.69
2	USA	528	2015.69	59.99	China	158	2018.52	8.37
3	England	187	2017.87	18.39	England	65	2015.54	25.22
4	Australia	145	2018.36	16.26	South Korea	60	2017.07	18.02
5	Taiwan	123	2016.67	9.86	Australia	59	2016.05	13.9
6	South Korea	101	2018.76	16.1	Taiwan	59	2014.34	10.76
7	Germany	90	2017.1	23.31	Germany	51	2016.2	15.35
8	France	73	2019.39	16.16	Canada	28	2014.89	11.75
9	Canada	69	2017.52	26.29	Netherlands	27	2013.41	41
10	Spain	66	2018.17	13.09	Finland	20	2013.15	18.85
11	New Zealand	57	2019.20	17.53	France	18	2016.12	16.89
12	India	51	2020.62	9.25	Switzerland	17	2017.47	12.71
13	Netherlands	44	2015.98	34.89	New Zealand	15	2017.20	14.60
14	Turkey	43	2019.26	11.88	Spain	15	2016.86	11.47
15	Singapore	37	2016.56	43.73	Italy	13	2016.46	11.15
16	Ireland	33	2018.81	20.88	Austria	12	2017.67	8.75
17	Italy	32	2020.33	7.75	Belgium	11	2014.91	39.82
18	Switzerland	32	2018.00	20.22	Scotland	11	2015.82	20.64
19	Malaysia	31	2020.03	17.52	Turkey	11	2017.90	9.64
20	Israel	30	2018.21	26.70	India	10	2019.00	8.70
					Japan	10	2017.60	17.10

According to Table 2, this paper further analyzes the geographical distribution of these two research fields within the top 7 most productive countries or regions (see Figure 3). It shows that the geographical distribution of investor sentiment research is not very different from that of trading behavior research because the output of investor sentiment research is much larger. In the USA, China and Australia, most of the publications come from the eastern region while in England, output is more evenly distributed and in Taiwan, South Korea and Germany, the output in the western region is higher than that in the east. It can be inferred that the geographical distribution of investor sentiment and trading behavior research is basically consistent with the distribution of the economically developed regions.



(a)



(b)

Figure 3. The geographical distribution comparison of the top 7 countries and regions (1991-2022) which were generated using Google Earth Maps in CiteSpace. (a)The geographical distribution of the top 7 productive countries and regions of investor sentiment research. (b) The geographical distribution of the top 7 productive countries and regions of trading behavior research.

3.1.3. Representative Journals and Authors (RQ3)

Table 3 displays the top 10 productive journals in the fields of investor sentiment and trading behavior. It includes the average publication time and average citations of these journals using VOS viewer. It can be seen from Table 3 that these journals are mostly focused on economics or finance and the journals with the largest number of publications in the field of investor sentiment and trading behavior research are the *International Review of Financial Analysis* and the *Journal of Banking & Finance* respectively. In addition, four journals are highly productive in both fields (italicized in Table 3) including the *Journal of Banking & Finance*, *Finance Research Letters*, *Journal of Financial Economics*, *Emerging Markets Finance and Trade*, the rest are not the same. Moreover, the latest active journals are *Finance Research Letters* and the most average cited journals are the *Journal of Financial Economics* in these two fields.

Table 3. Top 10 most productive journals in investor sentiment and trading behavior research

Research field	No.	Journals	Records	APY	AC
Investor sentiment	1	International review of financial analysis	83	2019.55	12.48
	2	*Journal of banking & finance*	72	2015.49	39.50
	3	*Finance research letters*	68	2019.84	11.40
	4	Journal of behavioral finance	66	2016.75	9.14
	5	North American journal of economics and finance	59	2019.37	8.24
	6	*Journal of financial economics*	52	2014.21	149.71
	7	Pacific-basin finance journal	51	2018.10	15.45
	8	*Emerging markets finance and trade*	49	2017.93	11.51
	9	International review of economics & finance	48	2018.65	10.81
	10	Applied economics	40	2018.55	10.38
Trading behavior	1	*Journal of banking & finance*	30	2013.93	29.00
	2	Pacific-basin finance journal	23	2016.39	15.17
	3	*Emerging markets finance and trade*	21	2014.47	7.86
	4	*Journal of financial economics*	20	2012.85	72.50
	5	Physica A: Statistical mechanics and its applications	17	2013.41	6.82
	6	Asia-pacific journal of financial studies	16	2012.31	5.69
	7	*Finance research letters*	15	2020.00	7.53
	8	Journal of economic behavior & organization	15	2018.60	10.40
	9	Journal of futures markets	15	2014.47	9.67
	10	North American journal of economics and finance	15	2019.47	11.80

Table 4 shows the outputs, average publication time and average citations of the authors in the investor sentiment and trading behavior research fields using VOS viewer.

Table 4. Most productive authors in investor sentiment(documents≥10) and trading behavior research (≥ 5)

Research field	No.	Author	Records	APY	AC
Investor sentiment	1	Yang, Chunpeng	31	2016.14	11.97
	2	*Ryu, Doojin*	27	2019.48	16.11
	3	Gupta, Rangan	16	2020.27	12.44
	4	Qadan, Mahmoud	13	2019.31	13.69
	5	Zhang, Wei	13	2019.09	13.77
	6	Ferrer, Elena	12	2016.58	13.00
	7	Xiong, Xiong	12	2020.50	3.50
	8	Li, Jinfang	11	2017.55	10.55
	9	*Yang, Heejin*	11	2019.36	18.64
	10	Demirer, Riza	10	2020.00	12.50
		Santamaria, Rafael	10	2016.10	13.90
Trading behavior	1	*Ryu, Doojin*	21	2019.90	16.62
	2	*Yang, Heejin*	9	2019.44	22.78
	3	Yao, Shouyu	6	2021.00	13.50
	4	Zhou, Liyun	6	2018.40	15.67
	5	Cho, Hoon	5	2020.00	15.80
	6	Kim, Karam	5	2020.60	14.00
	7	Meyer, Steffen	5	2020.60	7.40
	8	Smales, Lee A.	5	2018.20	22.60
	9	Wang, Chunfeng	5	2020.80	16.20

According to Table 4, the authors with the largest number of publications in the field of investor sentiment and trading behavior research are *Yang, Chunpeng* and *Ryu, Doojin* respectively. In addition, *Ryu,* *Doojin* and *Yang, Heejin* are highly productive in both areas (italicized in Table 4). Meanwhile, in the investor sentiment research field, the two most recent active authors are *Xiong, Xiong*, and *Gupta, Rangan* and the two authors with the highest average citations are *Yang, Heejin* and *Ryu, Doojin*. In the trading behavior research field, the two most recent active authors are *Yao, Shouyu* and *Wang, Chunfeng*, and the two authors with the highest average citations are *Yang, Heejin* and *Smales, Lee A*.

Figure 4 examines the collaboration map of the top three writers in terms of the number of publications based on Table 4 discovering that these authors have developed their own cooperation networks. In the field of investor sentiment research, these three cooperative networks are independent of each other. The author who published the most papers is *Yang Chunpeng* formed a cooperative network with *Zhang Rengui*, *Li Jinfang*, *Zhou Liyun* and other scholars. The author with the second most articles is *ryu doojin* formed a cooperative network with Kim Jun Sik, Seo Sungwon, and Yang Heejin. The networks formed by *Gupta Rangan*, the author with the third publications are *Demirer Riza*, *Yong, Seong-Min*, *Ji Qiang* and other scholars. *Ji Qiang* played an important intermediary role in this network. In the field of trading behavior research, *Ryu Doojin* and *Yang Heejin* the top two authors exist in the same cooperative network which covers their cooperative relationship in the field of investor sentiment research. This indicates that the team has absorbed more scholars and is gradually paying more attention to the field of trading behavior. The third most prolific author, *Yao Shouyu* has formed a larger network of collaborations with *Wang Chunfeng*.

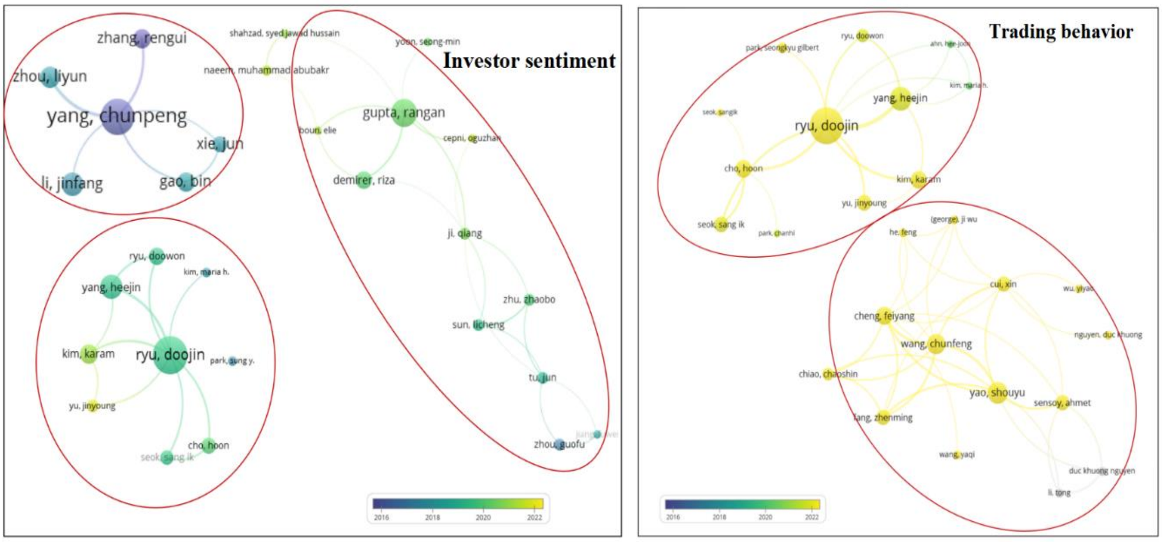


Figure 4. The top 3 productive authors cooperation network of investor sentiment research and trading behavior research generated using VOSviewer.

Note: Documents of authors in Gupta Rangan' cooperation network ≥5, others ≥1.

According to Table 5, Sungkyunkwan University has the largest production among the top 10 universities in the field of investor sentiment research with the remaining 80% coming from China. Moreover, the average publication time of these institutions was between 2019 and 2020 with *Hunan University* being the latest active institution and *NBER* and the *Hong Kong Polytechnic University* being the oldest. In terms of average citation times, the *NBER* has the highest influence followed by *the Central University of Finance and Economics* and *the Chinese Academy of Sciences*. Sungkyunkwan University has the largest production among the top ten universities in the field of trading behaviour research while the other institutions are considerably spread. Furthermore, the average publishing time of these schools is rather early with Beijing Normal University being the most recent active institution and the University of Wisconsin and Harvard University being the oldest. In terms of average citations, *Boston University* has the most influence followed by *MIT* and *Harvard University*.

When the above-mentioned study findings are compared, it is clear that between Tianjin University and the Chinese Academy of Sciences (italicised in Table 5), the distribution of investor mood and trading behaviour research domains in institutions differs with the exception of Sungkyunkwan University This feature is quite different from the distribution of countries or regions mentioned above which indicates that these two fields are not the same within the same country or region.

Table 5. Top 10 most productive institutions in investor sentiment and trading behavior research.

Research field	No.	Institutions	Records	APY	AC
Investor sentiment	1	*Sungkyunkwan University*	32	2019.52	12.81
	2	Southwestern university of finance and economics	31	2020.13	10.45
	3	South China university of technology	30	2019.25	7.43
	4	*Tianjin University*	29	2019.93	11.97
	5	Central University of finance and economics	28	2020.11	26.75
	6	*Chinese academy of sciences*	28	2019.31	19.50
	7	The Hong Kong polytechnic university	24	2017.43	15.63
	8	University of Chinese academy of sciences	24	2020.00	17.71
	9	Hunan University	23	2020.15	12.83
	10	NBER (National bureau of economic research)	23	2015.91	142.65
Trading behavior	1	*Sungkyunkwan University*	23	2019.04	17.52
	2	*Tianjin University*	19	2019.50	8.89
	3	The University of Sydney	14	2016.43	9.29
	4	Erasmus University Rotterdam	9	2012.22	79.33
	5	Harvard University	9	2007.89	98.33
	6	MIT (Massachusetts institute of technology)	9	2010.22	128.33
	7	University of Illinois	9	2012.78	47.56
	8	*Chinese academy of sciences*	8	2017.63	12.75
	9	Shanghai Jiao Tong University	8	2018.88	22.75
	10	Beijing Normal University	7	2020.33	2.00
		Boston University	7	2009.14	229.00
		Korea advanced institute of science and technology	7	2019.71	13.29
		National Taiwan University	7	2014.71	26.29
		University of California, Berkeley	7	2011.86	46.29
		University of Wisconsin	7	2006.43	35.71

3.2. Thematic Clusters and Hot Topics Comparison Analysis (RQ4)

Keywords in literature are essential components that reflect the main research objects, methods or topics. The dynamic growth of hot topics in a subject may be visualised using temporal overlay analysis and co-occurrence analysis of keywords. Moreover, the impact of these keywords can be assessed by analyzing their average citation frequency.

A total of 3756 and 1725 keywords were respectively extracted in the research fields of investor sentiment and trading behavior after synonym replacement and merging. VOS viewer was used to perform co-occurrence analysis on these high-frequency keywords and the results are shown in Figures 5 and 6 . Figures 5(a) and 6(a) show the theme clusters of author keywords. It shows the time evolution of keywords and the average citation times of these keywords in the theme clusters.

By using predefined threshold settings for keyword cluster analysis (with a minimum occurrence of 10 times), a total of 89 keywords were filtered and classified into six clusters (each color represents a cluster) as shown in Figure 5(a).They are presented in the following order based on cluster size: Cluster#1: Sentiment applied research, Cluster#2: Investor psychology, Cluster#3: Behavioral finance, Cluster#4: Return predictability, Cluster#5: Volatility and Cluster#6: Social media. According to Figure 5(b), the most prevalent topics in the investor sentiment research sector evolve from investor psychology to behavioural finance, volatility, and return predictability." In the past two years, the focus has shifted to "Sentiment applied research" and "Social media." Moreover, according to the average citation times given in Figure 5(c), the most influential themes are investor psychology and return predictability.

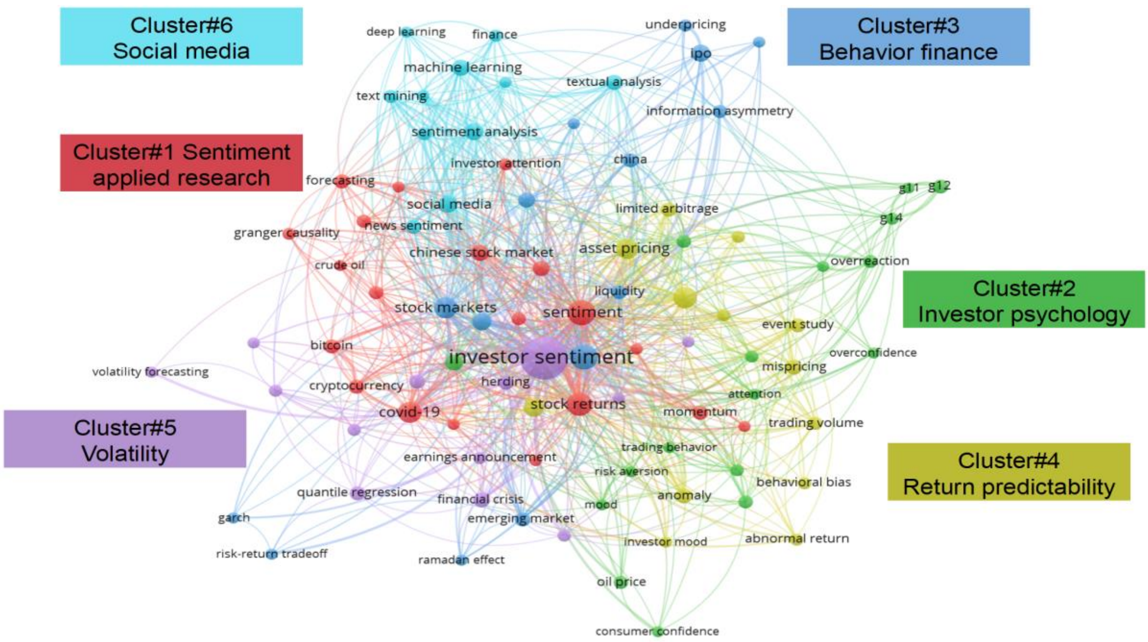
"Clusters #2 investor psychology" and "Cluster #3 behavior finance" are two early-emerging clusters. Cluster #2 mainly focuses on topics related to investor psychology such as *overreaction* and *underreaction* which have the highest influence in the investor sentiment research field. Subsequently, the research focus gradually shifted to *individual investors*, *overconfidence*, *stock prices*, *mutual funds* and other related keywords. Additionally, *oil prices* and *attention* have been frequent topics in this cluster. Cluster #3 primarily concentrates on traditional behavior finance with more active keywords including *stock markets*, *volatility*, *Initial Public Offerings* (*IPOs*) and *market sentiment*. Earlier keywords in this cluster included *market timing*, *liquidity* and *information asymmetry* which then transitioned to *volatility*, *China*, *the Ramadan effect*, *risk-return trade-off*, *emerging markets*, *market sentiment* and *housing prices*. The more influential keywords in this cluster include *risk-return trade-off* and *volatility*. According to Figure 5, IPOs were strongly connected with *China*, *information* *asymmetry* and *under-pricing* suggesting that the reality of under-pricing in IPOs was once an important topic and was related to information asymmetry. The keyword related to the research method in this cluster is *Generalized Autoregressive Conditional Heteroscedasticity (GARCH*).

"Cluster #4 return predictability and "Cluster #5 volatility" are two clusters that emerged in the middle of the research period. Cluster #4 mainly studies topics related to return predictability with *market efficiency*, *asset pricing* and *idiosyncratic volatility* being the earlier topics in this cluster. The research then focuses on stock returns such as the *cross-section of stock returns, return predictability* and *abnormal retur*n. The more recent keyword is behavioral bias and the most influential keyword is *trading volume* with the keyword related to the research method being the *event study*. Cluster #5 mainly studies topics related to the volatility of stocks. Other prevalent words in this cluster besides investor sentiment include financial crisis, herding etc. In the early stage, this cluster focused on *institutional investors* and *short selling* and then it became more related to volatility such as *implied volatility*, *volatility forecasting* and *volatility index (VIX)*. The keywords that have emerged recently include *uncertainty* and *corporate social responsibility (CSR)*. The most influential keywords include *investor sentiment* and *CSR* with the keyword related to the research method being *quantile regression*.

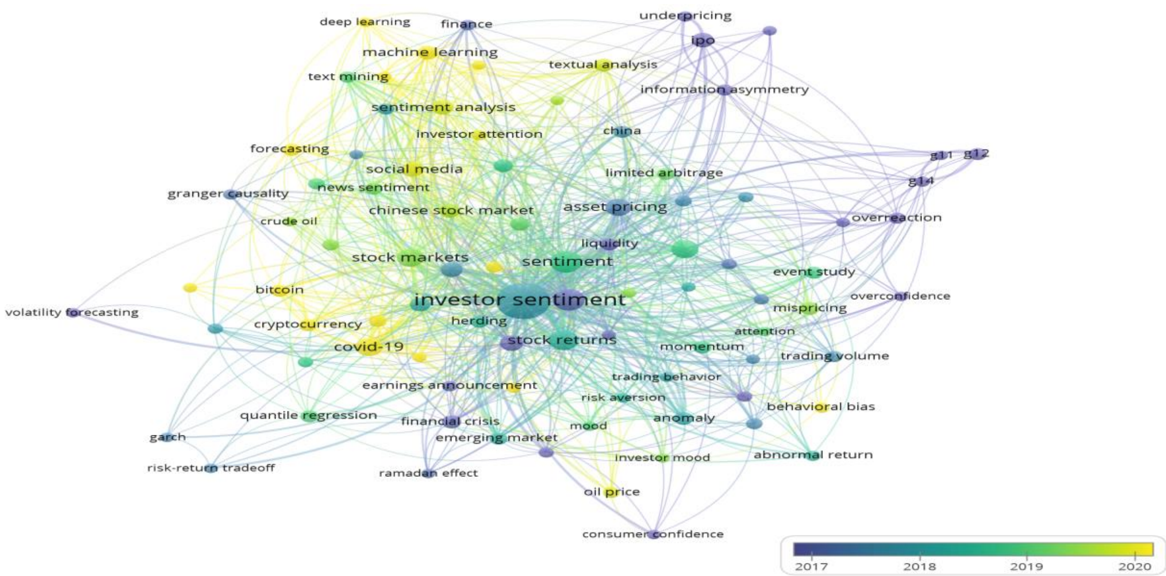
"Cluster #1 sentiment applied research and Cluster #6 social media" are the two most recent clusters that have emerged. The largest cluster is cluster #1 primarily focuses on applied research related to investor sentiment including topics such as *stock returns*, *COVID-19*, *predictability* and *bitcoin*. The occurrence of these keywords is relatively high indicating significant attention in the field. Recently, keywords such as *COVID-19*, *spill over*, *bitcoin*, *Google trends*, *cryptocurrency*, *economic policy uncertainty (EPU)* and *forecasting* have emerged with the most influential keywords being *out-of-sample forecasts*, *Twitter*, the *business cycle* followed by *momentum*, *crude oil and economic policy uncertainty*. The research methods related to this cluster include *granger causality* and *out-of-sample forecasts*. Cluster #6 primarily focuses on sentiment analysis from the perspective of social media such as *news sentiment* and *big data*. Other keywords are mostly related to research methods such as *machine learning*, *textual analysis*, *text mining* and *deep learning* which have emerged mainly in 2019-2020. The most influential keywords in this cluster include *finance* and *trading strategy*.

The high-frequency prevalent topics include stock return predictability, asset pricing, market efficiency and volatility aside from investor sentiment or behavioural finance in the research field of investor sentiment. In addition, COVID-19, machine learning and social media are also high-frequency keywords. Underreaction and overreaction are the most influential keywords.

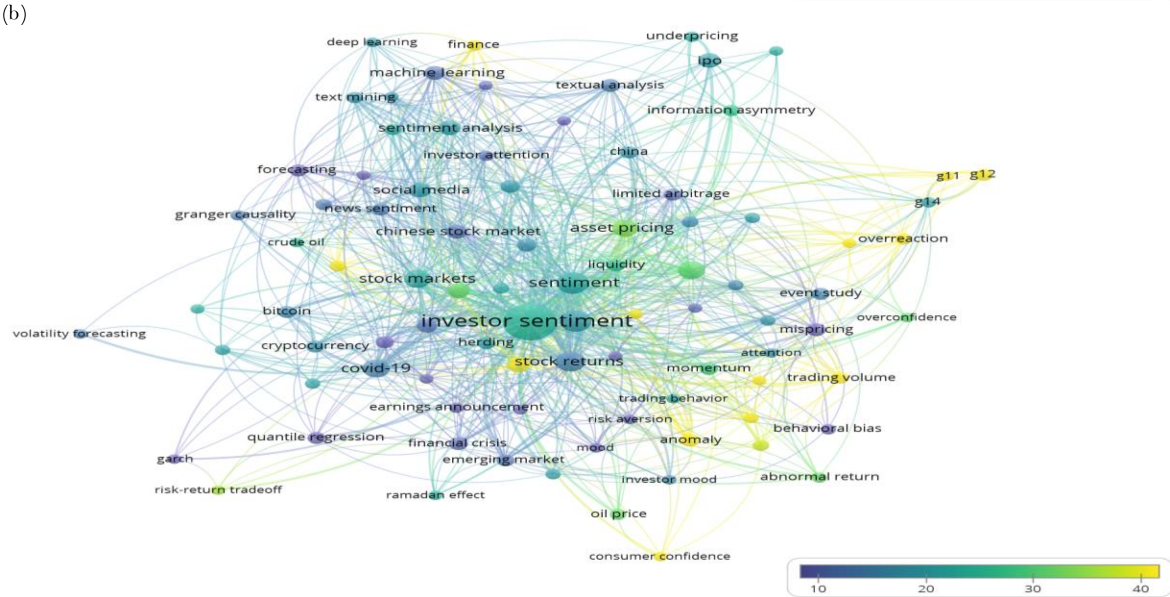
Keywords in the trading behavior research field can be divided into four clusters using keyword cluster analysis with specific threshold settings (minimum occurrence of 5 times), resulting in the selection of 69 keywords and their co-occurrence relationship is depicted in Figure 6. The clusters are labeled as cluster#1 insider trading, cluster#2 trading behavior applied research, cluster#3 market efficiency and cluster#4 investor sentiment ranked by cluster size. The evolution process based on the average time of clustering formation begins with "insider trading followed by market efficiency and investor sentiment". Over the past two years, the focus has been on trading behavior applied research. Investor sentiment and insider trading are the most influential topics based on average citation times.



(a)



(b)



(c)

Figure 5 (a). Topic clustering based on author keywords in the field of investor sentiment research generated by VOSviewer. (b) depicts the APY and (c) includes the AC based on (a) (occurrences of the keyword ≥ 5, the cluster size ≥ 10, the cluster resolution = 1).

Figure 6 shows that cluster 1 mainly focuses on topics related to trading such as *insider trading*, *disposition effects*, *trading strategies*, etc. In this cluster, *behavioral finance*, *institutional investors*, *disposition effect* and *insider trading* have high co-occurrence frequency. The latest hot keyword is *stock price crash risk* and the most influential keywords include *microstructure*, *trading*, *manipulation* and *post-earnings announcement drift (PEAD)*. Cluster #3 market efficiency and cluster #4 investor sentiments emerged in the middle period. Cluster# 3 mainly studies topics related to market efficiency with keywords such as *liquidity*, *market microstructure* and *market efficiency*. The latest hot keyword in this cluster is *high-frequency trading*, and the most influential keyword is *liquidity*. Cluster 4 started to focus on investor sentiment and investor types including *individual investor* and *foreign investor* which began to receive widespread attention. Hot keywords in this cluster include *individual investor*, *investor sentiment*, *trading volume* and the influential keywords are *financial crisis* and *trading volume*. Cluster #2 trading behavior applied research is a relatively new cluster with active keywords in the past two years including *COVID-19*, *risk-taking*, *bitcoin*, *cryptocurrency* and *retail investor*. The influential words in this cluster include *herding* and *feedback trading*.

COVID-19, risk-taking and bitcoin are also newly emerged high-frequency terms. Moreover, microstructure, manipulation and herding are the most influential keywords.

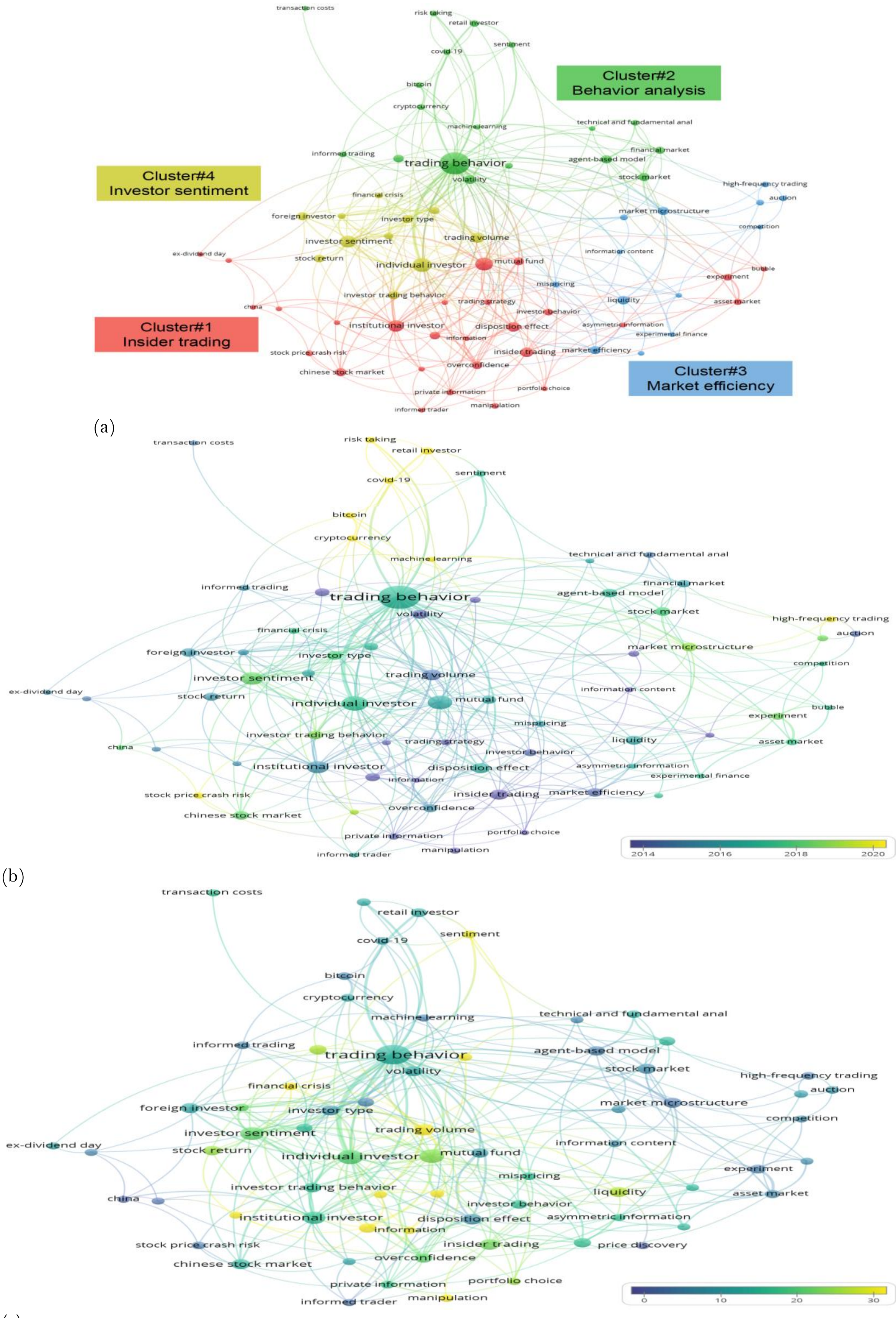


Figure 6 (a). Topic clustering based on author keywords in the field of trading behavior research generated by VOSviewer. (b) depicts the APY and (c) includes the AC based on (a). (Occurrences of the keyword ≥ 5, the cluster size ≥ 10, the cluster resolution = 1).

There is a tendency towards convergence in the high-frequency keywords in investor sentiment and trading behavior. For example, among the high-frequency keywords appearing in Figures 5 and 6, there are 26 common keywords, accounting for about 38% of the high-frequency keywords in trading behavior. COVID-19, bitcoin, cryptocurrencies and machine learning have all become important topics in both fields in recent years. However, these two fields also have their differences. The investor sentiment field focuses more on stock price-related topics (such as return predictability, asset pricing, market efficiency, and volatility) as well as IPO and social media. The trading behavior field is more concerned with investor types, trading volume, internal trading and disposition effects.

3.3. Research Clusters and Key Documents (RQ6 and RQ7)

Based on Section 2.3.3, the co-citation analysis was conducted using CiteSpace and the research clusters were determined based on the co-citation information as proposed by Chen (2006).

The simultaneous appearance of specific references across a collection of articles implies an alternative methodology for categorizing research and offers valuable insights into diverse patterns within the field of study. In this study, the LLR method is used to acquire noun phrases from the titles of citing references and then determine the basic content and label names of each cluster. The names of clusters reflect the frontiers of research on cited references and highly cited references are considered the knowledge base of matching clusters.

Figures 7 (a) and (b) depict the results of co-citation analysis for the domains of investor sentiment and trading behavior respectively. The effectiveness of the clustering results can be assessed using modular Q and silhouette indicators. The modular Q metric allows networks to be divided into distinct modules with values ranging from 0 to 1. Higher modularity values indicate a better network structure. Cluster silhouette values, ranging from -1 to 1 are used to represent the uncertainties associated with interpreting the nature of the clusters (Chen et al., 2010; Rousseeuw, 1987).

A value of 1 signifies complete separation from other clusters. The modular Q values for Figures 7 (a) and (b) are 0.8246 and 0.9428 suggesting good quality of the resulting network clustering. The average silhouette value is 0.9114 for Figure 7 (a) and 0.9732 for Figure 7 (b) indicating relatively good homogeneity. In Figures 7 (a) and (b), the left-hand charts display the research clusters formed based on co-citation analysis. Larger labels in the cluster indicate a higher count of cited publications within that cluster while larger nodes in the cluster correspond to papers with higher citation frequencies. The color of each cluster represents the average publication time of the cited papers within that cluster. The right-hand charts display the top 5 papers that have been cited most frequently within each cluster. Table 6 shows the co-citation analysis results for the top clusters within these two domains. Table 7 displays the highly cited references within the five largest clusters.

Figure 7 (a) illustrates that the reference co-citation network of investor sentiment research consists of 12 clusters with the largest connected component.

In these clusters, the earlier-formed clusters contain a lower number of papers with the research frontier primarily focusing on "catering theory" and subsequently shifting towards "IPO pricing and behavioral finance". In the next few years, the research began to focus on "*shareholder empowerment*", "*closed-end fund*" and "*dynamic asset pricing models*". In 2012, cluster sizes expand and additional research focused on excess return and everyday happiness. In 2017, "*economic policy uncertainty*" and "*international strategic alliance*" began to become the forefront of research and then the forefront turned to "*bitcoin return*". The latest research frontiers focus on the "*COVID-19 pandemic*". This study will next examine the top 10 clusters of investor sentiment research in chronological sequence of appearance.

According to Table 6, four clusters evolved throughout the early stages of the research (2004-2008) namely clusters 4, 7, 8 and 3 in chronological order. Cluster 4 is the 5th largest cluster labelled "IPO pricing" by the LLR and consists of 85 referenced sources. Cook, Kieschnick, and Van Ness (2006) is the major citing article of the cluster which states that investment bankers have an incentive to push for IPOs to attract sentiment investors into the market. The top three cited papers in this cluster are Baker and Wurgler (2007); Barber, Lee, Liu, and Odean (2009) and Alexander, Vikram, and Rajdeep (2006) forming the knowledge base on the subject. This cluster also focuses on the pre-IPO market, market condition, IPO market and secondary market return.

Cluster #7 consisting of 61 cited references in the same period is the 8th largest cluster. "Behavioural finance" is the label of this cluster according to the LLR. According to Subrahmanyam (2008), the major citing article of the cluster synthesizes the behavioral finance literature of the past two decades. The top three cited papers in this cluster are Baker and Wurgler (2006); Brown and Cliff (2005) and Brown and Cliff (2004). This cluster also focuses on commercial real estate valuation, property fundamentals, cyclic determinants and macroeconomic factors.

Cluster #8 with 51 cited references is the 9th largest cluster. Based on the LLR, "shareholder empowerment" is the label of this cluster. Bratton and Wachter (2010) propose that shareholder empowerment supports the management in trying to maximize the market price of stocks which can lead to significant agency costs and contribute to a market crisis. The three most frequently cited papers within this cluster are Polk and Sapienza (2008); Kumar and Lee (2006) and Barberis, Shleifer, and Wurgler (2005). This cluster explores topics such as individual investor, diversification choice, mispricing return premium and cross-country IPOs. Cluster #3 with 91 cited references is the 4th largest cluster. Based on the LLR, "closed-end fund" is the label of this cluster and Nagel (2013) reviews the latest studies in the field of empirical analysis of asset pricing.

Ayadi, Ben-Ameur, Lazrak, and Wang (2013) examine the validity of the closed-end fund discount (CEFD) as an indicator of investor sentiment in Canadian equities and conclude that CEFD is not a significant pricing factor. The three most frequently cited papers within this cluster are Chung, Hung, and Yeh (2012); Frazzini and Lamont (2008) and Lemmon and Portniaguina (2006) which focus on empirical cross-sectional asset pricing, costly external finance, macroeconomics and consumer attitudes in the stock market.

As mentioned in section 3.1, research on investor sentiment developed rapidly after 2012. Four clusters (#1, 2, 0, and 9) were formed during this period (2012-2017). Cluster #1 with 135 cited references is the second largest cluster and is identified as "excess return" according to the LLR method. Seok, Cho, Park, and Ryu (2019).

Yang and Zhou (2016) introduced a novel metric for evaluating the level of individual stock crowded trade and investigated the combined influence of individual stock crowding and investor sentiment on excess returns. Huang, Jiang, Tu, and Zhou (2015); Stambaugh, Yu, and Yuan (2012) and Fama and French (2015) focus on the Korean stock market, the idiosyncratic volatility puzzle, market maturity and individual stock.

Cluster #2 with 101 cited references is the third-largest cluster during this period. The LLR describes it as "everyday happiness." Zhang, Zhang, Shen, and Zhang (2017) found that provincial investor sentiment (PIS) is positively correlated with stock returns using provincial TV ratings as a new indicator of PIS. You, Guo, and Peng (2017) also explore the dynamic causality between Twitter happiness sentiment and stock returns. Garcia (2013); Chen, De, Hu, and Hwang (2014) and Kim and Kim (2014) focus on financial news and mass media.

Cluster #0 with 180 cited references is the largest cluster during this period. It is labeled "economic policy uncertainty (EPU)" based on the LLR. Seok, Cho, and Ryu (2019) frequently cited papers within this cluster. Da, Engelberg, and Gao (2015); Baker, Bloom, and Davis (2016) and Renault (2017) also focus on nonlinear causality, energy futures market, oil prices and stock volatility. For example, Chen and Chen (2022) demonstrate quantile Granger causality between happiness, EPU and the S&P 500 where increased happiness at high EPU stabilizes stock market bubble cycles. Zhu, Wu, Ren, and Yu (2022) find long-term transmission of sentiment effects on returns from developed capital markets to emerging capital markets and observe a gradual increase in the negative impact of EPU from short-term to long-term.

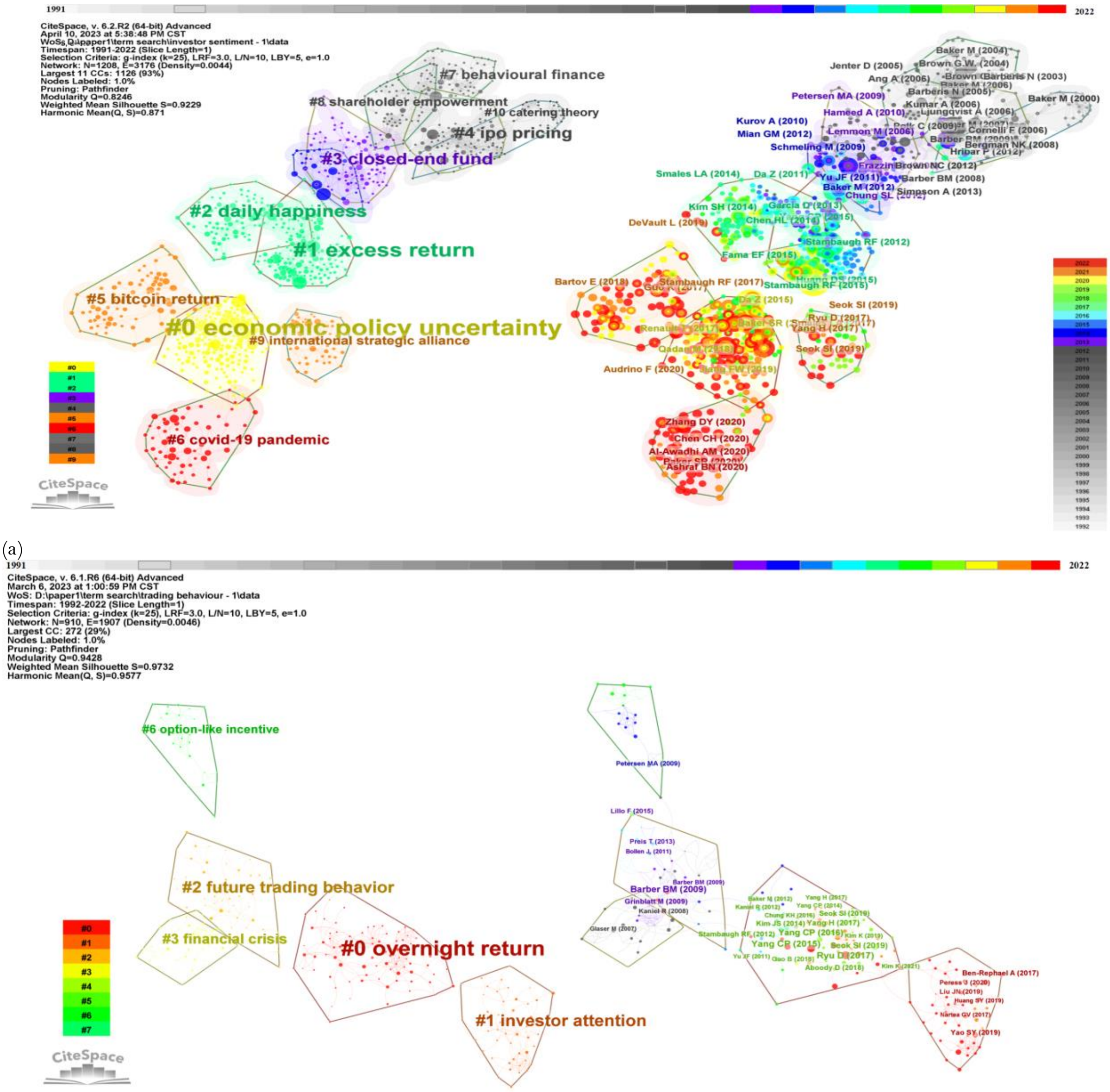
Cluster # 9 with 50 cited references is the 10th largest cluster during this period. It is labeled "international strategic alliance" based on the LLR. Seok, Cho, Park, et al. (2019). Ryu, Kim, and Ryu (2019) explore the impact of international strategic alliances (ISAs) on firm level in the context of the 2008 global financial crisis (GFC).

The three most frequently cited papers within this cluster are Smales (2017); Ryu, Kim, and Yang (2017) and Yang, Ryu, and Ryu (2017) which focus on overnight returns, foreign ownership, firm performance and macroeconomic news announcements.

Clusters # 5 and 6 were formed at the most recent stage (2018-2019). Cluster #5 with 75 cited references is the 6th largest cluster. " Bitcoin return" is the label of this cluster and the major article of the cluster is cited by Bouteska, Mefteh-Wali, and Dang (2022) which shows that investor sentiment exerted a significant influence on Bitcoin returns during the COVID-19 pandemic. The three most frequently cited papers within this cluster are Guo, Sun, and Qian (2017); Stambaugh and Yuan (2017) and DeVault, Sias, and Starks (2019) which focus on the cryptocurrency market, predictive power, deep learning, and mediating effects.

Cluster #6 with 62 cited references is the 7th largest cluster. Based on the LLR, the COVID-19 pandemic is the label of this cluster and the major article of the cluster is cited by Cevik, Kirci Altinkeski, Cevik, and Dibooglu (2022) which uses Google search volume indices to represent negative and positive investor sentiment related to COVID-19 and its vaccines and demonstrate their effectiveness as predictors of stock returns and volatility among the ongoing pandemic.

The three most frequently cited papers within this cluster are Zhang, Hu, and Ji (2020); Baker, Bloom, Davis, and Terry (2020) and Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi (2020) which focus on the COVID-19 crisis, event study and global equity market.



(b)

Figure 7. Landscape of investor sentiment research and trading behavior research. (a) Clusters and key documents of investor sentiment research. (b) Clusters and key documents of trading behavior research. Constructed using CiteSpace version6.1. R6. Timespan: 1991–2022, with slice length set at 1 and selection criterion as g-index ($g^2 \leq k \sum_{i \leq g} c_i, k \in Z^+$,k=25) per slice.

Note: Aboody, Even-Tov, Lehavy, and Trueman (2018), Ang, Hodrick, Xing, and Zhang (2006), Ashraf (2020), Audrino, Sigrist, and Ballinari (2020), Baker and Stein (2004), Baker and Wurgler (2000), Baker, Wurgler, and Yuan (2012), Barber and Odean (2008), Barberis and Shleifer (2003), Barberis et al. (2005), Bartov, Faurel, and Mohanram (2018), Bergman and Roychowdhury (2008), Bollen, Mao, and Zeng (2011), Brown and Cliff (2004), Brown, Christensen, Elliott, and Mergenthaler (2012), Chen, Liu, and Zhao (2020), Chung, Park, and Ryu (2016), Cornelli, Goldreich, and Ljungqvist (2006), Da, Engelberg, and Gao (2011), Frazzini and Lamont (2008), Gao and Yang (2018), Hameed, Kang, and Viswanathan (2010), Hribar and McInnis (2012), Huang, Huang, and Lin (2019), Jenter (2005), Jiang, Lee, Martin, and Zhou (2019), Kaniel, Liu, Saar, and Titman (2012), Kim, Ryu, and Yang (2019), Kurov (2010), Lemmon and Portniaguina (2006), Lillo, Miccichè, Tumminello, Piilo, and Mantegna (2015), Ljungqvist, Nanda, and Singh (2006), Mian and Sankaraguruswamy (2012), Nartea, Kong, and Wu (2017), Park and Lee (2009), Preis et al. (2013), Qadan and Nama (2018), Schmeling (2009), Simpson (2013), Smales (2014) and Yu and Yuan (2011).

The five largest related clusters of trading behaviour studies will be examined in chronological order of appearance in the following study. According to Tables 6 and 7, the early-stage clusters (2008-2009) comprise clusters 3 and 2 in proper order. Cluster #3 with 37 cited references is the 4th largest cluster. Financial crisis is the label of this cluster and the major article of the cluster is cited by Hoffmann, Post, and Pennings (2013) which examines how individual investor perceptions changed and finds that overall individual investors continued to trade actively during the crisis based on the LLR. The top three papers in this cluster are cited by Kaniel et al. (2008); Glaser and Weber (2007) and Goetzmann and Kumar (2008) which focus on individual investor perception, IQ and overconfident trader. Cluster #2 with 48 cited references is the third largest cluster. Based on the LLR, " Future trading behavior" is the label of this cluster and the major article of the cluster is cited by Bohlin and Rosvall (2014) which found that investors with similar portfolio structures largely traded in similar ways. The top three papers in this cluster are cited by Barber et al. (2009); Grinblatt and Keloharju (2009) and Preis et al. (2013). This cluster also focuses on stock portfolio structure, individual investor, market direction guesses and win-stay lose-shift strategies.

The clusters that appeared in the next stage (2011-2016) included clusters 6 and 0 in sequence. Cluster #6 with 25 cited references is the 5th largest cluster. "Option-like incentive" is the label of this cluster and the major article of the cluster is cited by Nadler, Jiao, Johnson, Alexander, and Zak (2018) who conducted experimental studies testing how testosterone had a causal effect on transactions and prices ultimately led to larger and longer-lasting asset price bubbles. Holmen, Kirchler, and Kleinlercher (2014) studies the effect of option incentives on price formation and trading behavior and find that it is reasonable for subjects with option incentives to trade at inflated prices because it increases their expected pay-outs. The top three papers in this cluster are cited by Petersen (2008); Cheung, Hedegaard, and Palan (2014) and Eckel and Füllbrunn (2015). This cluster also focuses on asset trading, wall street, behavioral uncertainty and traders' confidence. Cluster #0 with 82 cited references is the largest cluster. " Overnight return" is the label of this cluster and the major article of the cluster is cited by Seok, Cho, Park, et al. (2019) stating that overnight returns are not really a measure of investor sentiment for a specific company in the Korean stock market although they are partly related to investor sentiment. The top three papers in this cluster are cited by Yang and Zhou (2015); Ryu et al. (2017) and Yang and Zhou (2016). This cluster also focuses on stock market responses, market dynamics, index futures market and analyst recommendations.

Cluster #1 was formed at the most recent stage (2018). Cluster #1 with 50 cited references is the second-largest cluster. The major article of the cluster is cited by Yao, Sensoy, Nguyen, and Li (2022) which examines the dual impact of investor attention on the liquidity of 597 cryptocurrencies. The three most frequently cited papers within this cluster are Yao, Wang, Cui, and Fang (2019); Ben-Rephael, Da, and Israelsen (2017) and Peress and Schmidt (2020). This cluster also focuses on stock price crash risk, cryptocurrency market liquidity, double-edged swords and retail trade.

This paper discovers that the frontiers and knowledge bases of these two research domains overlap significantly when comparing the co-citation analysis of investor sentiment and trading behaviour. Newer frontiers both cover COVID-19, energy prices and cryptocurrency like bitcoin.

Table 6. Top largest clusters in investor sentiment and trading behavior research based on co-citation analysis

Research term	Number	Size	Silhouette	APY	Label	Major citing article
Investor sentiment	0	180	0.874	2017	Economic policy uncertainty	Cook et al. (2006)
	1	135	0.871	2012	Excess return	Seok, Cho, Park, et al. (2019)
	2	101	0.91	2012	Daily happiness	Zhang et al. (2017)
	3	91	0.862	2008	Closed-end fund	Nagel (2013)
	4	85	0.928	2004	Ipo pricing	Cook et al. (2006)
	5	75	0.937	2018	Bitcoin return	Bouteska et al. (2022)
	6	62	0.973	2019	COVID-19 pandemic	Cevik et al. (2022)
	7	61	0.93	2004	Behavioural finance	Subrahmanyam (2008)
	8	51	0.942	2006	Shareholder empowerment	Bratton and Wachter (2010)
	9	50	0.944	2017	International strategic alliance	Seok, Cho, Park, et al. (2019)
	10	41	0.973	2003	Catering theory	Lowry (2003)
Trading behavior	0	82	0.989	2016	Overnight return	Seok, Cho, Park, et al. (2019)
	1	50	0.986	2018	Investor attention	Yao et al. (2022)
	2	48	0.934	2009	Future trading behavior	Bohlin and Rosvall (2014)
	3	37	0.949	2008	Financial crisis	Hoffmann et al. (2013)
	6	25	1	2011	Option-like incentive	Nadler et al. (2018)

Table 7. Highly cited references in the top 5 clusters according to Table 6.

Research term	Cluster	Citations	Title	Reference
Investor sentiment	0	88	The sum of all fears investor sentiment and asset prices	Da et al. (2015)
	0	63	Measuring economic policy uncertainty	Baker et al. (2016)
	0	57	Intraday online investor sentiment and return patterns in the U.S. stock market	Renault (2017)
	1	94	Investor sentiment aligned: A powerful predictor of stock returns	Huang et al. (2015)
	1	92	Investor sentiment and anomalies	Stambaugh et al. (2012)
	1	53	A five-factor asset pricing model	Fama and French (2015)
	2	37	Sentiment during recessions	Garcia (2013)
	2	25	Wisdom of crowds: The value of stock opinions transmitted through social media	Chen et al. (2014)
	2	21	Investor sentiment from internet message postings and the predictability of stock returns	Kim and Kim (2014)
	3	20	When does investor sentiment predict stock returns?	Chung et al. (2012)
	3	16	Dumb money: Mutual fund flows and the cross-section of stock returns	Frazzini and Lamont (2008)
	3	13	Consumer confidence and asset prices: Some empirical evidence	Lemmon and Portniaguina (2006)
	4	62	Investor sentiment in the stock market	Baker and Wurgler (2007)
	4	23	*Do retail trades move markets?*	Barber et al. (2009)
	4	19	Hot markets, investor sentiment and IPO pricing	Alexander et al. (2006)
Trading behavior	0	14	Investor sentiment, trading behavior and stock returns	Ryu et al. (2017)
	0	14	*Investor trading behavior, investor sentiment and asset prices*	Yang and Zhou (2015)
	0	12	Individual stock crowded trades, individual stock investor sentiment and excess returns	Yang and Zhou (2016)
	1	7	It depends on where you search: Institutional investor attention and underreaction to news	Ben-Rephael et al. (2017)
	1	7	Idiosyncratic skewness, gambling preference and cross-section of stock returns: Evidence from China	Yao et al. (2019)
	1	6	Size and value in China	Liu, Stambaugh, and Yuan (2019)
	2	13	Just how much do individual investors lose by trading?	Barber et al. (2009)
	2	7	Sensation seeking, overconfidence, and trading activity	Grinblatt and Keloharju (2009)
	2	6	How news affects the trading behaviour of different categories of investors in a financial market?	Lillo et al. (2015)
	3	6	Individual investor trading and stock returns	Kaniel et al. (2008)
	3	5	Overconfidence and trading volume	Glaser and Weber (2007)
	6	6	*Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches*	Petersen (2008)

4. Discussion

The comparative analysis of this paper provides a descriptive explanation of investor sentiment and trading behavior, identifying trends, patterns and major contributions. Despite the extensive research conducted in both domains, scholars have not yet established a uniform set of metrics for measuring investor sentiment or trading behavior. Furthermore, there is still no clear agreement about the two's relationship.

This study does not offer perspectives on the precision of ideas, the validity of models or measuring indexes, the value of sentiment or trading behaviour indicators in predicting asset returns or the efficacy of these concepts in asset pricing.

The analysis reveals several noteworthy findings. Firstly, the number of publications in the field of investor sentiment has experienced an exponential growth rate while the growth rate of research in the field of trading behavior has slowed in recent years. Secondly, this research received more attention and generated more publications than trading behavior despite the fact that research on investor sentiment began relatively late. Thirdly, the majority of literature in both fields comes from Western countries and China. The United States, China, and England are the top three in both fields. It is worth noting that among the top 7 productive countries or regions, research output is primarily concentrated in economically developed regions.

The scientific fields of investor sentiment and trading behavior research are highly concentrated with significant overlap between them and most related papers are published in academic journals focused on finance and economics. The *Journal of Financial Economics* has the highest average influence followed by the *Journal of Banking & Finance* and the *Pacific-Basin Finance Journal* which is relatively important. Moreover, *Finance Research Letters* is the most recent active journal. The *International Review of Financial Analysis* and the *Journal of Behavioral Finance* are more important within the field of investor sentiment research whereas the *Journal of Economic Behavior & Organization* holds greater importance in trading behavior research.

Yang et al. (2017) found that the highest average influence was associated with relatively high outputs and average influence in both fields. Yang Chunpeng is the most productive scholar in investor sentiment research whereas Xiong Xiong is the most recent active scholar. For trading behavior research, Yao Shouyu is the most recent active scholar. It is worth noting that different institutions have made varying contributions to each research area. Sungkyunkwan University, Tianjin University and the Chinese Academy of Sciences are the only institutions that have made significant contributions to both fields.

A comparative analysis of research indicates a gradual convergence trend between investor sentiment and trading behavior. Many research areas have evolved in both domains during the previous five years such as COVID-19, Bitcoin, cryptocurrency and machine learning which have become prevalent in the last two years. There are certain differences between these two fields despite some similarities. The investor sentiment field focuses more on stock price-related topics (such as return predictability, asset pricing, market efficiency and volatility), as well as IPO and social media while the trading behavior field is more concerned with investor types, trading volume, internal trading and disposition effects. Investor sentiment research includes spill over effects, forecasting, economic policy uncertainty, google trends, and corporate social responsibility (CSR). On the other hand, the field of trading behavior research focuses on high-frequency trading and risk-taking.

The majority of research frontiers and practical applications are focused within the domain of financial market research. These frontiers, in addition to typical asset pricing and stock return research, include emerging issues like financial crises, social media, bitcoin and COVID-19. Investor sentiment is concerned with issues such as IPO pricing and economic policy uncertainty whereas trading behaviour is concerned with issues such as option incentives and trading strategies. Additionally, this paper identifies highly cited articles that constitute the critical knowledge base of each subfield.

This section highlights methodological limitations and general discussion related to the study. The clustering method used in this study is based on the inclusion of specific text strings which may not capture all relevant literature. Future research could explore the stability of the current findings and investigate whether similar results can be obtained by only using data from original research articles. Furthermore, the results of this study should be interpreted with caution given the different interpretations of the concepts, scope and focus of investor sentiment and trading behavior.

The study also reveals that investor sentiment and trading behavior have laid the foundation for a diverse array of concepts and methodologies. This complexity along with the varying capital market contexts and trading mechanisms, presents challenges for investors to make informed methodological choices. Further method validation and support for investors are necessary to address these challenges.

5. Conclusion

This paper presents a scientometric analysis that compares the research conducted in two critical domains of behavioral finance, namely investor sentiment and trading behavior. This research can offer valuable insights into their concerned concepts and methodological issues, the geographic regions, authors and institutions driving these research domains and the knowledge bases they rely on. This study implements multiple bibliometric mapping methodologies to shed light on these concerns. Furthermore, the most influential articles in each research area are identified and their evolutionary patterns are charted.

The analysis of the literature on investor sentiment and trading behavior reveals several key findings. Firstly, the number of publications in the field of investor sentiment has grown exponentially; research activity in trading behavior has slowed in recent years. Secondly, investor sentiment has attracted more attention and generated more publications than trading behavior. Thirdly, research in both fields is primarily concentrated in economically developed regions with western countries such as the United States and England leading in research activity and influence. Furthermore, research in these two fields is highly concentrated with significant overlap and most publications appearing in finance and economics journals.

A comparative analysis of research hotspots indicates a convergence trend between investor sentiment and trading behavior research with common hotspots such as COVID-19, Bitcoin, cryptocurrency and machine learning while the investor sentiment field focuses on stock price-related topics and the trading behavior field is more concerned with investor types and disposition effects. Both fields concentrate on financial market research with emergent frontiers like financial crises, social media, and cryptocurrency. Highly cited articles show some overlap between the two fields with the trading behavior knowledge base mostly related to investor sentiment.

Finally, this paper suggests some potential avenues for future research. Future researchers may focus on examining asset pricing and excess returns in emerging markets and performing cross-regional comparisons given the significance of national capital market environments and trading systems in determining the pricing of financial assets and the increasing attention of emerging economies like India to this field. Moreover, interdisciplinary research between the two fields is gaining more attention which will lead to more comprehensive research in the future.

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