



Leading research trends on trading strategies

Javier Oliver-Muncharaz, Fernando García

► To cite this version:

Javier Oliver-Muncharaz, Fernando García. Leading research trends on trading strategies. Finance, Markets and Valuation, 2020, 6 (2), pp.27-54. 10.46503/LHTP1113 . hal-03149330

HAL Id: hal-03149330

<https://hal.science/hal-03149330>

Submitted on 22 Feb 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Finance, Markets and Valuation

Leading research trends on trading strategies

Tendencias líderes de investigación sobre estrategias de trading

Javier Oliver-Muncharaz ¹, Fernando García ²

¹Departamento de Economía y Ciencias Sociales, Universidad Politécnica de Valencia. Valencia, España. Email: jaolmun@ade.upv.es

²Departamento de Economía y Ciencias Sociales, Universidad Politécnica de Valencia. Valencia, España. Email: fergarga@esp.upv.es

JEL: G10; G17

Abstract

Trading strategies have attracted the attention of academic researchers and practitioners for a long time, but most specially in recent years due to the explosion of high-quality databases and computation capacity. Numerous studies are devoted to the analysis and proposal of trading strategies which cover aspects such as trend prediction, variables selection, technical analysis, pattern recognition etc. and apply many different methodologies. This paper conducts a meta-literature review which covers 1187 research articles from 1984 to 2020. The aim of this paper is to show the increasing importance of the topic and present a systematic study of the leading research areas, countries, institutions and authors contributing to this field. Moreover, a network analysis to identify the main research streams and future research opportunities is conducted.

Keywords: Trading strategy; Literature survey; Stock market

Resumen

La creación de estrategias de inversión siempre ha atraído la atención de los académicos y de los inversores profesionales, pero, indudablemente, esta popularidad ha aumentado en los últimos años, con la aparición de bases de datos más completas y mayor potencia de cálculo de las computadoras. Son numerosos los estudios que analizan y proponen estrategias de inversión y que tratan aspectos como la predicción de la tendencia, la selección de variables, el análisis técnico, el reconocimiento de patrones etc. aplicando diferentes metodologías. En este trabajo se realiza un estudio bibliográfico que abarca 1187 artículos de investigación desde 1984 hasta 2020. El objetivo es mostrar la creciente importancia de este campo de investigación y presentar un análisis sistemático de los países, instituciones y autores que más están contribuyendo al avance del conocimiento. Además, se realiza un análisis de redes para identificar las principales áreas de investigación y las tendencias futuras.

Keywords: Estrategia de inversión; Revisión bibliográfica; Mercado bursátil

DOI:
10.46503/LHTP1113

Corresponding author
Fernando García

Received: 10 Sep 2020
Revised: 22 Oct 2020
Accepted: 11 Nov 2020

Finance, Markets and
Valuation
ISSN 2530-3163.

1 Introduction

In the last decades, the importance of the financial markets has increased dramatically all over the globe. Many investors approach the different financial markets, such as the stocks markets, bonds markets, foreign exchange market, etc.; seeking for a high and rapid return. Therefore, not just big mutual fund managers but also individual investors and academics, of course, are interested in the development of robust trading strategies which make it possible to beat the market and obtain high yields.

Investors can use different approaches to manage their wealth. Do investors believe that the market is efficient, that is, that it is not possible to beat the market in terms of return and risk, then they choose a passive portfolio strategy (F. García & Guijarro, 2011). In this case, investors replicate a stock index buying Exchange Trading Funds (ETF) or implementing partial index tracking methodologies (Baccarin & Marazzina, 2015; F. García, Guijarro, & Moya, 2011, 2013; F. García, Guijarro, & Oliver, 2017; Papantonis, 2016). There are many stock indices available, so investors can decide which specific market they want to track. Currently, sustainable stock indices are gaining popularity, as investors are more concerned with corporate social responsibility issues (Arribas, Espinós-Vañó, García, & Morales-Bañuelos, 2019; Arribas, Espinós-Vañó, García, & Tamošiūnienė, 2019) or as they believe that sustainable companies have a better performance (F. García, González-Bueno, Guijarro, & Oliver, 2020; Maciková, Smorada, Dorčák, Beug, & Markovič, 2018; Simionescu & Dumitrescu, 2018). Nevertheless, investors should pay attention to the index construction methodology to make sure the assets in the index really match their interest (Arribas, Espinós-Vañó, García, & Oliver, 2019). Passive portfolio strategies are specially recommended for long term investments or for markets with a very strong trend.

Active portfolio management is opposite to passive management. In this case, investors believe that it is possible to beat the markets consistently. Usually, investors pick up a number of assets to build their portfolio in order to maximize return and minimize risk. This investment strategy was introduced by Markowitz (Markovitz, 1959) and has been further developed by many other researchers (García, González-Bueno, Oliver, & Riley, 2019; F. García, González-Bueno, Guijarro, & Oliver, 2020; F. García, González-Bueno, Guijarro, Oliver, & Tamošiūnienė, 2020).

Finally, investors may not be interested in portfolio management, but concentrate on a small number of assets and apply short-term strategies to speculate with the evolution of asset prices. In this case, investors are interested in determining the market trend (F. García, Guijarro, Oliver, & Tamošiūnienė, 2018) or use trading rules based on pattern recognition or technical analysis (Arévalo, García, Guijarro, & Peris, 2017; Cervelló-Royo, Guijarro, & Michniuk, 2015).

In this paper, we will analyze the raise of research papers devoted to the last topic, the speculative use of short-term trading strategies. This research field has experienced a boom since in the last decade databases cover more years and more assets, computation capacity has improved considerably, and artificial intelligence has been further developed. In this context, it is useful to gain an overview of the research field and identify the major actors and the most attractive topics. To achieve our goal, we conduct a bibliometric analysis of a corpus including 1,187 research papers included in the Web of Science database.

The remainder of the paper is structured as follows: In the next section we describe the methodology and the sample selection process, then we present the results of the different analysis performed and finally we summarize the main outcomes in the conclusions section.

2 Research methodology

The aim of this research is to identify and evaluate the existing body of research in the field of trading strategies to get a precise picture of the most influential papers, authors, institutions and journals. To this end, we conduct a citation and co-citation analysis. Finally, we find out which are the main topics and research interests in the field, which can be helpful to suggest future lines of research.

To achieve these goals, we apply both quantitative and qualitative techniques. First, we apply a structured literature review for data collection and data evaluation in order to collect the most influential papers, those with the highest impact in this field and to figure out the topics which have attracted researchers' interest the most. Second, a bibliometric analysis is performed. Bibliometric analysis is suited to handle hundreds of papers and can provide a comprehensive picture of the research field. Finally, we utilize a content analysis to investigate the main areas of research. The bibliometric analysis conducted in this research has been applied on various topics (Feng, Zhu, & Lai, 2017; Guijarro & Tsinaslanidis, 2020), but rarely on the field of finance, with only a few exceptions in recent years, such as the paper by Bahoo, Alon, and Paltrinieri (2020) devoted to sovereign wealth funds, the paper by Helbing (2019) which reviews the literature on IPOs, and the article by Zamore, Djan, Alon, and Hobdari (2018) which focuses on credit risk.

2.1 Sample selection

The first step in the data collection process consists on selecting the database to be used. In this study, we choose ISI Web of Science (WoS) Core Collection, which is one popular database and has a wide coverage of most prominent journals related with the topic of trading strategies. This database has a powerful research engine and can conduct a number of interesting analysis.

In order to select the papers in the sample, we impose some conditions.: only research papers are considered which are written in English. All research areas are eligible. We do not include any condition regarding the timespan either, which lasts from 1900 until 2020.

Then, we search the papers using the topics “trading strategy” and “trading strategies”. In order to more precisely focus the scope of the articles, we use following research strategy: “trading strategy” or “trading strategies” and “stock market” not “portfolio”. Doing this, we concentrate on those research articles which deal with the speculative use of short-term trading strategies and erase from the database all papers applying portfolio selection strategies.

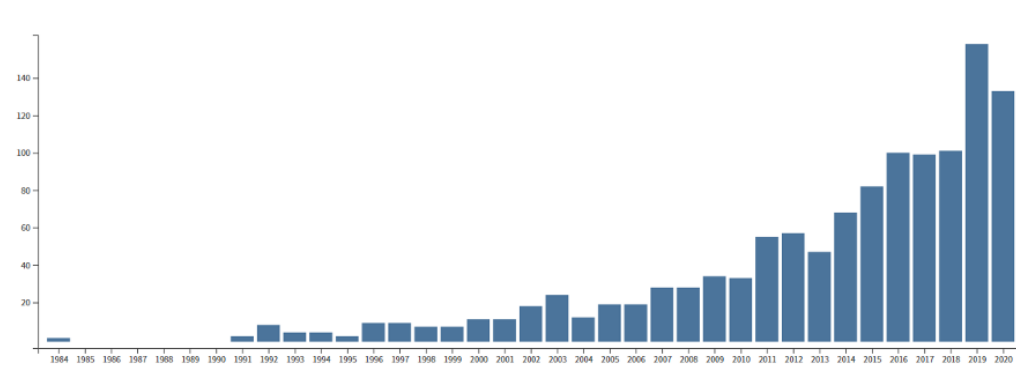
As the result of the searching strategy, 1,187 articles are saved (Table 1). The search results include information for each article regarding title, authors and their affiliations, journal, year of publication, volume and number, abstract, keywords, total cites received and cites per year, as well as the reference list. Table 1 shows the main results of the searching strategy.

3 Descriptive analysis

In order to gain an overview of the selected sample, we conduct a preliminary descriptive analysis. The sample includes 1,187 publications, which have been cited 17,369 times by 14,155 citing articles. The h-index of the sample is 65. The average citations per paper is 14.63.

Figure 1 shows the number of publications per year. The oldest paper was published in 1984 (Bilson, 1984). Then, several years past until the next paper was published in 1991. Since then, the topic experiences an increasing trend, especially since year 2004. In our sample, in year 2004 a total of 12 articles were published, compared to 158 in 2019. Interestingly, the last 3 years account for 34% of the publications, which is a sign of the increasing importance of the

Database	Web of Science Core Collection
Timespan	All years
Search date	27 October 2020
Search terms	“Trading strategy” OR “Trading strategies” AND “Stock market” NOT “Portfolio”
Language	English
Document type	Article
Number of articles	1,187
Number of journals	418
Number of research areas	36
Number of authors	2,445

Table 1. Searching strategy and key figures**Figure 1.** Total publications by year

Source: Web of Science

research in trading strategies at present.

The papers analyzed were published in 418 different journals. The 10 journals responsible for the publication of the most papers in the field account for 20% of the total papers. Figure 2 shows the 10 top journals publishing in this research area. The most important journal is “Quantitative Finance”, with 39 papers. The second most prominent journal is Journal of Banking Finance, followed by Expert Systems with Applications, which have published 36 and 34 articles, respectively, according to the search in the Web of Science database.

Interestingly, many of the journals which have been attracted by the topic are not specialized in finance, but in mathematical methodologies. Therefore, it is worthy to investigate the research areas involved in the study and development of trading strategies. As presented in Figure 3, the papers have been published in journals assigned to different research areas. It must be noted that a paper can simultaneously be assigned to more than one area. Most papers have been assigned to the area of “Business Economics”, a total of 519. That means, 66% of the papers dealing with trading strategies belong to this research area. The remaining areas have not a direct relation with business, economics or finance, but with mathematics, computing and engineering. In fact, the second most prominent area is “Mathematics” including 214

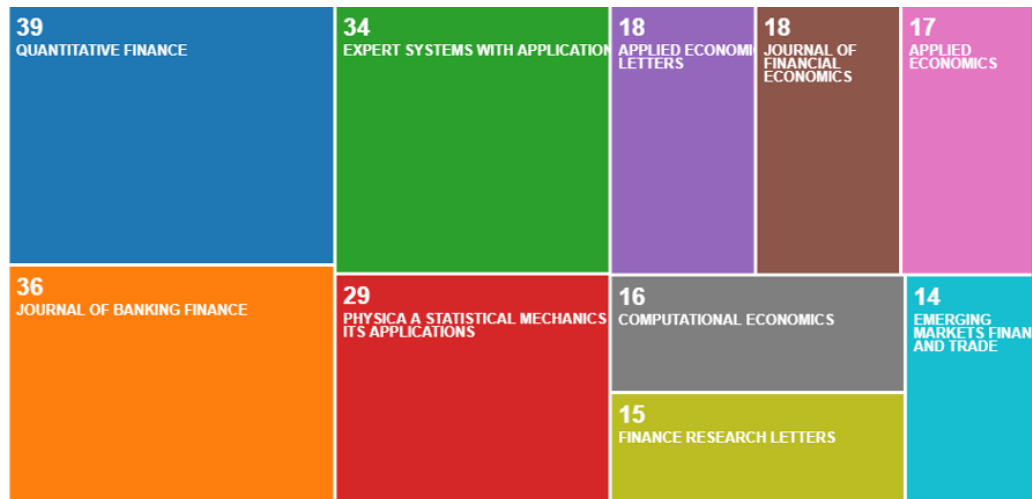


Figure 2. Top publishing journals contributing to the field of trading strategies

Source: Web of Science

papers and representing 18% of the sample, followed by “Computer science” (157 articles representing 13% of the sample) and “Engineering” (100 articles representing 8% of the papers in the sample). The remaining 6 areas are: “Operations research management science” (97 articles), “Mathematical methods in social science” (96 articles), “Physics” (54 articles), “Science technology other topics” (27 articles), “Energy fuels” (22 articles) and “Telecommunications” (58 articles). The 1,187 papers have been assigned to 36 different research areas. Although most of the papers are assigned to the “Business Economics” area, it is noteworthy that many other areas are also involved, especially those in the field of computing and mathematics. This is surely related to the kind of quantitative research which is conducted currently regarding trading strategies.

It is possible to use the Web of Science database to identify the authors who have published the most articles in a specific field. Table 2 shows the 10 authors with the most publications regarding trading strategies. Logically, the number of papers written by a single author is very low compared with the total number of papers in the field and there are no dominant authors in the field. In the selected sample of papers, there are 2,445 authors who have researched on trading strategies. The author with the most publications is Hui ECM, who has published 10 papers, that is, less than 1% of all papers. This author has mainly analyzed calendar effects (Hui & Chan, 2015, 2018, 2019; Hui, Wright, & Yam, 2013) and alternative strategies to buy-and-hold (Hui & Chan, 2014; Hui & Yam, 2014).

There are two authors ranking second on the list: Plastun A. and Narayan, PK.

Plastun, A. has specialized in the research of market anomalies and market inefficiencies (Caporale, Gil-Alana, & Plastun, 2016, 2017; Caporale, Gil-Alana, Plastun, & Makarenko, 2015; Caporale & Plastun, 2017, 2019a, 2019b; Plastun, Sibande, Gupta, & Wohar, 2020). Plastun A. has worked together with Caporale GM, who is the fourth author on the list, with 7 papers on the topic of trading strategies.

Narayan, PK has focused on intraday financial markets (Khademalomoom & Narayan, 2019; Phan, Sharma, & Narayan, 2016) and the impact of financial news (Narayan & Bannigidadmath, 2017; Narayan, Phan, Narayan, & Bannigidadmath, 2017). All the three authors mentioned

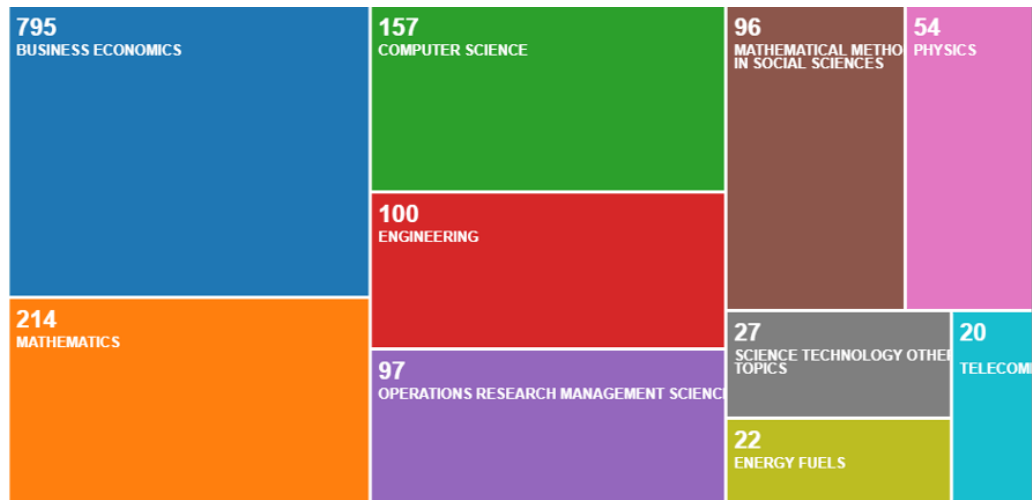


Figure 3. Top 10 research areas contributing to the research on trading strategies

Source: Web of Science

Author	Number of Publications
HUI ECM	10
NARAYAN PK	8
PLASTUN A	8
CAPORALE GM	7
CHAN KKK	7
DUNIS CL	7
STUBINGER J	7
SASS J	6
WU ME	6
BEKIROSD	5

Table 2. Top 10 authors with most publications on trading strategies

Source: Web of Science

University	Number of Publications
Hong Kong Polytechnic University	16
Chinese University of Hong Kong	15
National University of Singapore	15
University of Pennsylvania	14
New York University	13
University of Illinois	13
University of Oxford	13
Columbia University	12
Cornell University	11
Tsinghua University	11

Table 3. Top 10 institutions with most publications on trading strategies

Source: Web of Science

started publishing their research in 2014 or later. It is also interesting that all of them work together with other authors, building solid research cooperation links.

The top 10 institutions involved in the research and development of trading strategies are listed on Table 3. Hong Kong Polytechnic University contributes most with 16 papers, followed by the Chinese University of Hong Kong and the National University of Singapore, each of them contributing with 15 papers to the sample. There is no leading institution and more than 1,150 institutions are involved in the research and improvement of trading strategies. This is an important sign of the relevance of this topic, which can attract the attention of researchers working in many different organizations around the globe.

As for the geographic distribution of the contributing organizations, Figure 4 shows the top 10 countries where most organizations are located. The USA is the leading country, where 341 institutions are located, followed by People's Republic of China (193 institutions) and England (141). When analyzing the country of origin, we notice that institutions from the USA participate in 28% of the papers dealing with trading strategies. This country is clearly the leading country in the field, which can be explained by the importance of the USA in the international financial markets and the key role played in the international financial system by US financial institutions.

4 Citation analysis

The citation of an article is a sign of its acceptance by peers. Therefore, the number of citations may be used to proxy the influence of a publication or an author. Figure 5 shows the evolution of the number of times the papers in the sample have been cited since 1986. The number of citations has experienced a continuous increasing trend, as the topic “trading strategies” is becoming more popular among researchers. The trend has a steep slope specially since 2015. The reason for the fall of citations in 2020 is that our research is conducted in October 2020, so the papers that will be cited in the next two months are not included in the analysis.

The most prominent papers on trading strategies ranked by total citations are listed on Table 4. None of the authors of these papers are among the most productive authors in the field. It is interesting to note that the papers cover a wide range of topics within the field of

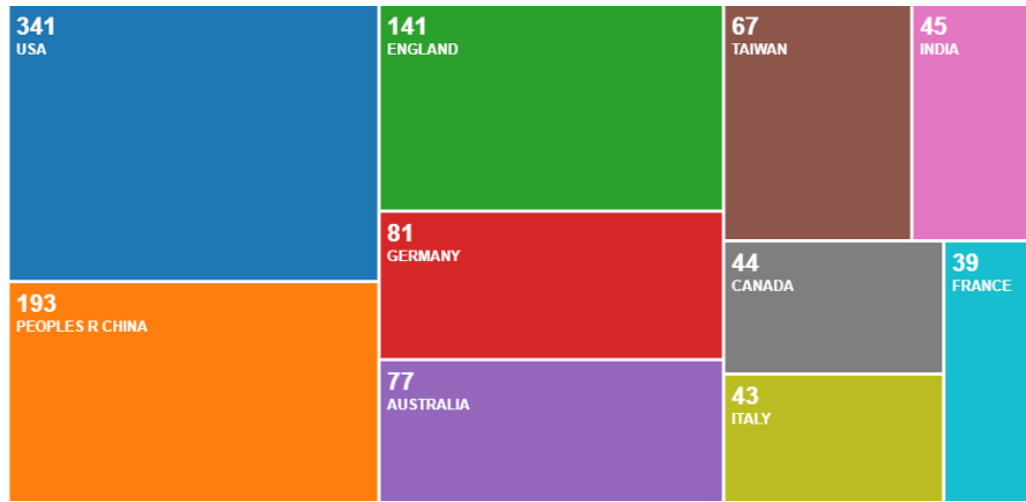


Figure 4. Top 10 countries contributing to the research on trading strategies

Source: Web of Science

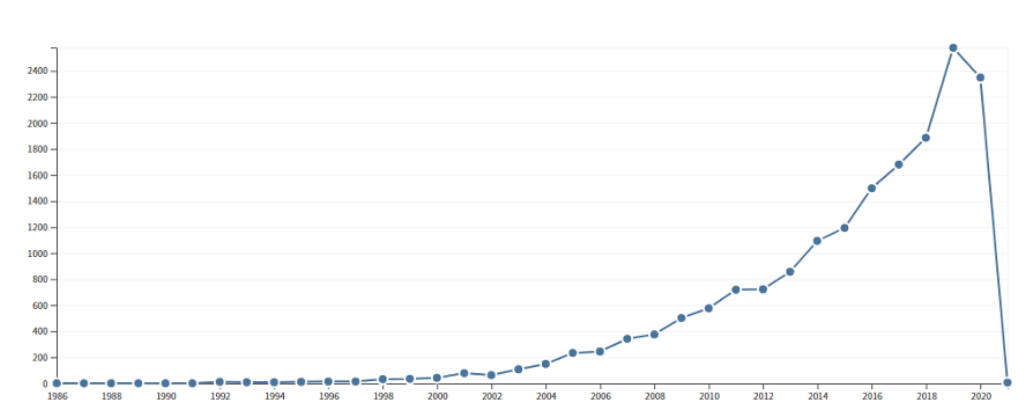


Figure 5. Number of citations per year

Source: Web of Science

Rank	Title	Authors and year	Total citations
1	Do Institutional Investors Prefer Near-Term Earnings over Long-Run Value?	(Bushee, 2001)	842
2	Driven to Distraction: Extraneous Events and Underreaction to Earnings News	(Hirshleifer, Lim, & Teoh, 2009)	346
3	Tools of the trade: the socio-technology of arbitrage in a Wall Street trading room	(Beunza, 2004)	270
4	Separating microstructure noise from volatility	(Bandi & Russell, 2006)	263
5	Short-Sale Strategies and Return Predictability	(Diether, Lee, & Werner, 2008)	255
6	Firm valuation, earnings expectations, and the exchange-rate exposure effect	(Bartov & Bodnar, 1994)	239
7	2005 report on socially responsible investing trends in the United States	(Kempf & Osthoff, 2007)	229
8	Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index	(A.-S. Chen, Leung, & Daouk, 2003))	209
9	The use of data mining and neural networks for forecasting stock market returns	(Enke & Thawornwong, 2005)	196
10	The price dynamics of common trading strategies	(Farmer & Joshi, 2002)	195

Table 4. Top 10 institutions with most publications on trading strategies

Source: Web of Science

trading strategies. So, it is not possible to identify which topics are more trendy, that is, the main approaches researchers are utilizing to develop and propose new trading strategies. It must be highlighted that almost all papers in table 4 are more than 15 years old. Therefore, we perform the same analyses just for the last 5 years.

The results of this analysis are shown on Table 5. Here we find 3 articles by Narayan and Bannigidadmath (2017); Narayan, Narayan, and Westerlund (2015); Phan et al. (2016), who is one of the most productive authors in this field and was included in Table 2. This table is much more instructive than Table 4 regarding the main subareas in the field of trading strategies, as there appear some clear lines of research. We can suppose that in the last years, as the interest in the field has increased, researchers have specialized and some trading strategies and research approaches outstand and become more important.

Table 5. Top 20 cited articles in the database, restricted to articles published since 2015

Rank	Title	Authors and year	Total citations
1	Dynamic Mode Decomposition: Data-Driven Modeling of Complex Systems	(Mann & Kutz, 2016)	117

Table 5. Top 20 cited articles in the database, restricted to articles published since 2015

Rank	Title	Authors and year	Total citations
2	Forecasting daily stock market return using dimensionality reduction	(Zhong & Enke, 2017)	84
3	News Trading and Speed	(Foucault, Hombert, & Roşu, 2016)	71
4	Google searches and stock returns	(Bijl, Kringhaug, Molnár, & Sandvik, 2016)	59
5	Intraday volatility interaction between the crude oil and equity markets	(Phan et al., 2016)	44
6	Risk-Averse Energy Trading in Multi-energy Microgrids: A Two-Stage Stochastic Game Approach	(C. Li, Xu, Yu, Ryan, & Huang, 2017)	41
7	An intelligent short term stock trading fuzzy system for assisting investors in portfolio management	(Chourmouziadis & Chatzoglou, 2016)	39
8	The profitability of pairs trading strategies: distance, cointegration and copula methods	(Rad, Low, & Faff, 2016)	38
9	Does Financial News Predict Stock Returns? New Evidence from Islamic and Non-Islamic Stocks	(Narayan & Bannigidadmath, 2017)	36
10	Using Volume Weighted Support Vector Machines with walk forward testing and feature selection for the purpose of creating stock trading strategy	(Żbikowski, 2015)	33
11	Do order imbalances predict Chinese stock returns? New evidence from intraday data	(Narayan et al., 2015)	31
12	Stock return predictability and investor sentiment: A high-frequency perspective	(Naranjo & Santos, 2019)	30
13	Empirical analysis: stock market prediction via extreme learning machine	(X. Li et al., 2014)	30
14	Trade the tweet: Social media text mining and sparse matrix factorization for stock market prediction	(A. Sun, Lachanski, & Fabozzi, 2016)	28
15	An intelligent pattern recognition model for supporting investment decisions in stock market	(T.-L. Chen & Chen, 2016)	28
16	Trading on Twitter: Using Social Media Sentiment to Predict Stock Returns	(Sul, Dennis, & Yuan, 2016)	27

Table 5. Top 20 cited articles in the database, restricted to articles published since 2015

Rank	Title	Authors and year	Total citations
17	Using Twitter to Predict the Stock Market Where is the Mood Effect?	(Nofer & Hinz, 2015)	26
18	News-based trading strategies	(Feuerriegel & Prendinger, 2016)	25
19	Interval-valued time series forecasting using a novel hybrid Holt(I) and MSVR model	Xiong, Li, and Bao (2017)	24
20	The skewness of commodity futures returns	(Fernandez-Perez, Frijns, Fuertes, & Miffre, 2018)	23

Market sentiment analysis has emerged as one important area of research, and several authors use different sources, like twitter and google searches. In fact, 5 out of the 20 most cited papers published since 2015 deal with market sentiment analysis and use social media as information source. The impact of news on stock returns is becoming an increasingly popular area of research, as well, and 3 of the 20 most cited papers use the news to develop trading strategies. Therefore, we can identify a research trend that uses other information than the traditional information of asset prices and the indicators that are calculated upon them. Nevertheless, price information remains the most important input to develop trading strategies. This information is mainly used applying different artificial intelligence approaches.

In order to identify the most influential authors we conduct a citation analysis. The dataset is analyzed using R (Team, 2013) a free software environment for statistical computing and graphics. Following Guijarro and Tsinaslanidis (2020), we analyze the relevance of different authors in the topic according to the number of publications and the number of citations per year. Figure 6 gives one line to each author, where the extremes represent the year of the first (left circle) and last publication (right circle). The diameter of the circles varies in proportion to the number of papers published each year and the color denotes the number of cites received. This analysis is different than the simple citations count. Therefore, the list of the authors included in Figure 6 does not exactly match the list of the most cited authors which could be extracted from Table 5. It is noteworthy, that most authors in Figure 6 are also among the most prolific authors, as shown in Table 2.

Figure 6 distinguishes two main groups of authors: Those who started publishing in the field of trading strategies before the 2008 financial crisis and those who started later. The authors in this last group publish more papers per year and publish almost every year. Their work also receives more citations. This result also shows a change in the research dynamics in the field, as the most prominent authors are devoted to the topic and publish on a continuous basis. The number of citations per year received by the papers has also increased since 2016.

It is interesting to mention that just few papers have achieved a high number of citations. As shown in Figure 7, only 2 papers have received more than 300 citations for the whole period analyzed. Most papers have received just one citation (151 papers) or zero citations (258 papers), which represents a third of the sample.

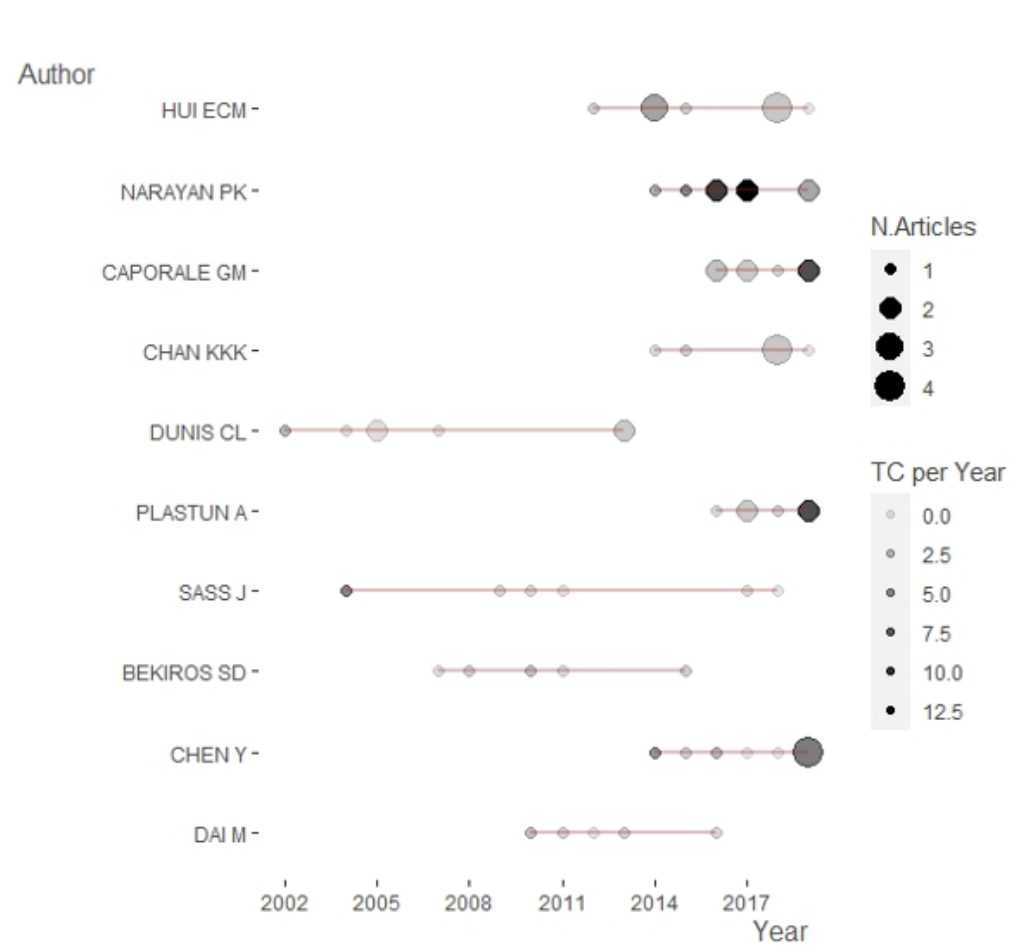


Figure 6. Authors' relevance according to the number of publications and citations received

Source: Web of Science

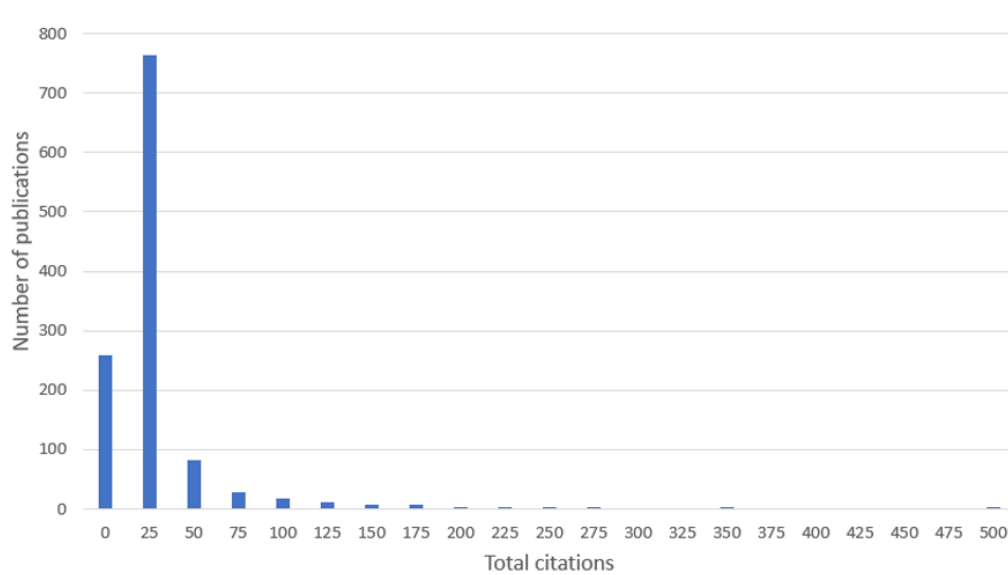


Figure 7. Distribution of citations per paper

Source: Web of Science

5 Co-citation analysis

In the previous sections we have analyzed the most basic bibliometric measures. So, we have analyzed the number of papers published and the citations received, which can be used as a proxy to quantify the influence and recognition obtained by a research work. Next, we perform a co-citation analysis. This kind of analysis measures the correlation between two different papers. According to [Guijarro and Tsinaslanidis \(2020\)](#), co-citation implies that two articles are cited in a third article, hence we can assume both cited papers are related. The co-citation analysis is performed using the VOSViewer software, which is a tool for creating maps based on network data and for visualizing and exploring these maps [van Eck and Waltman \(2009\)](#).

First, we make a co-citation analysis of journals. This analysis shows the relevance of the main journals publishing in the field of trading strategies. As Figure 8 shows, the Journal of Finance is the most co-cited journal. Figure 8 also shows that it is possible to build clusters using the co-citation analysis. In this case, we identify 5 clusters, which are represented with different colors. The green cluster groups journals in the field of economic theory. The red cluster covers the journals which focus in the development of trading methodologies. The blue cluster includes the journals which are specialized in the analyses of the financial markets. The violet cluster groups the econometric journals. Finally, the yellow cluster includes journals publishing in the field of accounting.

Second, we make a co-citation analysis of authors. The results are shown in Figure 9. Interestingly, none of the most prominent and influent authors according to the previous analysis appears in the co-citation analysis. Most papers in Figure 9 were published in the last century. Such is the case of the seminal works by Fama ([Engle, Lilien, & Robins, 1987](#); [Fama, 1970, 1973](#); [Fama & French, 1992](#); [Jegadeesh, 1993](#); [Markovitz, 1959](#); [Markowitz, 1952](#)). We can suppose that those papers are cited in the introductory section of many papers, that is why they are so important in the co-citation analysis. In fact, they do not really deal with trading strategies, but with other topics like portfolio selection, market efficiency or econometric modelling. The

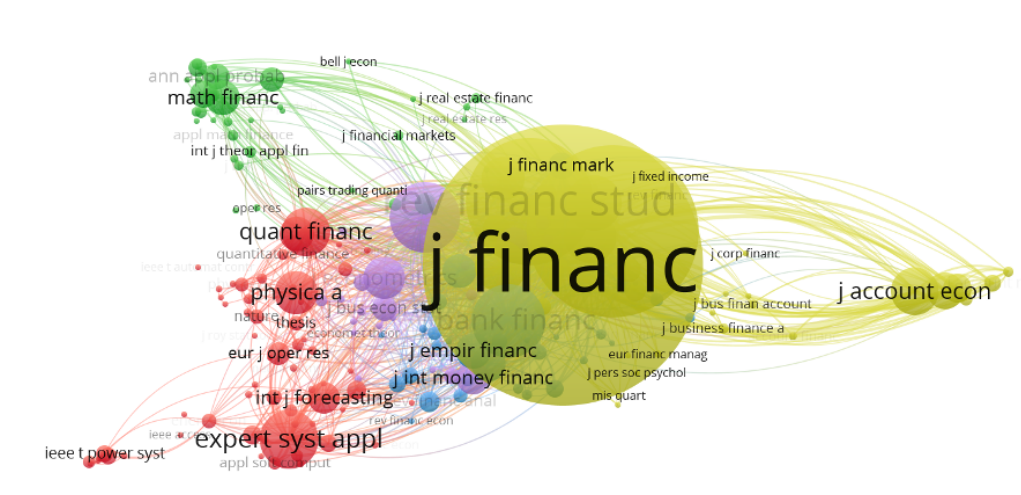


Figure 8. Co-citation analysis. Journals

Source: Web of Science

only paper older than 20 years which is mentioned on figure 9 and that actually proposes trading strategies is the one by Brock et al. (Brock, Lakonishok, & LeBaron, 1992). Market sentiment analysis was also proposed in the late 1990s by Barberis et al. (Barberis, Shleifer, & Vishny, 1998). Moreover, this result reveals that it is becoming more difficult for authors to receive many citations. In fact, as research becomes more specific on the one hand, but on the other hand more and more papers are written in the field of trading strategies, it becomes very difficult for authors to be up-to-date and have a precise overview of the state of the art. As a result, it is becoming increasingly difficult that two papers are cited simultaneously by a third paper. Furthermore, new methodologies and approaches are constantly proposed, so the citation life of articles is reduced. The only exception are the very first papers which introduced the topic and the basic methodologies, which are still often mentioned in the introduction of the papers.

6 Leading topics in trading strategy research

In order to extract the leading topics in the research and development of trading strategies, we have conducted a co-work network analysis. As explained by [Feng et al. \(2017\)](#), a co-word analysis is a content analysis method which uses keywords of documents to capture scientific maps within a field. Based on high frequencies of words that appear in the article, it generates a network relationship among different keywords. For a clear understanding of the obtained network, we will use the visualization tools in VOSviewer. VOS mapping is used to generate a two dimensional diagram to reflect the location of two elements according to the distance between them. Figure 10 shows the outcome of this analysis. A concept with yellow color and higher density indicates that the concept is more frequently used in the field.

From the co-word analysis we can figure out what are some of the main topics researchers are interested in. So, we see that the concept “stock market” is an important keyword, which is a logical outcome. It is rather difficult to clearly extract different isolated research fields, as most keywords are related with each other and refer to very basic concepts in the field of trading strategies, but, nevertheless, we can identify three clusters. The first one deals with market efficiency (keywords: anomaly, excess return, momentum, abnormal return, January, year),

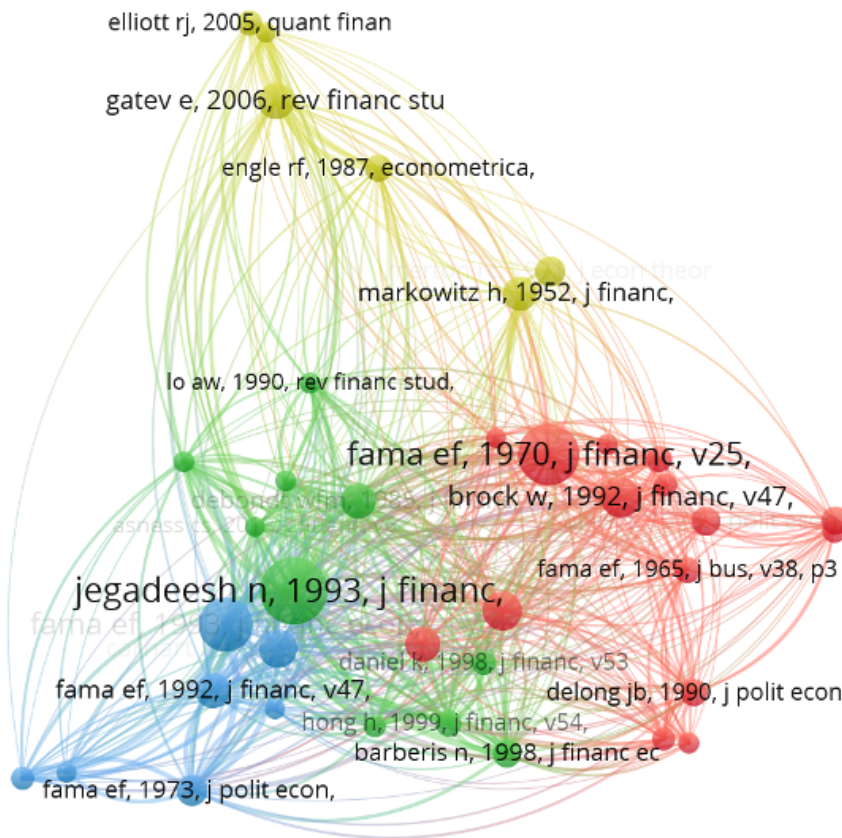


Figure 9. Co-citation analysis. Authors

Source: Web of Science



Figure 10. Heat map of the co-word network on trading strategies

Source: Web of Science

Cluster 1. Market efficiency	Cluster 2. Trading rules and forecasting	Cluster 3: Pairs trading
Foucault et al. (2016)	Zhong and Enke (2017)	Yang, Tsai, Shyu, and Chang (2016)
Bijl et al. (2016)	T.-L. Chen and Chen (2016)	Knoll, Stübinger, and Grotke (2018)
Phan et al. (2016)	Arévalo et al. (2017)	H. J. Chen, Chen, Chen, and Li (2019)
Chourmouziadis and Chatzoglou (2016)	Kumar, Meghwani, and Thakur (2016)	Endres and Stübinger (2019)
Narayan and Bannigodmath (2017)	Thenmozhi and Chand (2015)	Leung and Zhou (2019)
C. Li et al. (2017)	F. García et al. (2018)	Wen, Ma, Wang, and Wang (2018)
L. Sun, Najand, and Shen (2016a)	Picasso, Merello, Ma, Oneto, and Cambria (2019)	
Sul et al. (2016)	Y. Kim, Ahn, Oh, and Enke (2017)	
Xiong et al. (2017)	S. Chen, Bao, and Zhou (2016)	
Zhou, min Zhou, Yang, and Yang (2019)	de Souza, Ramos, Pena, Sobreiro, and Kimura (2018)	

Table 6. Top articles in each cluster on citations which have been published since 2016

Source: Web of Science

the second cluster deals with trading rules and forecasting (keywords: algorithm, indicator, trading strategy, technical analysis, technical indicator, neural network, prediction, trend), and the third group, which is smaller and more isolated, deals with a specific trading strategy: pairs trading (keywords: pairs, pairs trading strategy, spread). Table 6 shows the top articles in each cluster based on citations which have been published since 2016.

The analysis of the leading topics makes it possible to identify some research directions which are becoming more popular in recent years and will lead the future research on trading strategies. We can group them regarding the information used and the data processing tools applied. As for the information employed, most papers use price information, whereas other articles analyze social media (Jin, Shen, & Zhang, 2016), mainly twitter (Bartov, Faurel, & Mohanram, 2017; Behrendt & Schmidt, 2018; Ruan, Durrresi, & Alfantoukh, 2018; A. Sun et al., 2016), or news (Y. Zhang, Song, Shen, & Zhang, 2016). Papers which use price information can be divided into those which apply pattern recognition and candlesticks (Arévalo et al., 2017; Goumatianos, Christou, Lindgren, & Prasad, 2017; Ko, Song, & Chang, 2018; Naranjo & Santos, 2019; Ni, Cheng, Huang, & Day, 2018; P. Tsinaslanidis & Guijarro, 2020) and those focusing on technical analysis (C.-H. Chen, Su, & Lin, 2016; S. Chen et al., 2016; de Souza et al., 2018; Detzel, Liu, Strauss, Zhou, & Zhu, 2020; Eiamkanitchat, Moontuy, & Ramingwong, 2016; Gerritsen, 2016; Jiang, Tong, & Song, 2017; Lam, Dong, & Yu, 2019; Maciel, 2018; Trivedi, 2020; Ye, Zhang, Zhang, Fujita, & Gong, 2016). Papers that analyze social media and news mostly apply sentiment analysis (Checkley, Higón, & Alles, 2017; Renault, 2017; L. Sun, Najand, & Shen, 2016b).

Regarding the data processing tools, most recent papers utilize artificial intelligence to extract information from the data. Most common machine learning techniques include neural networks (Borovkova & Tsiamas, 2019; Krauss, Do, & Huck, 2017; Maknickiene, Lapinskaite, & Maknickas, 2018; Sezer & Ozbayoglu, 2018; Tsantekidis et al., 2017; Wang, Xu, Huang, & Yang, 2019), support vector machines (Y. Chen & Hao, 2018; Nti, Adekoya, & Weyori, 2020; Tang, Dong,

& Shi, 2019), Bayesian approaches (Ardia, Gatarek, Hoogerheide, & van Dijk, 2016; Barone-Adesi, Fusari, Mira, & Sala, 2020; Billio, Casarin, & Osuntuyi, 2018; Boako, Omane-Adjepong, & Frimpong, 2015; Huang, Kong, Li, Yang, & Li, 2018; Huptas, 2018; Ito, Noda, & Wada, 2015; Maragoudakis & Serpanos, 2015), and Markov models (Bejaoui & Karaa, 2016; Billio et al., 2018; Chang & Lee, 2017; Liu & Wang, 2017; Rundo, Trenta, Stallo, & Battiato, 2019; Song, Ryu, & Webb, 2018; M. Zhang, Jiang, Fang, Zeng, & Xu, 2019). Natural language processing is also becoming popular in the field of sentiment analysis (Feuerriegel & Prendinger, 2016; Pröllochs, Feuerriegel, & Neumann, 2016; Schnaubelt, Fischer, & Krauss, 2020). Finally, other processing tools like dynamic time warping are gaining popularity (S. Kim et al., 2018; P. Tsinaslanidis & Guijarro, 2020; P. E. Tsinaslanidis, 2018).

7 Conclusions

The development of trading strategies has become a popular field of research in the past 5 years and many scholars from different research areas have been attracted into this multidisciplinary topic. In this paper we have used the ISI Web of Science database to analyze the research papers published on this topic during the last decades by means of both a descriptive and a bibliometric analysis. A total of 1,187 articles have been collected using the search tools in the ISI Web of Science Database. For the citation and co-citation analysis we have employed R and VOSviewer, respectively, in order to provide a better visualization of the data and generate clusters.

Results show that since 2015 papers published on trading strategies have experienced a sharp increase. The field has evolved from an emerging field to a clearly consolidated one. The authors are located in many different countries, although the USA is clearly the leading country, and work in many different organizations and institutions. No institution has taken the lead, as there are many organizations which are very active in this research topic. The research background of the authors also differs, which proofs that this is a multidisciplinary field. In fact, the study of the journals which publish articles on trading strategies also endorse this finding. Not just journals specialized in finance, business and economics, but also those which are focused on mathematics, software and computer science, among others, are contributing to the development of new and more complex trading strategies.

The citation analysis shows that the number of citations has been dramatically increasing in the last years, but there are no leading authors in the field. Around one third of all papers have receive one citation or no citation at all. Moreover, top cited papers dealing with trading strategies are rather old, as they were published before the topic started its growing trend. Besides, the result of the co-citation analysis shows that the most co-cited papers were published in the last century and do not actually deal with trading strategies, but with economic theories about the financial markets and econometric methodologies. Therefore, the mere analysis of citations does not shed light into the analysis of the present situation regarding the development of trading strategies. The analysis performed to identify the most relevant authors in the field, which considers the number of publications and the citations received, reveals that most of them have been very active since 2015, and gives some clues about present research lines. To better identify the most important research directions at present, we conduct a co-word analysis and we label 3 different clusters: market efficiency, trading rules and forecasting, and pairs trading. The analysis of the leading topics uncovers the most promising research topics on trading strategies. Main research lines differ regarding the data source employed: traditional price and financial information, news and social media. According to

the approach used to define the trading strategy, most papers are using technical analysis, pattern recognition and candlesticks, and sentiment analysis approaches. The number of data processing tools is increasing constantly, as databases become more exhaustive and accessible and new methods are developed. Most of them make use of artificial intelligence, like machine learning techniques and natural language processing.

Finally, we may conclude that the future path of research on the development of trading strategies will be shaped by the increase of computational capacity, the use of new information sources and the development of artificial intelligence and other data processing methods.

References

- Ardia, D., Gatarek, L., Hoogerheide, L., & van Dijk, H. (2016). Return and risk of pairs trading using a simulation-based bayesian procedure for predicting stable ratios of stock prices. *Econometrics*, 4(4), 14. doi: <https://doi.org/10.3390/econometrics4010014>
- Arévalo, R., García, J., Guijarro, F., & Peris, A. (2017). A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting. *Expert Systems with Applications*, 81, 177–192. doi: <https://doi.org/10.1016/j.eswa.2017.03.028>
- Arribas, I., Espinós-Vañó, M., García, F., & Morales-Bañuelos, P. (2019). The inclusion of socially irresponsible companies in sustainable stock indices. *Sustainability*, 11(7), 2047. doi: <https://doi.org/10.3390/su11072047>
- Arribas, I., Espinós-Vañó, M. D., García, F., & Oliver, J. (2019). Defining socially responsible companies according to retail investors' preferences. *Entrepreneurship and Sustainability Issues*, 7(2), 1641–1653. doi: [https://doi.org/10.9770/jesi.2019.7.2\(59\)](https://doi.org/10.9770/jesi.2019.7.2(59))
- Arribas, I., Espinós-Vañó, M. D., García, F., & Tamošiūnienė, R. (2019). Negative screening and sustainable portfolio diversification. *Entrepreneurship and Sustainability Issues*, 6(4), 1566–1586. doi: [https://doi.org/10.9770/jesi.2019.6.4\(2\)](https://doi.org/10.9770/jesi.2019.6.4(2))
- Baccarin, S., & Marazzina, D. (2015). Passive portfolio management over a finite horizon with a target liquidation value under transaction costs and solvency constraints. *IMA Journal of Management Mathematics*, 27(4), 471–504. doi: <https://doi.org/10.1093/imaman/dpv002>
- Bahoo, S., Alon, I., & Paltrinieri, A. (2020). Sovereign wealth funds: Past, present and future. *International Review of Financial Analysis*, 67, 101418. doi: <https://doi.org/10.1016/j.irfa.2019.101418>
- Bandi, F. M., & Russell, J. R. (2006). Separating microstructure noise from volatility. *Journal of Financial Economics*, 79(3), 655–692. doi: <https://doi.org/10.1016/j.jfineco.2005.01.005>
- Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307–343. doi: [https://doi.org/10.1016/s0304-405x\(98\)00027-0](https://doi.org/10.1016/s0304-405x(98)00027-0)
- Barone-Adesi, G., Fusari, N., Mira, A., & Sala, C. (2020). Option market trading activity and the estimation of the pricing kernel: A bayesian approach. *Journal of Econometrics*, 216(2), 430–449. doi: <https://doi.org/10.1016/j.jeconom.2019.11.001>
- Bartov, E., & Bodnar, G. M. (1994). Firm valuation, earnings expectations, and the exchange-rate exposure effect. *The Journal of Finance*, 49(5), 1755–1785. doi: <https://doi.org/10.1111/j.1540-6261.1994.tb04780.x>
- Bartov, E., Faurel, L., & Mohanram, P. S. (2017). Can twitter help predict firm-level earnings and stock returns? *The Accounting Review*, 93(3), 25–57. doi: <https://doi.org/10.2308/accr-51865>
- Behrendt, S., & Schmidt, A. (2018). The twitter myth revisited: Intraday investor sentiment,

- twitter activity and individual-level stock return volatility. *Journal of Banking & Finance*, 96, 355–367. doi: <https://doi.org/10.1016/j.jbankfin.2018.09.016>
- Bejaoui, A., & Karaa, A. (2016). Revisiting the bull and bear markets notions in the tunisian stock market: New evidence from multi-state duration-dependence markov-switching models. *Economic Modelling*, 59, 529–545. doi: <https://doi.org/10.1016/j.econmod.2016.08.018>
- Beunza, D. (2004). Tools of the trade: the socio-technology of arbitrage in a wall street trading room. *Industrial and Corporate Change*, 13(2), 369–400. doi: <https://doi.org/10.1093/icc/dth015>
- Bijl, L., Kringhaug, G., Molnár, P., & Sandvik, E. (2016). Google searches and stock returns. *International Review of Financial Analysis*, 45, 150–156. doi: <https://doi.org/10.1016/j.irfa.2016.03.015>
- Billio, M., Casarin, R., & Osuntuyi, A. (2018). Markov switching GARCH models for bayesian hedging on energy futures markets. *Energy Economics*, 70, 545–562. doi: <https://doi.org/10.1016/j.eneco.2017.06.001>
- Bilson, J. F. O. (1984). Purchasing power parity as a trading strategy. *The Journal of Finance*, 39(3), 715. doi: <https://doi.org/10.2307/2327931>
- Boako, G., Omane-Adjepong, M., & Frimpong, J. M. (2015). Stock returns and exchange rate nexus in ghana: A bayesian quantile regression approach. *South African Journal of Economics*, 84(1), 149–179. doi: <https://doi.org/10.1111/saje.12096>
- Borovkova, S., & Tsiamas, I. (2019). An ensemble of LSTM neural networks for high-frequency stock market classification. *Journal of Forecasting*, 38(6), 600–619. doi: <https://doi.org/10.1002/for.2585>
- Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance*, 47(5), 1731–1764. doi: <https://doi.org/10.1111/j.1540-6261.1992.tb04681.x>
- Bushee, B. J. (2001). Do institutional investors prefer near-term earnings over long-run value? *Contemporary Accounting Research*, 18(2), 207–246. doi: <https://doi.org/10.1506/j4gu-bhwh-8hme-le0x>
- Caporale, G. M., Gil-Alana, L., & Plastun, A. (2016). Searching for inefficiencies in exchange rate dynamics. *Computational Economics*, 49(3), 405–432. doi: <https://doi.org/10.1007/s10614-016-9567-2>
- Caporale, G. M., Gil-Alana, L., & Plastun, A. (2017). Short-term price overreactions: Identification, testing, exploitation. *Computational Economics*, 51(4), 913–940. doi: <https://doi.org/10.1007/s10614-017-9651-2>
- Caporale, G. M., Gil-Alana, L., Plastun, A., & Makarenko, I. (2015). Intraday anomalies and market efficiency: A trading robot analysis. *Computational Economics*, 47(2), 275–295. doi: <https://doi.org/10.1007/s10614-015-9484-9>
- Caporale, G. M., & Plastun, A. (2017). Price gaps: Another market anomaly? *Investment Analysts Journal*, 46(4), 279–293. doi: <https://doi.org/10.1080/10293523.2017.1333563>
- Caporale, G. M., & Plastun, A. (2019a). The day of the week effect in the cryptocurrency market. *Finance Research Letters*, 31. doi: <https://doi.org/10.1016/j.frl.2018.11.012>
- Caporale, G. M., & Plastun, A. (2019b). On stock price overreactions: frequency, seasonality and information content. *Journal of Applied Economics*, 22(1), 602–621. doi: <https://doi.org/10.1080/15140326.2019.1692509>
- Cervelló-Royo, R., Guijarro, F., & Michniuk, K. (2015). Stock market trading rule based on pattern recognition and technical analysis: Forecasting the DJIA index

- with intraday data. *Expert Systems with Applications*, 42(14), 5963–5975. doi: <https://doi.org/10.1016/j.eswa.2015.03.017>
- Chang, Y.-H., & Lee, M.-S. (2017). Incorporating markov decision process on genetic algorithms to formulate trading strategies for stock markets. *Applied Soft Computing*, 52, 1143–1153. doi: <https://doi.org/10.1016/j.asoc.2016.09.016>
- Checkley, M., Higón, D. A., & Alles, H. (2017). The hasty wisdom of the mob: How market sentiment predicts stock market behavior. *Expert Systems with Applications*, 77, 256–263. doi: <https://doi.org/10.1016/j.eswa.2017.01.029>
- Chen, A.-S., Leung, M. T., & Daouk, H. (2003). Application of neural networks to an emerging financial market: forecasting and trading the taiwan stock index. *Computers & Operations Research*, 30(6), 901–923. doi: [https://doi.org/10.1016/s0305-0548\(02\)00037-0](https://doi.org/10.1016/s0305-0548(02)00037-0)
- Chen, C.-H., Su, X.-Q., & Lin, J.-B. (2016). The role of information uncertainty in moving-average technical analysis: A study of individual stock-option issuance in taiwan. *Finance Research Letters*, 18, 263–272. doi: <https://doi.org/10.1016/j.frl.2016.04.026>
- Chen, H. J., Chen, S. J., Chen, Z., & Li, F. (2019). Empirical investigation of an equity pairs trading strategy. *Management Science*, 65(1), 370–389. doi: <https://doi.org/10.1287/mnsc.2017.2825>
- Chen, S., Bao, S., & Zhou, Y. (2016). The predictive power of japanese candlestick charting in chinese stock market. *Physica A: Statistical Mechanics and its Applications*, 457, 148–165. doi: <https://doi.org/10.1016/j.physa.2016.03.081>
- Chen, T.-L., & Chen, F.-Y. (2016). An intelligent pattern recognition model for supporting investment decisions in stock market. *Information Sciences*, 346–347, 261–274. doi: <https://doi.org/10.1016/j.ins.2016.01.079>
- Chen, Y., & Hao, Y. (2018). Integrating principle component analysis and weighted support vector machine for stock trading signals prediction. *Neurocomputing*, 321, 381–402. doi: <https://doi.org/10.1016/j.neucom.2018.08.077>
- Chourmouziadis, K., & Chatzoglou, P. D. (2016). An intelligent short term stock trading fuzzy system for assisting investors in portfolio management. *Expert Systems with Applications*, 43, 298–311. doi: <https://doi.org/10.1016/j.eswa.2015.07.063>
- de Souza, M. J. S., Ramos, D. G. F., Pena, M. G., Sobreiro, V. A., & Kimura, H. (2018). Examination of the profitability of technical analysis based on moving average strategies in BRICS. *Financial Innovation*, 4(1). doi: <https://doi.org/10.1186/s40854-018-0087-z>
- Detzel, A., Liu, H., Strauss, J., Zhou, G., & Zhu, Y. (2020). Learning and predictability via technical analysis: Evidence from bitcoin and stocks with hard-to-value fundamentals. *Financial Management*. doi: <https://doi.org/10.1111/fima.12310>
- Diether, K. B., Lee, K.-H., & Werner, I. M. (2008). Short-sale strategies and return predictability. *Review of Financial Studies*, 22(2), 575–607. doi: <https://doi.org/10.1093/rfs/hhn047>
- Eiamkanitchat, N., Moontuy, T., & Ramingwong, S. (2016). Fundamental analysis and technical analysis integrated system for stock filtration. *Cluster Computing*, 20(1), 883–894. doi: <https://doi.org/10.1007/s10586-016-0694-2>
- Endres, S., & Stübinger, J. (2019). A flexible regime switching model with pairs trading application to the s&p 500 high-frequency stock returns. *Quantitative Finance*, 19(10), 1727–1740. doi: <https://doi.org/10.1080/14697688.2019.1585562>
- Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: The arch-m model. *Econometrica*, 55(2), 391. doi: <https://doi.org/10.2307/1913242>

- Enke, D., & Thawornwong, S. (2005). The use of data mining and neural networks for forecasting stock market returns. *Expert Systems with Applications*, 29(4), 927–940. doi: <https://doi.org/10.1016/j.eswa.2005.06.024>
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383. doi: <https://doi.org/10.2307/2325486>
- Fama, E. F. (1973). A NOTE ON THE MARKET MODEL AND THE TWO-PARAMETER MODEL. *The Journal of Finance*, 28(5), 1181–1185. doi: <https://doi.org/10.1111/j.1540-6261.1973.tb01449.x>
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427–465. doi: <https://doi.org/10.1111/j.1540-6261.1992.tb04398.x>
- Farmer, J., & Joshi, S. (2002). The price dynamics of common trading strategies. *Journal of Economic Behavior & Organization*, 49(2), 149–171. doi: [https://doi.org/10.1016/s0167-2681\(02\)00065-3](https://doi.org/10.1016/s0167-2681(02)00065-3)
- Feng, Y., Zhu, Q., & Lai, K.-H. (2017). Corporate social responsibility for supply chain management: A literature review and bibliometric analysis. *Journal of Cleaner Production*, 158, 296–307. doi: <https://doi.org/10.1016/j.jclepro.2017.05.018>
- Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., & Miffre, J. (2018). The skewness of commodity futures returns. *Journal of Banking & Finance*, 86, 143–158. doi: <https://doi.org/10.1016/j.jbankfin.2017.06.015>
- Feuerriegel, S., & Prendinger, H. (2016). News-based trading strategies. *Decision Support Systems*, 90, 65–74. doi: <https://doi.org/10.1016/j.dss.2016.06.020>
- Foucault, T., Hombert, J., & Roşu, I. (2016). News trading and speed. *The Journal of Finance*, 71(1), 335–382. doi: <https://doi.org/10.1111/jofi.12302>
- García, González-Bueno, Oliver, & Riley. (2019). Selecting socially responsible portfolios: A fuzzy multicriteria approach. *Sustainability*, 11(9), 2496. doi: <https://doi.org/10.3390/su11092496>
- García, F., González-Bueno, J., Guijarro, F., & Oliver, J. (2020). Forecasting the environmental, social, and governance rating of firms by using corporate financial performance variables: A rough set approach. *Sustainability*, 12(8), 3324. doi: <https://doi.org/10.3390/su12083324>
- García, F., González-Bueno, J., Guijarro, F., Oliver, J., & Tamošiūnienė, R. (2020). MULTIOBJECTIVE APPROACH TO PORTFOLIO OPTIMIZATION IN THE LIGHT OF THE CREDIBILITY THEORY. *Technological and Economic Development of Economy*, 26(6), 1165–1186. doi: <https://doi.org/10.3846/tede.2020.13189>
- García, F., & Guijarro, F. (2011). Crisis bursátil: ¿es preferible una estrategia de gestión activa o pasiva? *INNOVAR. Revista de Ciencias Administrativas y Sociales*, 21(39), 123–131.
- García, F., Guijarro, F., & Moya, I. (2011). The curvature of the tracking frontier: A new criterion for the partial index tracking problem. *Mathematical and Computer Modelling*, 54(7-8), 1781–1784. doi: <https://doi.org/10.1016/j.mcm.2011.02.015>
- García, F., Guijarro, F., & Moya, I. (2013). A MULTIOBJECTIVE MODEL FOR PASSIVE PORTFOLIO MANAGEMENT: AN APPLICATION ON THE s&p 100 INDEX. *Journal of Business Economics and Management*, 14(4), 758–775. doi: <https://doi.org/10.3846/16111699.2012.668859>
- García, F., Guijarro, F., & Oliver, J. (2017). Index tracking optimization with cardinality constraint: a performance comparison of genetic algorithms and tabu search heuristics. *Neural Computing and Applications*, 30(8), 2625–2641. doi: <https://doi.org/10.1007/s00521-017-2882-2>
- García, F., Guijarro, F., Oliver, J., & Tamošiūnienė, R. (2018). HYBRID FUZZY NEURAL NETWORK TO

- PREDICT PRICE DIRECTION IN THE GERMAN DAX-30 INDEX. *Technological and Economic Development of Economy*, 24(6), 2161–2178. doi: <https://doi.org/10.3846/tede.2018.6394>
- Gerritsen, D. F. (2016). Are chartists artists? the determinants and profitability of recommendations based on technical analysis. *International Review of Financial Analysis*, 47, 179–196. doi: <https://doi.org/10.1016/j.irfa.2016.06.008>
- Goumatianos, N., Christou, I. T., Lindgren, P., & Prasad, R. (2017). An algorithmic framework for frequent intraday pattern recognition and exploitation in forex market. *Knowledge and Information Systems*, 53(3), 767–804. doi: <https://doi.org/10.1007/s10115-017-1052-2>
- Guijarro, F., & Tsinaslanidis, P. (2020). Analysis of academic literature on environmental valuation. *International Journal of Environmental Research and Public Health*, 17(7), 2386. doi: <https://doi.org/10.3390/ijerph17072386>
- Helbing, P. (2019). A review on IPO withdrawal. *International Review of Financial Analysis*, 62, 200–208. doi: <https://doi.org/10.1016/j.irfa.2018.09.001>
- Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, 64(5), 2289–2325. doi: <https://doi.org/10.1111/j.1540-6261.2009.01501.x>
- Huang, Q., Kong, Z., Li, Y., Yang, J., & Li, X. (2018). Discovery of trading points based on bayesian modeling of trading rules. *World Wide Web*, 21(6), 1473–1490. doi: <https://doi.org/10.1007/s11280-018-0534-9>
- Hui, E. C. M., & Chan, K. K. K. (2014). Can we still beat “buy-and-hold” for individual stocks? *Physica A: Statistical Mechanics and its Applications*, 410, 513–534. doi: <https://doi.org/10.1016/j.physa.2014.05.061>
- Hui, E. C. M., & Chan, K. K. K. (2015). Testing calendar effects on global securitized real estate markets by shiryaev-zhou index. *Habitat International*, 48, 38–45. doi: <https://doi.org/10.1016/j.habitatint.2015.03.009>
- Hui, E. C. M., & Chan, K. K. K. (2018). NEW TESTS OF CALENDAR EFFECTS ON EQUITY AND SECURITIZED REAL ESTATE MARKETS. *International Journal of Strategic Property Management*, 22(4), 314–336. doi: <https://doi.org/10.3846/ijspm.2018.4400>
- Hui, E. C. M., & Chan, K. K. K. (2019). Alternative trading strategies to beat “buy-and-hold”. *Physica A: Statistical Mechanics and its Applications*, 534, 120800. doi: <https://doi.org/10.1016/j.physa.2019.04.036>
- Hui, E. C. M., Wright, J. A., & Yam, S. C. P. (2013). Calendar effects and real estate securities. *The Journal of Real Estate Finance and Economics*, 49(1), 91–115. doi: <https://doi.org/10.1007/s11146-012-9398-4>
- Hui, E. C. M., & Yam, S.-C. P. (2014). CAN WE BEAT THE “BUY-AND-HOLD” STRATEGY? ANALYSIS ON EUROPEAN AND AMERICAN SECURITIZED REAL ESTATE INDICES. *International Journal of Strategic Property Management*, 18(1), 28–37. doi: <https://doi.org/10.3846/1648715x.2013.862190>
- Huptas, R. (2018). Point and density prediction of intra-day volume using bayesian linear ACV models: evidence from the polish stock market. *Quantitative Finance*, 18(5), 749–760. doi: <https://doi.org/10.1080/14697688.2017.1414491>
- Ito, M., Noda, A., & Wada, T. (2015). The evolution of stock market efficiency in the US: a non-bayesian time-varying model approach. *Applied Economics*, 48(7), 621–635. doi: <https://doi.org/10.1080/00036846.2015.1083532>
- Jegadeesh, N. (1993). Treasury auction bids and the salomon squeeze. *The Journal of Finance*, 48(4), 1403–1419. doi: <https://doi.org/10.1111/j.1540-6261.1993.tb04759.x>

- Jiang, F., Tong, G., & Song, G. (2017). Technical analysis profitability without data snooping bias: Evidence from chinese stock market. *International Review of Finance*, 19(1), 191–206. doi: <https://doi.org/10.1111/irfi.12161>
- Jin, X., Shen, D., & Zhang, W. (2016). Has microblogging changed stock market behavior? evidence from china. *Physica A: Statistical Mechanics and its Applications*, 452, 151–156. doi: <https://doi.org/10.1016/j.physa.2016.02.052>
- Kempf, A., & Osthoff, P. (2007). The effect of socially responsible investing on portfolio performance. *European Financial Management*, 13(5), 908–922. doi: <https://doi.org/10.1111/j.1468-036x.2007.00402.x>
- Khademalomoom, S., & Narayan, P. K. (2019). Intraday effects of the currency market. *Journal of International Financial Markets, Institutions and Money*, 58, 65–77. doi: <https://doi.org/10.1016/j.intfin.2018.09.008>
- Kim, S., Lee, H., Ko, H., Jeong, S., Byun, H., & Oh, K. (2018). Pattern matching trading system based on the dynamic time warping algorithm. *Sustainability*, 10(12), 4641. doi: <https://doi.org/10.3390/su10124641>
- Kim, Y., Ahn, W., Oh, K. J., & Enke, D. (2017). An intelligent hybrid trading system for discovering trading rules for the futures market using rough sets and genetic algorithms. *Applied Soft Computing*, 55, 127–140. doi: <https://doi.org/10.1016/j.asoc.2017.02.006>
- Knoll, J., Stübinger, J., & Grottkke, M. (2018). Exploiting social media with higher-order factorization machines: statistical arbitrage on high-frequency data of the s&p 500. *Quantitative Finance*, 19(4), 571–585. doi: <https://doi.org/10.1080/14697688.2018.1521002>
- Ko, B., Song, J. W., & Chang, W. (2018). Crash forecasting in the korean stock market based on the log-periodic structure and pattern recognition. *Physica A: Statistical Mechanics and its Applications*, 492, 308–323. doi: <https://doi.org/10.1016/j.physa.2017.09.074>
- Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the s&p 500. *European Journal of Operational Research*, 259(2), 689–702. doi: <https://doi.org/10.1016/j.ejor.2016.10.031>
- Kumar, D., Meghwani, S. S., & Thakur, M. (2016). Proximal support vector machine based hybrid prediction models for trend forecasting in financial markets. *Journal of Computational Science*, 17, 1–13. doi: <https://doi.org/10.1016/j.jocs.2016.07.006>
- Lam, Dong, & Yu. (2019). Value premium and technical analysis: Evidence from the china stock market. *Economies*, 7(3), 92. doi: <https://doi.org/10.3390/economies7030092>
- Leung, T., & Zhou, Y. (2019). Optimal dynamic futures portfolio in a regime-switching market framework. *International Journal of Financial Engineering*, 06(04), 1950034. doi: <https://doi.org/10.1142/s2424786319500348>
- Li, C., Xu, Y., Yu, X., Ryan, C., & Huang, T. (2017). Risk-averse energy trading in multienergy microgrids: A two-stage stochastic game approach. *IEEE Transactions on Industrial Informatics*, 13(5), 2620–2630. doi: <https://doi.org/10.1109/tii.2017.2739339>
- Li, X., Xie, H., Wang, R., Cai, Y., Cao, J., Wang, F., ... Deng, X. (2014). Empirical analysis: stock market prediction via extreme learning machine. *Neural Computing and Applications*, 27(1), 67–78. doi: <https://doi.org/10.1007/s00521-014-1550-z>
- Liu, Z., & Wang, S. (2017). Decoding chinese stock market returns: Three-state hidden semi-markov model. *Pacific-Basin Finance Journal*, 44, 127–149. doi: <https://doi.org/10.1016/j.pacfin.2017.06.007>
- Maciel, L. (2018). Technical analysis based on high and low stock prices forecasts: evidence for brazil using a fractionally cointegrated VAR model. *Empirical Economics*, 58(4), 1513–1540.

doi: <https://doi.org/10.1007/s00181-018-1603-8>

- Maciková, L., Smorada, M., Dorčák, P., Beug, B., & Markovič, P. (2018). Financial aspects of sustainability: An evidence from slovak companies. *Sustainability*, 10(7), 2274. doi: <https://doi.org/10.3390/su10072274>
- Maknickiene, N., Lapinskaite, I., & Maknickas, A. (2018). Application of ensemble of recurrent neural networks for forecasting of stock market sentiments. *Equilibrium*, 13(1), 7–27. doi: <https://doi.org/10.24136/eq.2018.001>
- Mann, J., & Kutz, J. N. (2016). Dynamic mode decomposition for financial trading strategies. *Quantitative Finance*, 16(11), 1643–1655. doi: <https://doi.org/10.1080/14697688.2016.1170194>
- Maragoudakis, M., & Serpanos, D. (2015). Exploiting financial news and social media opinions for stock market analysis using MCMC bayesian inference. *Computational Economics*, 47(4), 589–622. doi: <https://doi.org/10.1007/s10614-015-9492-9>
- Markovitz, H. M. (1959). *Portfolio selection: Efficient diversification of investments*. John Wiley.
- Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91. doi: <https://doi.org/10.1111/j.1540-6261.1952.tb01525.x>
- Naranjo, R., & Santos, M. (2019). A fuzzy decision system for money investment in stock markets based on fuzzy candlesticks pattern recognition. *Expert Systems with Applications*, 133, 34–48. doi: <https://doi.org/10.1016/j.eswa.2019.05.012>
- Narayan, P. K., & Bannigidadmath, D. (2017). Does financial news predict stock returns? new evidence from islamic and non-islamic stocks. *Pacific-Basin Finance Journal*, 42, 24–45. doi: <https://doi.org/10.1016/j.pacfin.2015.12.009>
- Narayan, P. K., Narayan, S., & Westerlund, J. (2015). Do order imbalances predict chinese stock returns? new evidence from intraday data. *Pacific-Basin Finance Journal*, 34, 136–151. doi: <https://doi.org/10.1016/j.pacfin.2015.07.003>
- Narayan, P. K., Phan, D. H. B., Narayan, S., & Bannigidadmath, D. (2017). Is there a financial news risk premium in islamic stocks? *Pacific-Basin Finance Journal*, 42, 158–170. doi: <https://doi.org/10.1016/j.pacfin.2017.02.008>
- Ni, Y., Cheng, Y., Huang, P., & Day, M.-Y. (2018). Trading strategies in terms of continuous rising (falling) prices or continuous bullish (bearish) candlesticks emitted. *Physica A: Statistical Mechanics and its Applications*, 501, 188–204. doi: <https://doi.org/10.1016/j.physa.2018.02.038>
- Nofer, M., & Hinz, O. (2015). Using twitter to predict the stock market. *Business & Information Systems Engineering*, 57(4), 229–242. doi: <https://doi.org/10.1007/s12599-015-0390-4>
- Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). Efficient stock-market prediction using ensemble support vector machine. *Open Computer Science*, 10(1), 153–163. doi: <https://doi.org/10.1515/comp-2020-0199>
- Papantonis, I. (2016). Cointegration-based trading: evidence on index tracking & market-neutral strategies. *Managerial Finance*, 42(5), 449–471. doi: <https://doi.org/10.1108/mf-12-2014-0318>
- Phan, D. H. B., Sharma, S. S., & Narayan, P. K. (2016). Intraday volatility interaction between the crude oil and equity markets. *Journal of International Financial Markets, Institutions and Money*, 40, 1–13. doi: <https://doi.org/10.1016/j.intfin.2015.07.007>
- Picasso, A., Merello, S., Ma, Y., Oneto, L., & Cambria, E. (2019). Technical analysis and sentiment embeddings for market trend prediction. *Expert Systems with Applications*, 135, 60–70. doi: <https://doi.org/10.1016/j.eswa.2019.06.014>

- Plastun, A., Sibande, X., Gupta, R., & Wohar, M. E. (2020). Price gap anomaly in the US stock market: The whole story. *The North American Journal of Economics and Finance*, 52, 101177. doi: <https://doi.org/10.1016/j.najef.2020.101177>
- Pröllochs, N., Feuerriegel, S., & Neumann, D. (2016). Negation scope detection in sentiment analysis: Decision support for news-driven trading. *Decision Support Systems*, 88, 67–75. doi: <https://doi.org/10.1016/j.dss.2016.05.009>
- Rad, H., Low, R. K. Y., & Faff, R. (2016). The profitability of pairs trading strategies: distance, cointegration and copula methods. *Quantitative Finance*, 16(10), 1541–1558. doi: <https://doi.org/10.1080/14697688.2016.1164337>
- Renault, T. (2017). Intraday online investor sentiment and return patterns in the u.s. stock market. *Journal of Banking & Finance*, 84, 25–40. doi: <https://doi.org/10.1016/j.jbankfin.2017.07.002>
- Ruan, Y., Durreesi, A., & Alfantoukh, L. (2018). Using twitter trust network for stock market analysis. *Knowledge-Based Systems*, 145, 207–218. doi: <https://doi.org/10.1016/j.knosys.2018.01.016>
- Rundo, F., Trenta, F., Stallo, A. L. D., & Battiato, S. (2019). Advanced markov-based machine learning framework for making adaptive trading system. *Computation*, 7(1), 4. doi: <https://doi.org/10.3390/computation7010004>
- Schnaubelt, M., Fischer, T. G., & Krauss, C. (2020). Separating the signal from the noise – financial machine learning for twitter. *Journal of Economic Dynamics and Control*, 114, 103895. doi: <https://doi.org/10.1016/j.jedc.2020.103895>
- Sezer, O. B., & Ozbayoglu, A. M. (2018). Algorithmic financial trading with deep convolutional neural networks: Time series to image conversion approach. *Applied Soft Computing*, 70, 525–538. doi: <https://doi.org/10.1016/j.asoc.2018.04.024>
- Simionescu, L., & Dumitrescu, D. (2018). Empirical study towards corporate social responsibility practices and company financial performance. evidence for companies listed on the bucharest stock exchange. *Sustainability*, 10(9), 3141. doi: <https://doi.org/10.3390/su10093141>
- Song, W., Ryu, D., & Webb, R. I. (2018). Volatility dynamics under an endogenous markov-switching framework: a cross-market approach. *Quantitative Finance*, 18(9), 1559–1571. doi: <https://doi.org/10.1080/14697688.2018.1444551>
- Sul, H. K., Dennis, A. R., & Yuan, L. I. (2016). Trading on twitter: Using social media sentiment to predict stock returns. *Decision Sciences*, 48(3), 454–488. doi: <https://doi.org/10.1111/dec.12229>
- Sun, A., Lachanski, M., & Fabozzi, F. J. (2016). Trade the tweet: Social media text mining and sparse matrix factorization for stock market prediction. *International Review of Financial Analysis*, 48, 272–281. doi: <https://doi.org/10.1016/j.irfa.2016.10.009>
- Sun, L., Najand, M., & Shen, J. (2016a). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance*, 73, 147–164. doi: <https://doi.org/10.1016/j.jbankfin.2016.09.010>
- Sun, L., Najand, M., & Shen, J. (2016b). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance*, 73, 147–164. doi: <https://doi.org/10.1016/j.jbankfin.2016.09.010>
- Tang, H., Dong, P., & Shi, Y. (2019). A new approach of integrating piecewise linear representation and weighted support vector machine for forecasting stock turning points. *Applied Soft Computing*, 78, 685–696. doi: <https://doi.org/10.1016/j.asoc.2019.02.039>

- Team, R. C. (2013). *R: A language and environment for statistical computing*. Vienna, Austria.
- Thenmozhi, M., & Chand, G. S. (2015). Forecasting stock returns based on information transmission across global markets using support vector machines. *Neural Computing and Applications*, 27(4), 805–824. doi: <https://doi.org/10.1007/s00521-015-1897-9>
- Trivedi, S. R. (2020). Technical analysis using heiken ashi stochastic: To catch a trend, use a HAS-TOC. *International Journal of Finance & Economics*. doi: <https://doi.org/10.1002/ijfe.2245>
- Tsantekidis, A., Passalis, N., Tefas, A., Kannianen, J., Gabbouj, M., & Iosifidis, A. (2017). Forecasting stock prices from the limit order book using convolutional neural networks. In *2017 IEEE 19th conference on business informatics (CBI)*. IEEE. doi: <https://doi.org/10.1109/cbi.2017.23>
- Tsinaslanidis, P., & Guijarro, F. (2020). What makes trading strategies based on chart pattern recognition profitable? *Expert Systems*. doi: <https://doi.org/10.1111/exsy.12596>
- Tsinaslanidis, P. E. (2018). Subsequence dynamic time warping for charting: Bullish and bearish class predictions for NYSE stocks. *Expert Systems with Applications*, 94, 193–204. doi: <https://doi.org/10.1016/j.eswa.2017.10.055>
- van Eck, N. J., & Waltman, L. (2009). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, 84(2), 523–538. doi: <https://doi.org/10.1007/s11192-009-0146-3>
- Wang, Q., Xu, W., Huang, X., & Yang, K. (2019). Enhancing intraday stock price manipulation detection by leveraging recurrent neural networks with ensemble learning. *Neurocomputing*, 347, 46–58. doi: <https://doi.org/10.1016/j.neucom.2019.03.006>
- Wen, D., Ma, C., Wang, G.-J., & Wang, S. (2018). Investigating the features of pairs trading strategy: A network perspective on the chinese stock market. *Physica A: Statistical Mechanics and its Applications*, 505, 903–918. doi: <https://doi.org/10.1016/j.physa.2018.04.021>
- Xiong, T., Li, C., & Bao, Y. (2017). Interval-valued time series forecasting using a novel hybrid HoltI and MSVR model. *Economic Modelling*, 60, 11–23. doi: <https://doi.org/10.1016/j.econmod.2016.08.019>
- Yang, J.-W., Tsai, S.-Y., Shyu, S.-D., & Chang, C.-C. (2016). Pairs trading: The performance of a stochastic spread model with regime switching-evidence from the s&p 500. *International Review of Economics & Finance*, 43, 139–150. doi: <https://doi.org/10.1016/j.iref.2015.10.036>
- Ye, F., Zhang, L., Zhang, D., Fujita, H., & Gong, Z. (2016). A novel forecasting method based on multi-order fuzzy time series and technical analysis. *Information Sciences*, 367–368, 41–57. doi: <https://doi.org/10.1016/j.ins.2016.05.038>
- Zamore, S., Djan, K. O., Alon, I., & Hobdari, B. (2018). Credit risk research: Review and agenda. *Emerging Markets Finance and Trade*, 54(4), 811–835. doi: <https://doi.org/10.1080/1540496x.2018.1433658>
- Żbikowski, K. (2015). Using volume weighted support vector machines with walk forward testing and feature selection for the purpose of creating stock trading strategy. *Expert Systems with Applications*, 42(4), 1797–1805. doi: <https://doi.org/10.1016/j.eswa.2014.10.001>
- Zhang, M., Jiang, X., Fang, Z., Zeng, Y., & Xu, K. (2019). High-order hidden markov model for trend prediction in financial time series. *Physica A: Statistical Mechanics and its Applications*, 517, 1–12. doi: <https://doi.org/10.1016/j.physa.2018.10.053>
- Zhang, Y., Song, W., Shen, D., & Zhang, W. (2016). Market reaction to internet news: Information diffusion and price pressure. *Economic Modelling*, 56, 43–49. doi: <https://doi.org/10.1016/j.econmod.2016.03.020>

- Zhong, X., & Enke, D. (2017). Forecasting daily stock market return using dimensionality reduction. *Expert Systems with Applications*, 67, 126–139. doi: <https://doi.org/10.1016/j.eswa.2016.09.027>
- Zhou, F., min Zhou, H., Yang, Z., & Yang, L. (2019). EMD2fnn: A strategy combining empirical mode decomposition and factorization machine based neural network for stock market trend prediction. *Expert Systems with Applications*, 115, 136–151. doi: <https://doi.org/10.1016/j.eswa.2018.07.065>