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Review

A literature review of technical analysis on stock markets☆,☆☆

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ABSTRACT

Several studies have been published in the last 55 years exploring technical analysis. However, there is a lack of research that consolidates the available knowledge concerning technical analysis. The main goal of this paper is, by classifying and coding published papers, to summarize and systematize the significant research that has contributed to the development of the field. Our paper contributes to the existing literature on technical analysis by presenting an overview of characteristics of the literature and potential knowledge gaps in this area, focusing on the analysis of stocks. The paper also discusses suggestions for future research in technical analysis.

Contents

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1. Introduction

A considerable number of studies have inferred that predicting stock market returns is a difficult task (Teixeira & Oliveira, 2010; Zielonka, 2004). The nonlinear and nonstationary features of the stock market make it a complicated system (Bisoi & Dash, 2014, p. 41). There is also the fact that, as observed by Ticknor (2013, p. 5501), the complexity of the stock market is associated with a considerable number of factors such as political events, market news, quarterly earnings reports, international influence and conflicting trading behaviour. Vanstone and Finnie (2009, p. 6669) directed attention to the idea that some techniques were developed to predict future price returns, for instance, technical and fundamental analysis. According to Park and Irwin (2009), participants in different financial markets use technical analysis; however, academics do not give technical analysis substantial support (Brock, Lakonishok, & LeBaron, 1992, p. 1732; Menkhoff, 2010, p. 2573; Menkhoff & Taylor, 2007, p. 938; Mitra, 2011, p. 135–136; Zhu & Zhou, 2009, p. 520), even though it is easy to find in financial markets, as rightly highlighted by Schulmeister (2009, p. 190). This fact was notably highlighted by Lo, Mamaysky, and Wang (2000, p. 1705) in their famous paper, "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation", as quoted:

> "It has been argued that the difference between fundamental analysis and technical analysis is not unlike the difference between astronomy and astrology. Among some circles, technical analysis is known as 'voodoo finance.' '

Fundamental analysis utilizes economic factors to estimate the intrinsic values of securities, whereas technical analysis relies on historical data on stock prices (Chavarnakul & Enke, 2009, p. 3517; Teixeira & Oliveira, 2010, p. 6885). In general, fundamental analysis has as its cornerstone the essence of Graham's work, as shown in his famous book *Intelligent Investor*, which in turn recommends buying stocks based on a set of stock-selection rules. A number of authors, such as Oppenheimer and Schlarbaum (1981, p. 357) and Metghalchi, Chang, and Marcucci (2008, p. 489) tested these rules and applied them and concluded that it is possible to achieve returns higher than those obtained by the buy-and-hold strategy, considering even the semi-strong form of the efficient markets hypothesis.

Technical analysis has been understood as a set of tools that allow for predicting future returns in financial assets by studying past market data, mostly stock price and volume (Park & Irwin, 2007, p. 786; Wei, Chen, & Ho, 2011, p. 13625; Yamamoto, 2012, p. 3033; Zhu & Zhou, 2009, p. 521). Recent studies have combined traditional technical analysis trading rules with intelligent system techniques and statistical models as well, including Bisoi and Dash (2014, p. 41), Wei et al. (2011, p. 13625), Ticknor (2013, p. 5501) and Kazem, Sharifi, Hussain, Saberi, and Hussain (2013, p. 947). Some of these techniques are neural networks, fuzzy systems, evolutionary computation and genetic algorithms. These techniques can be applied along with technical trading rules to form a trading system that can predict the future direction of security prices using past price and volume data (Gorgulho, Neves, & Horta, 2011, p. 14072).

In this paper, we focus on presenting a literature review about the main studies of technical analysis published in the last years. Bearing this in mind, we:

- Summarize the especially relevant papers that describe mainly technical analysis on stock markets;
- Categorize and codify the different characteristics of these papers; and
- Present areas that have been scarcely studied or that have no previous studies.

Consequently, taking these objectives into mind, we believe that we can provide valuable insights toward future studies and new areas of research. To fulfil this goal, we classified and systematized over 85 articles on technical analysis and other trading techniques. We then selected papers published from 1959 to 2014 that specifically studied and tested any type of trend forecasting or technical analysis system or that combined two or more of them, which was the case in many of the considered studies. The widespread use of technical analysis by practitioners and the high number of scientific papers dealing with the theme, as showed in our literature review, are strong evidence of relevance for both the market and the academia. In more detailed terms, we also give a brief descriptive background and summary of each paper's contributions (available on the Internet Appendix). It is worth noting that, although artificial markets are not the subject of this study, some papers on this topic were included in the analysis, as they contained the keywords used in our search of the *Scopus* database. Readers interested in this theme may see references to, for example, Ehrentreich (2008), Schredelseker and Hauser (2008), Zenobia, Weber, and Daim (2009) and Mizuta (2016).

Since we conduct a review of papers on technical analysis, we briefly discuss diverse aspects of the studies such as methodology, type of applications, operational tools, and so on. More particularly, even though we include the discussion on performance of trading rules, the focus of the paper is not to specifically investigate market efficiency or performance of strategies under the presence of transaction costs or adjusted for risk levels.

The paper is structured as follows: Section 2 describes the method for research and the basis for the literature review. Section 3 gives a brief conceptual foundation of technical analysis. Subsequently, the classification, coding and analysis of the papers are provided in Section 4. Considering this classification, the main results and discussion are presented in Section 5. The paper ends with Section 6, with the findings, conclusions and suggestion for further work being presented.

2. Describing the research method and the basis for the literature review

The prediction of financial asset returns is a subject that encompasses many knowledge areas such as financial econometrics, investment analysis, corporate finance, and, most recently, behavioural finance (Chavarnakul & Enke, 2009, p. 3517; Parisi & Vasquez, 2000, p. 152–153; Roberts, 1959, p. 1). However, to limit the range of this study, a keyword search was conducted that followed the review literature framework proposed by Lage Junior and Godinho Filho (2010, p. 14) and tested by Jabbour (2013, p. 145) in the most important academic databases and publisher websites, such as example, *Elsevier*, *Taylor & Francis*, *JStor* and *Springer*. More specifically, the following words were utilized in these searches: (a) technical analysis; (b) trading; (c) trend prediction; (d) stock prediction; (e) stock trading system; (f) predictability; and (g) stock market.

Subsequently, the papers were submitted to a full read to guarantee that they were within the research range of this paper, and fundamental analysis papers were eliminated because that is not within the scope of this paper. Nevertheless, some papers in this study do discuss fundamental analysis in a positive manner. The steps taken to classify and codify the papers were the following:

Table 1
The system of classification and coding used.

Classification	Meanings	Categories
1	Economy	A – advanced country. B – developing country. C – not applicable.
2	Methodology	A – trading system. B – computational technique. C – macroeconomic model. D – chart pattern.
3	Application	A – on market. B – artificial market. C – not applicable.
4	Transaction costs	A – considered. B – not considered.
5	Operational tools	A – stochastic. B – relative strength index. C – genetic algorithm. D – evolutionary reinforcement learning. E – statistical analysis. F – moving averages. G – econometric models (AR, ARMA, ARIMA, e GARCHT). H – neural network. I – other.
6	Results	A – support technical analysis. B – does not support technical analysis. C – not applied.
7	Risk	A – considered. B – not considered. C – not applicable.
8	Risk adjust-ment	A – profitability considering risk adjustment and transaction costs. B – profitability considering only risk adjustment. C – profitability considering only transaction costs. D – profitability considering neither risk adjustment nor transaction costs. E – not applicable.

Source: Adapted from Jabbour (2013, p. 145).

- Step 1: Create classification categories and subcategories and perform a keyword search on academic databases and publisher websites to select papers;
- Step 2: Apply the categories to each selected paper within the scope of the study;
- Step 3: Analyse the description of the scientific production in the technical analysis study field; and
- Step 4: Provide insights for future research and analyse the gaps in the past studies.

The first step was taken considering the articles available in the above mentioned databases. The categories and subcategories created were based on the articles' most common themes, as shown in Table 1. The selected papers focused on technical analysis and other tools that improve trend predictability on stock markets. After selecting the papers, the articles were classified into each category and subcategory; this was the second step. The third step was executed to provide a broader view of the topic. The fourth step, which is also the conclusion of the study, helped to identify any gaps and gives ideas for future research on the matter.

Considering the previously mentioned framework, we selected 85 papers for this study. It is worth noting that many papers were excluded during the first screening because they focused on price formation, liquidity modelling and mainly portfolio management.

Finally, it is important to highlight that the search criteria may have precluded the analysis of papers that do not specifically mention or are not explicitly related to "technical analysis". Therefore, by following the literature review method that Lage Junior and Godinho Filho (2010) and Jabbour (2013) proposed, we may have left some important papers out of our study, including those that discuss the results of momentum strategies (Asness, Moskowitz, & Pedersen, 2013; Barroso & Santa-Clara, 2015; Fama & French, 2012; Jegadeesh & Titman, 1993, 2001; Novy-Marx, 2012) and by focusing on the more recent literature. However, this limitation is also found in Park and Irwin (2007).

3. A brief conceptual foundation of technical analysis

Technical analysis can be understood as a set of rules or charting that tends to anticipate future price shifts based on the study of certain information, such as, for example, purchase price, selling price, and volume traded, among others (Gorgulho et al., 2011, p. 14073; Lin, Yang, & Song, 2011, p. 11348; Oliveira, Nobre, & Zárate, 2013, p. 7597). Some of this information encompasses a series of historical market data that are widely used by practitioners to identify buy and sell signals (Omrane & Van Oppens, 2006, p. 949).

The first major academic study that considered technical analysis as a study subject was "Can Stock Market Forecasters Forecast?", written by Alfred Cowles 3rd and published in *Econometrica*, July 1933. In simple terms, this study verified whether 45 professional agencies were capable of predicting the future movements of the stock market (Cowles, 1933, p. 309). However, according to Northcott (2009, p. 15), Munehisa Homma was one of the first to employ the concepts of technical analysis in the rice market in the 1700s in Japan, in what is currently known as the candlestick pattern.

Chronologically, in approximately the late 1800s, Charles Dow employed principles of technical analysis with the daily closing prices of 11 relevant stocks and cofounded the Dow Jones Financial News Service. It is important to highlight that he discussed in a series of editorial and articles in the *Wall Street Journal* that constitute the theoretical foundation of technical analysis as it is understood today (Brock et al., 1992, p. 1731; Vanstone & Finnie, 2009, p. 6671; Zhu & Zhou, 2009, p. 520).

Observing this context, Fama and Blume (1966) verified the performance of filter rules in the U.S. stock market and indicated that filter rules are unable to overcome the buy-and-hold strategy. Subsequently, and in a remarkable way, Fama (1970) compiled ideas about market behaviour and investor performance and presented the efficient market hypothesis (EMH), which has at its core the assumption that prices reflect all information available. In this context, Jensen and Benington (1970, p. 481) advocate that using technical analysis, or more precisely, relative strength trading rules, does not overcome the buy-and-hold strategy, which was previously studied by Levy (1967, p. 596).

Nevertheless, other researchers and practitioners have found that technical analysis can be used as a tool to predict or indicate the movement of stock prices. In other words, some obtained results performed better than did buy-and-hold. Among these studies, special emphasis is given to Brock et al. (1992, p. 1757), Ratner and Leal (1999, p. 1904), Gunasekarage and Power (2001, p. 32), and, mainly, Lo et al. (2000, p. 1753), who stated that technical analysis *"can add value to the investment process"*.

Therefore, one stream of studies of technical analysis explores market efficiency, more specifically the weak form. In these context, some papers, e.g. Fernández-Rodríguez, González-Martel, and Sosvilla-Rivero (2000); Chan, Hameed, and Tong (2000), analyse whether results from trading rule strategies allow higher results. Other studies, however, e.g. Asness et al. (2013), acknowledge that there are strategies, such as momentum trading, that lead to positive risk-adjusted performance and then focus on studying underlying factor for these results.

In recent decades, studies that were published in the main and prestigious academic journals may either support or not support the adequacy of using technical analysis as an investment tool (Allen & Karjalainen, 1999; Allen & Yang, 2004; Dempster & Jones, 2001; Ellis & Parbery, 2005; Gunasekarage & Power, 2001; Jegadeesh & Titman, 2001; Lo et al., 2000; Neely, 2003; Sullivan, Timmermann, & White, 1999). During the research for this paper, two other review papers (Menkhoff & Taylor, 2007; Park & Irwin, 2007) that study the technical analysis and its use were found, both published in 2007, almost a decade ago. Park and Irwin's survey studies the profitability of technical analysis throughout the years. They conclude that papers classified as early studies found little profitability in technical analysis. Additionally, papers in the category of modern studies were more diversified in their findings: out of 95 studies, 56 found positive results, while the rest found negative and mixed results for the use of technical analysis.

The other paper, from Menkhoff and Taylor (2007), analysed facts about the use of technical analysis in foreign exchange markets. The authors conclude that the continued use of technical analysis can be explained by the need, for professionals, to have tools to assess the market and to make decisions. They also point out that technical analysis is a part of foreign exchange markets and that it remains a 'passionate obsession' for professionals in the field. Menkhoff and Taylor (2007) conclude that technical analysis, from an academic perspective, must be integrated in microeconomics at microstructural levels and that, from a practitioner's perspective, it should be frequently assessed as a tool for obtaining abnormal returns. However, they identified no paper that systematized the studies that have focused on technical analysis on stock markets using a systematic categorization of different elements of the studies. In other words, there remains a lack of research that classifies, categorizes and codifies these papers. Differently from the two previously mentioned papers, this study focuses on a broader range of research about technical analysis. We have considered any study on technical analysis that tries to identify the usefulness of it, the profitability, the different indicators, or the results of its use in different markets and different economic situations. Bearing this in mind, we believe that our study is a step forward into reviewing studies on technical analysis.

It is important to note that we present a succinct summary of the 85 previously-identified articles in the Internet Appendix to provide a broad, historical view of the papers covering technical analysis since the 1950s.

4. Classification of the papers

In this section, we present the classification for each revised study, as shown in Table 2. Next, a brief description of each category will be provided.

4.1. Economy

Analysis of different economies is a concern in the technical analysis literature because the volatility and size of the stock markets, the tax systems, people's education levels, and levels of political instability are different, and, these may influence operational dynamics (Wang, Chiao, et al., 2012; Yu, Nartea, Gan, & Yao, 2013).

Therefore, we sought to separate the articles in which the authors could be considered to have applied technical analysis because their results could have been influenced by the studied country's development level. Moreover, we believe that investments in the financial and capital markets are more interesting in advanced countries, which in its turn, supports more research.

4.2. Methodology

We classified the papers into four subcategories that were frequently identified in the papers that had technical analysis on stock markets as their main subject, as follows:

- Trading System: Recently, the interest in decision's support trading systems has increased (Rodríguez-González et al., 2011, p. 11489). Predicting stock price movement is a very difficult task. However, a non-linear approach such as an intelligent system can manage the uncertainty and imprecision in the stock market (Chavarnakul & Enke, 2009, p. 3519). Therefore, the trading system can be a different way of combining different tools, indicators and techniques to predict future market movements and to test the effectiveness of technical rules. Despite the wide study of trading systems in the existing literature, the majority of academic work in the area of systematic trading concerns individual trading rules (Dempster & Jones, 2001, p. 397);
- Computational Technique: In an effort to effectively address the uncertainties involved in trading stocks, futures and other assets, many traders use price-based strategies to enter and exit markets, such as stop-loss, price targets, price breakouts, planning horizons, and other strategies (Warburton & Zhang, 2006, p. 33). To achieve these goals, it is also common to use computational techniques that combine these different tools to use technology in their favour;
- Chart Patterns: Tests of technical analysis have restricted their studies to techniques that are expressed algebraically, such as filter rules and moving averages. However, practitioners utilize many alternative techniques, including an extensive category of exclusively visual patterns (Osler & Chang, 1995, p. 1). Chart patterns essentially entail identifying consistencies in time series by extracting non-linear patterns from noisy data (Omrane & Van Oppens, 2006, p. 951); and
- Not Applicable: This subcategory occurs when the studies do not apply to any of the previously presented subcategories.

Table 2
Classification of the analyzed studies.

Study	Economy	Methodology	Application	Transaction costs	Operational tools	Results	Risk	Risk adjustment
Roberts (1959)	A	D	A; B	B	E; I	A	B	D
Fama and Blume (1966)	A	B	A	A	I	A	B	C
Fama (1970)	A	D	A	B	I	C	C	E
Lo and MacKinlay (1988)	A	A	A	B	E	A	A	B
Neftci (1991)	A	A; D	A	B	F; I	A	B	D
Brock et al. (1992)	A	A	A	B	E; F	A	A	B
Ratner and Leal (1999)	A; B	A	A	A	F	A	B	C
Sullivan et al. (1999)	A	A; B	A	A	F; I	A;B	A	A
Vandewalle, Ausloos, and Boveroux (1999)	C	A	A	B	F	A	B	D
Chan et al. (2000)	B	A	A	B	I	A	A	B
Kim and Han (2000)	B	B	A	B	C; H	A	B	D
Lo et al. (2000)	A	D	A	B	E; I	A	B	D
Parisi and Vasquez (2000)	B	A	A	A	E; F	A	B	D
Gunasekarage and Power (2001)	B	A	A	B	F	A	B	D
Kwon and Kish (2002)	A	A	A	B	E; F; G	A	A	B
Dawson and Steeley (2003)	A	D	A	B	E	A	B	D
Goldbaum (2003)	C	A	B	B	E; F; I	B	B	D
Pérez-Cruz, Afonso-Rodríguez, and Giner (2003)	C	B	A	B	G; H	C	A	B
Chang, Lima, and Tabak (2004)	C	A	A	A	E; F	A	B	C
Hanousek and Podpiera (2004)	A	A	A	A	I	A	A	A
Töyli, Sysi-aho, and Kaski (2004)	A	A	A	B	E; G	A	A	B
Elliott, Hoek, and Malcolm (2005)	C	A	B	B	I	A	B	D
Ellis and Parbery (2005)	A	A	A	A	F	A	A	A
Fong and Yong (2005)	A	A	A	A	F	A	A	A
Hafner (2005)	A	B	A	B	E	C	A	B
Liu, Huang, and Zheng (2006)	A	A	A	B	I	A	B	E
Ming-Ming and Siok-Hwa (2006)	B	A	A	A	F	A	B	D
Warburton and Zhang (2006)	C	B	B	B	E; I	A	C	E
Kwon and Moon (2007)	A	A; B	A	A	C; H; I	A	B	C
Moon and Kim (2007)	C	A	A; B	A	C; F	A	C	E
Wang and Chan (2007)	A; B	D	A	B	F; I	A	A	B
Ahn, Kang, and Ryu (2008)	A	A	A	A	E; G	A	C	E
Bao and Yang (2008)	A	A; B	A	B	A; B; F	A	B	D
Huang, Yang, and Chuang (2008)	B	B	A	B	I	A	B	D
Chavarnakul and Enke (2009)	C	A; B	B	A	C; F; H; I	A	B	C
Friesen, Weller, and Dunham (2009)	A	D	A	B	I	A	A	B
Lee (2009)	C	B	A	B	D; I; H	A	B	D
Lin, Wang, and Tsai (2009)	A	A	A	B	C; F	A	C	E
Vanstone and Finnie (2009)	C	A	C	A	I	A	A	A
Vidotto, Migliato, and Zambon (2009)	B	A	A	B	F	A	B	D
Wang, Dong, and Deng (2009)	B	A	A; B	B	C; E	A	A	A
Zhu and Zhou (2009)	A	A	A; B	B	F	A	B	D
Chong and Lam (2010)	A	A	A	A	G; F	A	A	A
Creamer and Freund (2010)	A	A	A	A	C	A	A	A
How, Ling, and Verhoeven (2010)	A	A	A	A	C; E	A	B	C
Teixeira and Oliveira (2010)	B	A	A	A	A; B; F	A	A	A
Vanstone and Finnie (2010)	A	A	A	A	F; H	A	A	A
Giot and Petitjean (2011)	A	A	A	A	E; I	B	A	B
Rodríguez-González, García-Crespo, Colomo-Palacios, Iglesias, and Gómez-Berbís (2011)	A	A; B	A	B	B; H; F; I	A	B	D
Gorgulho et al. (2011)	A	A; B	A	A	B; C; F; I	A	A	A
Hendershott, Jones, and Menkveld (2011)	A	A	A	A	E	A	B	E
Jasemi, Kimiagari, and Memariani (2011)	A	B; C	A	B	H	A	B	D
Lin et al. (2011)	A	A; B	A	A	A; B; C; F; I	A	B	C
Mitra (2011)	B	A	A	A	E; F	A	B	C
Ni, Ni, and Gao (2011)	B	B	A	B	I	A	B	D
Tan, Quek, and Cheng (2011)	A	A	A	A	D; F	A	B	C
Tung and Quek (2011)	B	B	A	A	C; D; F; H	A	A	A
Wei et al. (2011)	B	B	A	B	E	A	B	D
Chang, Wang, and Zhou (2012)	A	B	A	B	H; I	A	B	D
Creamer (2012)	A	A; B	A	A	B; C; F; H	A	A	A
Dymova, Sevastianov, and Kaczmarek (2012)	B	A	A	A	F; I	A	B	C
Pavlov and Hurn (2012)	A	A	A	B	E; F	A	A	B
Pemy (2012)	A	A	A	B	A; C; E	A	B	D
Shynkevich (2012)	A	A	A	A	E; F; I	A	A	A
Wang, Chiao, and Chang (2012)	A	A	A	A	F; G	A	C	E

Table 2 (*Continued*)

Study	Economy	Methodology	Application	Transaction costs	Operational tools	Results	Risk	Risk adjustment
Yamamoto (2012)	A	A	A	A; B	I; F	A	B	C
Zapranis and Tsinaslanidis (2012)	A	D	A	A	E	A	B	D
Caporin, Ranaldo, and Santucci de Magistris (2013)	A	B	A	A	G	A	A	A
Chen, Kuo, Huang, and Chen (2013)	B	B	A	A	A; E; F; H	A	B	C
Kazem et al. (2013)	A	B	A	B	C; H; E; G	A	A	B
Lee (2013)	A	A	A	A	E	A	B	C
Oliveira et al. (2013)	C	B	A	B	H	A	B	D
Ticknor (2013)	A	B	A	B	A; B; F; H	A	B	D
Bisoi and Dash (2014)	B	A; B	A	B	A; B; E; F	A	B	D
Fortuny, Smedt, Martens, and Daelemans (2014)	A	A; B	A	B	B; D; A; I	A	A	B
Kaminski and Lo (2014)	A	B	A	B	I	C	A	A
Taylor (2014)	A	A	A	A	G; F; I	A	A	A
Cervelló-Royo, Guijarro, and Michniuk (2015)	A	C	A	A	I	A	A	B
Costa, Nazário, Bergo, Sobreiro, and Kimura (2015)	B	B	A	A	F	A	A	A
Gebka, Hudson, and Atanasova (2015)	A	A	A	A	F	A	A	A
Zhu, Jiang, Li, and Zhou (2015)	B	A	A	A	E; F	A; B	A	A
Wang (2015)	B	A; B	A	B	I	A; B	C	E
Shen and Tzeng (2015)	B	A	A	A	E; F	A	A	A
Tharavanij, Siraprapasiri, and Rajchamaha (2015)	B	A	A	A	A; B; F	A; B	A	A
Berutich, López, Luna, and Quintana (2016)	A	A; B	A; B	A	C; E; G	A	A	A

4.3. *Application*

(a) In the market: Technical trading techniques were developed by analysts based on daily use to forecast stock prices (Dawson & Steeley, 2003, p. 263). In light of this background, it is common to note that different authors utilize their trading systems in the market, using past prices to test them; and
(b) Artificial markets: The increase of the use of technical analysis approaches in artificial markets is observed in more recent articles. By using artificial data, one can isolate specific characteristics such as market rules or constraints, investor behaviour and biases, which could influence prices, as highlighted by Milone (2008, p. 27).

4.4. *Transactional costs*

Transaction costs are an important matter for technical analysts because they alter the results when they are added (Chang et al., 2004, p. 313; Kwon & Moon, 2007, p. 852; Ülkü & Prodan, 2013, p. 215). Many studies perform two types of analysis: considering and not considering transaction costs. Taking this into account, the observed studies could be classified as follows: (a) The authors considered or (b) did not consider transaction costs in their analyses.

4.5. *Operational tools*

In this paper, each study was analysed to be classified into one of the following subcategories:

(a) Stochastic: This method was first developed by George C. Lane. Some papers used the stochastic line as a KD line, leading to two smooth moving averages (Bisoi & Dash, 2014, p. 47). In general, stochastic oscillators attempt to measure when the closing price will approach the lowest price when there is an upward trend in the market in the period under consideration; when there is a down trend, stochastic oscillators attempt to measure when the closing price will approach the highest price in that period (Lin et al., 2011, p. 11350);
(b) Relative Strength Index: This index is a momentum oscillator that is very popular in financial technical analysis and was developed by Welles Wilder (Fortuny et al., 2014, p. 433; Lin et al., 2011, p. 11349). Normally, the RSI calculates and compares an asset's overbought or oversold conditions; however, there are many ways to determine this technical indicator depending on whether you want to calculate a normal RSI or a smoother RSI formula (Gorgulho et al., 2011, p. 14078; Lin et al., 2011, p. 11349; Rodríguez-González et al., 2011, p. 11490);
(c) Genetic Algorithm: The genetic algorithm approach is typically used to evolve trading rules and was first developed by Holland (Creamer, 2012, p. 532; Dempster & Jones, 2001, p. 398). This method helped to improve technical trading rules in the studies in which it was used. According to Neely (2003, p. 71) and Chavarnakul and Enke (2009, p. 3519), genetic algorithms are an optimization method that changes some inputs numbers to improve technical trading rules or their parameters just as chromosomes are manipulated in biology to help in evolution;
(d) Evolutionary Reinforcement Learning: Evolutionary reinforcement learning (ERL) is a way to improve the parameters of trading rules in technical analysis in the same way as genetic algorithms (Austin, Bates, Dempster, Leemans, & Williams, 2004, p. 38). However, ERL's system works differently from the genetic algorithm system. ERL consists of trial and error, which presents prize sections as feedback from the environment (Tan et al., 2011, p. 4742);
(e) Statistical Analysis: In this subcategory of the study, we selected every article that used statistical tools as a method to categorize or measure a technical trading rule. It is important to highlight that some articles used statistics to measure the returns of assets or trading rules;
(f) Moving Averages: These methods are momentum-based strategies that generate buy/sell signals. Moving averages generate a buy signal when the stock price crosses the moving average price from below to up and a sell signal when the stock price crosses the moving average price from above to down (Taylor, 2014, p. 289). They also generate buy/sell signals based on the interactions between the short and long moving averages (Shynkevich, 2012, p. 197);

(g) Econometric Models: For this study, we selected a number of papers that used econometric models as operational tools. Econometric models can be autoregressive (AR); autoregressive moving averages (ARMAs); autoregressive integrated moving average (ARIMAs); autoregressive conditional heteroscedasticity (ARCH); generalized autoregressive conditional heteroscedasticity (GARCH); or support vector regression (SVR), or they can take other forms. It is important to highlight that according to Kazem et al. (2013, p. 949), SVR has better prediction accuracy owing to its use of a risk minimization structure, and as Pérez-Cruz et al. (2003, p. 165) advocate, the GARCH model gives a simple model of the principal statistical characteristics of a return series;

(h) Neural Network: This method is based on biological neurosystems, and it is able to learn from examples to make forecasts in examples that have never been observed before (Zhang, Eddy Patuwo, & Hu, 1998, p. 37). In the technical analysis context, neural networks allow for trading rules to be remodelled because the parameters of the change generate as an output a prediction of the future situation of the series; neural networks are also better suited for small-range data (Oliveira et al., 2013, p. 7598; Ticknor, 2013, p. 5502). Consequently, neural networks are mostly used to improve on technical trading rules (Creamer, 2012, p. 531); and

(i) Other: In this subcategory, we classified every paper that utilized any other operational tool that was not previously mentioned.

4.6. Profitability, predictability and risk

Although many studies, for example, Park and Irwin (2007) and Schulmeister (2009) have analysed whether technical analysis is profitable and has predictive powers, and have found positive results on the subject, some papers have found the opposite. The results found in the papers in our database can be categorized as "supporting technical analysis", "not supporting technical analysis" and "technical analysis not applied".

The papers that support technical analysis have contributed to the research on the matter with their findings. Many of them found new models for technical trading with soft computing, artificial intelligence, fuzzy logic and others. The papers that did not support technical analysis found negative results regarding its profitability and predictability. These papers also support the efficient markets hypothesis and the random walk theory. However, not all of the papers took a definite position on the subject. We selected "not applied" for any papers that did not fit into either of the two categories mentioned above. These were the studies that did not focus on testing technical trading.

Not only have we classified studies according to profitability, but we have also analysed whether papers focusing on technical analysis take into consideration risk issues. As profitability can be affected by transaction costs and risk, we have added to the analysis two new categories: 7 – Risk, and 8 – Risk Adjustment. As state above, this is depicted in Table 1. In Category 7, we only indicate whether or not the paper considers risk. In Category 8, we evaluate whether profitability of strategy is adjusted for risk, for transaction costs, or for both. Surprisingly, less than 44% of the reviewed papers adjusted profitability using some risk indicator. Regarding the papers that considered risk adjustment, 62% (23/37, depicted in Table 3) also took into account transaction costs.

5. Results and discussion

Once the classification was completed, each category was statistically analysed with the objective of identifying the most expressive gaps. The results will now be presented and discussed along with the implications for the technical analysis study field.

5.1. Economy

After all 85 articles were classified, it was verified that 53 papers had studied stock markets in advanced countries. Another 23 studied developing economies, and 11 were classified as not applicable. Keeping this in mind, it was possible to identify that even though there is a growing number of studies on emerging countries, their numbers cannot be compared with the studies on advanced countries, which can in its turn be considered a gap (G_1), as shown below, in the technical analysis literature.

G_1 Why are there so few studies of technical analysis that focus on developing economies or emerging countries such as the BRICS[1]? Since there may be important market frictions in emerging markets and some data may have just recently become available, this technical analysis could be explored further. In addition, less mature markets may be less efficient in the weak form when compared to longer standing markets.

5.2. Methodology

The methodology category has four subcategories: trading system, computational technique, chart pattern and not applicable. The trading system methodology was utilized in 58 of the papers studied. The computational technique was applied in 31 of the papers, the chart pattern in only 2 of the papers, and the not applicable subcategory applied to 8. Considering our database of 85 articles, it is possible to identify as G_2 that chart patterns were the least utilized method. Therefore, chart patterns should be prioritized in future studies. However, these results may also indicate that chart patterns are falling into disuse by practitioners.

G_2 Can chart patterns be combined with recent pattern recognition computer algorithms to define trading strategies that can generate abnormal returns?

5.3. Application

The application category was divided into three subcategories. The in-the-market subcategory was reflected in 80 papers, whereas 9 papers fell into the artificial market subcategory, and the not applicable subcategory applied to 1 paper. Since most of the studies focus on the in-the-market subcategory, which represents more appropriate environments to test technical analysis, we do not identify gaps within this item.

5.4. Transaction costs

This category had only two subcategories, and their presence in the study was balanced. Forty-three papers had considered transactions costs, and 43 did not. Thus, although this category was balanced, it is important to highlight that, in most cases where the transaction costs have been considered, the gains were not significant. This, in turn, may cripple practitioners' utilization of technical analysis as a tool. Based on these results, we identify gap (G_3):

G_3 Is there a consensus about the use of transaction costs in studies of technical analysis applied to stock markets? How can transaction costs, in a standardized way, be used to analyse different

[1] Brazil, Russia, India, China and South Africa.

countries? It is important to highlight that countries may also have distinct rules, not only for transaction costs but for other market frictions, such as taxes, restrictions on short selling, and so on.

5.5. Operational tools

There were nine subcategories in this category. The stochastics tool was used in 9 of the papers, the relative strength index in 10 of the papers, the genetic algorithm in 15, evolutionary reinforcement learning in 4, statistical analysis in 30, moving averages in 44, econometric models in 10, neural networks in 15 and the subcategory other in 33 of the 85 papers studied. In simple terms, it was possible to predict that moving averages and statistical analysis would show a high number of observations. However, it was observed that genetic algorithms and neural networks have been considered prominent study fields. Moreover, there are few studies that utilize reinforcement learning as a technical analysis strategy, reflecting a gap (G_4) as, shown below, in the literature.

G_4 Why do so few studies combine technical analysis with other methods? Could it not enhance results of trading strategies to combine technical analysis with, for instance, machine learning tools?

It is important to highlight that the subcategory related to technical analysis focuses on single or a combination of technical analysis indicators. However, as indicated by Neely, Rapach, Tu, and Zhou (2014), technical analysis can be aggregated with other approaches to forecast prices, including macroeconomic variables.

5.6. Profitability, predictability and risk

Taking into account category 6, the results was divided into three subcategories, and there were, respectively, 79, 6 and 4 papers in the subcategories of *supports technical analysis*, *does not support technical analysis* and *not applicable*. In addition, the results of the empirical studies were analysed using different approaches.

- Focus on prediction of market prices or movements: Some papers assess the adequacy of technical analysis models by comparing predicted prices or movements with actual market realizations using error metrics such as mean absolute percentage error (MAPE), root mean square error (RSME) and mean square error (e.g., Bisoi & Dash, 2014; Ticknor, 2013; Wei et al., 2011). Therefore, some studies aim to analyse the accuracy of the forecasted prices; and
- Comparison with the returns of the buy-and-hold strategy: In another approach to presenting results, the performance of trading rules is compared to a benchmark usually given in the buy-and-hold portfolio strategy. However, some papers just compare profitability without taking into account the portfolio's level of risk (e.g., Dymova et al., 2012; Teixeira & Oliveira, 2010).

As a descriptive research study, our focus was to summarize, categorize and find a hiatus; thus, it is not possible to determine the reason for the numbers we found. One possible explanation for the support of technical analysis could be its wide diffusion as an analysis tool, its ease of use compared with other techniques and the way it improves market liquidity.

The results from Park and Irwin's (2007) literature review are not as favourable to technical analysis as are those in our more recent study. However, it is important to point out that our study, with its focus on stock markets, took into consideration different contexts, including those in emerging countries. In fact, Park and Irwin (2007) find that economic profits are more usual in emerging stock markets, whereas it is more difficult to reject the efficient market hypothesis in more developed countries, such as the US.

Therefore, a potential explanation for the favourable results regarding technical analysis in our study is related to the fact that the more recent literature explores contexts other than developed markets. Emerging markets can be more subject to market frictions, central bank interventions and market micro-structure deficiencies, which, as discussed by Park and Irwin (2007), are potential explanations for technical trading profits.

Publication bias may also have played a role in the recent results that reject the efficient market hypothesis. For instance, Franco, Malhotra, and Simonovits (2014, p. 1502), analysing social science studies, identify that papers with strong results are more probable to be published than papers that do not reject the null hypothesis. In addition, the authors suggest that studies without contingent evidence against the null findings are not even written up by authors. Therefore, both journals and authors may be biased in publishing results that do not find evidence of the benefits of technical analysis.

In practice, technical analysis can be appealing, as it can be employed by using both quantitative and qualitative assessments of regular and recurring patterns in price developments, according to Menkhoff and Taylor (2007).

It is important to highlight that not all papers studying performance of technical analysis take into consideration the risks of trading strategies. For instance, Allen and Karjalainen's (1999) study involves identifying technical trading rules using genetic algorithm comparing excess results in relation to a buy-and-hold strategy. The authors focus on results affected by transaction costs that can arise from a more active portfolio balancing. Mabu, Hirasawa, Obayashi, and Kuremoto (2013) use genetic network programming for establishing trading signals. However, the authors do not explicitly consider risk adjustment.

In contrast, Brock et al. (1992) explore trading signals testing hypothesis that incorporate risk, by using models such as GARCH-M and EGARCH. Fama and French (2012) analyses momentum strategies in international markets, considering excess returns and Sharpe ratio. We found that only 37 papers undergo an analysis of results using some risk adjustment mechanism (Category 7). Even though risk-adjusted returns are essential to assessing adequacy of strategies (Giot & Petitjean, 2011), only 23 papers focus on techniques that try to predict whether the market will go up or down in later periods or aim to minimize forecast errors related to actual prices. It would also be emphasized that different mechanisms for risk-adjusted returns are presented, including the Sharpe Ratio, Information Ratio and Sterling Ratio (e.g. Creamer & Freund, 2010 and Neely et al., 2014). Although there are different approaches to analyse the results from technical trading strategies, it is not clear whether good technical analysis predictors of market prices or portfolios, which are more lucrative than a buy-and-hold strategy, can create value for investors. Risk-adjusted measurements are necessary to assess the performance of these strategies. Therefore, we identify another gap (G_5):

G_5 Why do some studies not analyse risk-adjusted returns to assess whether technical analysis trading strategies create value? Would results favouring technical analysis just be the consequence of the non-consideration or underestimation of risk?

As in Menkhoff and Taylor's (2007) study of technical analysis in foreign exchange markets, in our review, the evidence supporting trading rules' risk-adjusted profitability (with a focus on stock markets) leaves an open question regarding why the market dynamics do not assimilate distortions and eliminate arbitrage opportunities. Finally, in order to present an overview of the characteristics

Table 3
Summary of results by classification and category.

		Classifications							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Categories	A	53	58	80	43	9	79	37	23
	B	23	31	9	43	10	6	41	14
	C	11	2	1	–	15	4	7	13
	D	–	8	–	–	4	–	–	26
	E	–	–	–	–	30	–	–	9
	F	–	–	–	–	44	–	–	–
	G	–	–	–	–	10	–	–	–
	H	–	–	–	–	15	–	–	–
	I	–	–	–	–	33	–	–	–

Table 4
Ranking of main authors.

Index or indice	Raking of main authors				
	1	2	3	4	5
n	Hirasawa, K.; Mabu, S.	Baba, N.	Chen, Y.; Yang, Y.	Enke, D.	Chang, Y.-H.; Hu, J.
Max	Allen, F.; Karjalainen, R.	Lo, A. W.; Mamayshy, H.; Wang, J.	Sullivan, R.; Timmermann, A.; White, H.	Han, I.; Kim, K.-J.	Hendershott, T.; Jones, C. M.; Menkveld, A. J.
Sum	Allen, F.; Karjalainen, R.	Lo, A. W.	Mamayshy, H.; Wang, J.	Sullivan, R.; Timmermann, A.; White, H.	Han, I.; Kim, K.-J.
h-index	Hirasawa, K.; Mabu, S.	Chan, S.-H.; Chang, Y.-H.; Chen, Y.; Enke, D.; Hu, J.; Li, J.; Marshall, B. R.; Wang, J.-L.; Yang, Y.	*	*	*
g-index	Hirasawa, K.; Mabu, S.	Enke, D.	Chang, Y.-H.; Chen, Y.	Hu, J.; Marshall, B. R.; Metghalchi, B. R.; Zhang, Q.	*

* There are many authors in this position.

of all papers, we have presented a summary of the results for each category in Table 3.

5.7. *Impact assessment of studies and author*

In the previous section, we presented the classification of papers into categories, following the review method from Lage Junior and Godinho Filho (2010) and Jabbour (2013). Aiming to present a broader discussion of the literature review in order to further summarize and systematically analyse the body of knowledge in technical analysis, we also discuss metrics that can be used to assess the main papers and authors in the field. We searched for papers in the *Scopus* database, considering “Technical Analysis” or “Technical Trading” or “Trading Rule” as keywords in the fields “Title” and “Stock” as keyword in the fields “Title, Abstract and Keywords”. We identified 331 documents (Articles, article-in-press, conference papers, editorial, errata, letters, notes, reviews, and short surveys) related to the keywords used.

Information (Authors, Title, Year, Source Title, Volume, Issue, Art. No., Page Start, Page End, Page Count, Cited by, DOI, Link, Document Type, Source, and EID) from these documents were analysed using the package CITation ANalysis (CITAN) for the R statistical and computing environment. This R package enables identification of main indicators and indices of scientific impact. Considering all authors of the documents, we obtained the following metrics:

- Productivity (n): This indicator represents the number of papers published by a researcher as the main author or co-author;
- Highest Citation Count (Max): This indicator represents the number of citations of the most cited paper from an author;
- Overall Citation Count (Sum): This indicator reflects the total number of citations considering all papers from a given author;
- *h-index* (h): This index, proposed by Hirsch (2005), aggregates the number of papers and citations of an author. For instance, if the researcher’s h-index is equal to 7, then there are at least 7 citations of 7 of the author’s papers; and
- *g-index* (g): This index, suggested by Egghe (2006) as a variant of the h-index, aims to identify the g papers that have at least g^2 citations.

More details about h and g can be found in Gagolewski (2011) and an interesting comparison between these indices is discussed by Costas and Bordons (2008). Table 6 (Available only on the Internet Appendix) depicts the metrics for the 81 main researchers identified, taking into account the 331 documents. It is important to highlight that the total number of authors in the sample of documents is 642.

From the results in Table 6, we can analyse metrics, as shown in Table 4. For instance, results indicate that studies from Allen and Karjalainen (1999) and Lo et al. (2000) can be considered the most influential and that researchers Kotaro Hirasawa and Shingo Mabu from Japan have been frequently publishing papers in the field of technical analysis.

6. Conclusions

This study aimed to review the academic literature on technical analysis, considering stock markets. Earlier studies have also presented a literature review of technical analysis, including Menkhoff and Taylor (2007) and Park and Irwin (2007). However, our paper includes recent references and focuses mainly on stocks and stock derivatives, whereas Menkhoff and Taylor (2007) analyse foreign exchange markets and Park and Irwin (2007) review stocks, exchange rates and the derivatives markets. This research topic is useful for many practitioners and academics. Among many studies, 85 papers were selected, classified and coded into six different categories and subcategories. Subsequently, a number of research recommendations were made as a result of the findings from this paper. Although technical analysis is not a new subject, there are still many ways to study it and many new techniques that can be researched and applied using it. For example, the results show that econometric models are not frequently used to reinforce technical analysis, and the same applies to the relative strength index and to evolutionary reinforcement learning.

The results presented in this paper also give direction to new studies on the topic. Furthermore, technical analysis will be strengthened as new research is composed and published. This type of literature review can support many researchers and professors who want to know what has been studied regarding technical analysis and what the results have been.

The review allowed a thorough analysis of characteristics of papers, identifying many dimensions of research on technical analysis which we discuss in our study. It is important that although risk adjusted performance of trading rules is an important issue, if we were told to focus our study on a review of technical analysis and market efficiency, a different approach and method would be necessary.

Finally, although we have advanced the discussion regarding technical analysis, bringing newer information into comparison with previous literature reviews such as Park and Irwin (2007) and Menkhoff and Taylor (2007), there are some limitations of our study, which can be taken into account in further research. We summarize these limitations:

- Recent studies, for instance, Liu, Lu, Lu, and Lin (2013b) and Liu, Lu, Lu, and Lin (2013a), emphasize the importance of citation networks to identify research groups that focus on a specific topic within a knowledge field. However, our study did not identify any relevant citation network in the papers;
- Although Section 3 briefly discusses the main concepts of technical analysis, the aim of the paper is not to establish a thorough analysis of techniques, relevance and evolution of the topic over the years. Our goal, rather, is to enhance and update previous studies such as Park and Irwin (2007) and Menkhoff and Taylor (2007), summarizing and systematizing the significant research following the reviewing method indicated by Lage Junior and Godinho Filho (2010) and Jabbour (2013);
- Despite the fact that this study focused on stock markets, the review method can be applied to other analyses; for instance, technical analysis applied to foreign exchange markets;
- In this paper, all items related to the category "Operational tools" were studied without combining different approaches for analysing stocks. For instance, we do not consider strategies that could use technical analysis linked to fundamental analysis. However, such mixed strategies could lead to better performance and could be subject of further studies; and
- The identified overall adequacy of technical analysis for stock markets can be biased due to at least two factors. On one hand, studies that do not result in abnormal returns of technical analysis trading strategies may have a hard time being published, since there is a considerable body of knowledge favouring the weak form of market efficiency. In addition, some papers do not disclose information about risk-adjusted returns. Therefore, although technical analysis could better predict the sign of a future return or the actual price of a stock, it is not clear whether it can lead to abnormal positive risk-adjusted performance.

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Appendix A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.qref.2017.01.014.

References

Ahn, H.-J., Kang, J., & Ryu, D. (2008 Dec). Informed trading in the index option market: The case of KOSPI 200 options. *Journal of Futures Markets*, *28*(12), 1118–1146.
Allen, F., & Karjalainen, R. (1999). Using genetic algorithms to find technical trading rules. *Journal of Financial Economics*, *51*(February (2)), 245–271.
Allen, D., & Yang, W. (2004). Do UK stock prices deviate from fundamentals? *Mathematics and Computers in Simulation*, *64*(February (3–4)), 373–383.
Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, *68*(May (3)), 929–985.
Austin, M., Bates, G., Dempster, M., Leemans, V., & Williams, S. (2004). Adaptive systems for foreign exchange trading. *Quantitative Finance*, *4*(August (4)), 37–45.
Bao, D., & Yang, Z. (2008). Intelligent stock trading system by turning point confirming and probabilistic reasoning. *Expert Systems with Applications*, *34*(January (1)), 620–627.
Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, *116*(April (1)), 111–120.
Berutich, J. M., López, F., Luna, F., & Quintana, D. (2016). Robust technical trading strategies using GP for algorithmic portfolio selection. *Expert Systems with Applications*, *46*(March (1)), 307–315.
Bisoi, R., & Dash, P. (2014). A hybrid evolutionary dynamic neural network for stock market trend analysis and prediction using unscented Kalman filter. *Applied Soft Computing*, *19*(June (1)), 41–56.
Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance*, *47*(December (5)), 1731–1764.
Caporin, M., Ranaldo, A., & Santucci de Magistris, P. (2013). On the predictability of stock prices: A case for high and low prices. *Journal of Banking & Finance*, *37*(December (12)), 5132–5146.
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*(August (14)), 5963–5975.
Chan, K., Hameed, A., & Tong, W. (2000). Profitability of momentum strategies in the international equity markets. *The Journal of Financial and Quantitative Analysis*, *35*(June (2)), 153–172.
Chang, E. J., Lima, E. J. A., & Tabak, B. M. (2004). Testing for predictability in emerging equity markets. *Emerging Markets Review*, *5*(September (3)), 295–316.
Chang, P.-C., Wang, D.-d., & Zhou, C.-l. (2012). A novel model by evolving partially connected neural network for stock price trend forecasting. *Expert Systems with Applications*, *39*(January (1)), 611–620.
Chavarnakul, T., & Enke, D. (2009). A hybrid stock trading system for intelligent technical analysis-based equivolume charting. *Neurocomputing*, *72*(October (16–18)), 3517–3528.
Chen, C.-C., Kuo, Y.-C., Huang, C.-H., & Chen, A.-P. (2013). Applying market profile theory to forecast Taiwan index futures market. *Expert Systems with Applications*, *41*(September (1)), 4617–4624.
Chong, T. T.-L., & Lam, T.-H. (2010). Predictability of nonlinear trading rules in the U.S. stock market. *Quantitative Finance*, *10*(November (9)), 1067–1076.
Costa, T. R. C. C. d., Nazário, R. T., Bergo, G. S. Z., Sobreiro, V. A., & Kimura, H. (2015). Trading system based on the use of technical analysis: A computational experiment. *Journal of Behavioral and Experimental Finance*, *6*(June (1)), 42–55.
Costas, R., & Bordons, M. (2008). Is g-index better than h-index? An exploratory study at the individual level. *Scientometrics*, *77*(June (2)), 267–288.
Cowles, A. (1933). Can stock market forecasters forecast? *Econometrica*, *1*(July (3)), 309–324.
Creamer, G., & Freund, Y. (2010). Automated trading with boosting and expert weighting. *Quantitative Finance*, *10*(April (4)), 401–420.
Creamer, G. (2012). Model calibration and automated trading agent for Euro futures. *Quantitative Finance*, *12*(April (4)), 531–545.
Dawson, E. R., & Steeley, J. M. (2003). On the existence of visual technical patterns in the UK stock market. *Journal of Business Finance & Accounting*, *30*(January (1–2)), 263–293.

Dempster, M. A. H., & Jones, C. M. (2001). A real-time adaptive trading system using genetic programming. *Quantitative Finance*, *1*(April (4)), 397–413.

Dymova, L., Sevastianov, P., & Kaczmarek, K. (2012). A stock trading expert system based on the rule-base evidential reasoning using Level 2 Quotes. *Expert Systems with Applications*, *39*(June (8)), 7150–7157.

Egghe, L. (2006). Theory and practise of the g-index. *Scientometrics*, *69*(October (1)), 131–152.

Ehrentreich, N. (2008). *Agent-based modeling: The Santa Fe Institute artificial stock market model revisited*. Heidelberg: Springer Science & Business Media. No. 978-3-540-73878-7

Elliott, R. J., Hoek, J. V. D., & Malcolm, W. P. (2005). Pairs trading. *Quantitative Finance*, *5*(June (3)), 271–276.

Ellis, C. A., & Parbery, S. A. (2005). Is smarter better? A comparison of adaptive, and simple moving average trading strategies. *Research in International Business and Finance*, *19*(September (3)), 399–411.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(May (2)), 383–417.

Fama, E. F., & Blume, M. E. (1966). Filter rules and stock-market trading. *Journal of Business*, *39*(January (1)), 226–241.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(September (3)), 457–472.

Fernández-Rodríguez, F., González-Martel, C., & Sosvilla-Rivero, S. (2000). On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market. *Economics Letters*, *69*(October (1)), 89–94.

Fong, W. M., & Yong, L. H. (2005). Chasing trends: Recursive moving average trading rules and internet stocks. *Journal of Empirical Finance*, *12*(January (1)), 43–76.

Fortuny, E. J. D., Smedt, T. D., Martens, D., & Daelemans, W. (2014). Evaluating and understanding text-based stock price prediction models. *Information Processing & Management*, *50*(March (2)), 426–441.

Franco, A., Malhotra, N., & Simonovits, G. (2014). Publication bias in the social sciences: Unlocking the file drawer. *Science*, *345*(August (6203)), 1502–1505.

Friesen, G. C., Weller, P. A., & Dunham, L. M. (2009). Price trends and patterns in technical analysis: A theoretical and empirical examination. *Journal of Banking & Finance*, *33*(June (6)), 1089–1100.

Gagolewski, M. (2011). Bibliometric impact assessment with R and the CITAN package. *Journal of Informetrics*, *5*(October (4)), 678–692.

Gebka, B., Hudson, R. S., & Atanasova, C. V. (2015). The benefits of combining seasonal anomalies and technical trading rules. *Finance Research Letters*, *14*(August (1)), 36–44.

Giot, P., & Petitjean, M. (2011). On the statistical and economic performance of stock return predictive regression models: An international perspective. *Quantitative Finance*, *11*(February (2)), 175–193.

Goldbaum, D. (2003). Profitable technical trading rules as a source of price instability. *Quantitative Finance*, *3*(June (3)), 220–229.

Gorgulho, A., Neves, R., & Horta, N. (2011). Applying a GA kernel on optimizing technical analysis rules for stock picking and portfolio composition. *Expert Systems with Applications*, *38*(May (11)), 14072–14085.

Gunasekarage, A., & Power, D. M. (2001). The profitability of moving average trading rules in South Asian stock markets. *Emerging Markets Review*, *2*(March (1)), 17–33.

Hafner, C. M. (2005). Durations, volume and the prediction of financial returns in transaction time. *Quantitative Finance*, *5*(April (2)), 145–152.

Hanousek, J., & Podpiera, R. (2004). Czech experience with market maker trading system. *Economic Systems*, *28*(June (2)), 177–191.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, *66*(January (1)), 1–33.

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences*, *November (102)*(46), 16569–16572.

How, J., Ling, M., & Verhoeven, P. (2010). Does size matter? A genetic programming approach to technical trading. *Quantitative Finance*, *10*(February (2)), 131–140.

Huang, C.-J., Yang, D.-X., & Chuang, Y.-T. (2008). Application of wrapper approach and composite classifier to the stock trend prediction. *Expert Systems with Applications*, *34*(May (4)), 2870–2878.

Jabbour, C. J. C. (2013). Environmental training in organisations: From a literature review to a framework for future research. *Resources, Conservation and Recycling*, *74*(May (1)), 144–155.

Jasemi, M., Kimiagari, A. M., & Memariani, A. (2011). A modern neural network model to do stock market timing on the basis of the ancient investment technique of Japanese Candlestick. *Expert Systems with Applications*, *38*(April (4)), 3884–3890.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(March (1)), 65–91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance*, *56*(2), 699–720.

Jensen, M. C., & Benington, G. A. (1970). Random walks and technical theories: Some additional evidence. *The Journal of Finance*, *25*(May (2)), 469–482.

Kaminski, K. M., & Lo, A. W. (2014). When do stop-loss rules stop losses? *Journal of Financial Markets*, *18*(March (1)), 234–254.

Kazem, A., Sharifi, E., Hussain, F. K., Saberi, M., & Hussain, O. K. (2013). Support vector regression with chaos-based firefly algorithm for stock market price forecasting. *Applied Soft Computing*, *13*(February (2)), 947–958.

Kim, K.-j., & Han, I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. *Expert Systems with Applications*, *19*(August (2)), 125–132.

Kwon, K.-Y., & Kish, R. J. (2002). A comparative study of technical trading strategies and return predictability: An extension of using NYSE and NASDAQ indices. *The Quarterly Review of Economics and Finance*, *42*(September (3)), 611–631.

Kwon, Y.-K., & Moon, B.-R. (2007). A hybrid neurogenetic approach for stock forecasting. *IEEE Transactions on Neural Networks*, *18*(May (3)), 851–864.

Lage Junior, M., & Godinho Filho, M. (2010). Variations of the Kanban system: Literature review and classification. *International Journal of Production Economics*, *125*(May (1)), 13–21.

Lee, M.-C. (2009). Using support vector machine with a hybrid feature selection method to the stock trend prediction. *Expert Systems with Applications*, *36*(October (8)), 10896–10904.

Lee, E. J. (2013). High frequency trading in the Korean index futures market. *Journal of Futures Markets*, *35*(August (1)), 31–35.

Levy, R. A. (1967). Relative strength as a criterion for investment selection. *The Journal of Finance*, *22*(December (4)), 595–610.

Lin, S.-K., Wang, S.-Y., & Tsai, P.-L. (2009). Application of hidden Markov switching moving average model in the stock markets: Theory and empirical evidence. *International Review of Economics & Finance*, *18*(March (2)), 306–317.

Lin, X., Yang, Z., & Song, Y. (2011). Intelligent stock trading system based on improved technical analysis and Echo State Network. *Expert Systems with Applications*, *38*(September (9)), 11347–11354.

Liu, W., Huang, X., & Zheng, W. (2006). Black-Scholes' model and Bollinger bands. *Physica A: Statistical Mechanics and its Applications*, *371*(November (2)), 565–571.

Liu, J. S., Lu, L. Y. Y., Lu, W.-M., & Lin, B. J. Y. (2013a]). Data envelopment analysis 1978–2010: A citation-based literature survey. *Omega*, *41*(January (1)), 3–15.

Liu, J. S., Lu, L. Y. Y., Lu, W.-M., & Lin, B. J. Y. (2013b]). A survey of DEA applications. *Omega*, *41*(October (5)), 893–902.

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, *1*(1), 41–66.

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *The Journal of Finance*, *55*(August (4)), 1705–1770.

Mabu, S., Hirasawa, K., Obayashi, M., & Kuremoto, T. (2013). Enhanced decision making mechanism of rule-based genetic network programming for creating stock trading signals. *Expert Systems with Applications*, *40*(November (16)), 6311–6320.

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking & Finance*, *34*(November (11)), 2573–2586.

Menkhoff, L., & Taylor, M. P. (2007). The obstinate passion of foreign exchange professionals: Technical analysis. *Journal of Economic Literature*, *45*(December (4)), 936–972.

Metghalchi, M., Chang, Y.-H., & Marcucci, J. (2008). Is the Swedish stock market efficient? Evidence from some simple trading rules. *International Review of Financial Analysis*, *17*(June (3)), 475–490.

Milone, L. (2008). *Complexity and artificial markets, Vol. 614*. pp. 27–37. Springer. Ch. Market Behavior Under Zero-Intelligence Trading and Price Awareness.

Ming-Ming, L., & Siok-Hwa, L. (2006). The profitability of the simple moving averages and trading range breakout in the Asian stock markets. *Journal of Asian Economics*, *17*(February (1)), 144–170.

Mitra, S. K. (2011). How rewarding is technical analysis in the Indian stock market? *Quantitative Finance*, *11*(February (2)), 287–297.

Mizuta, T. (2016). A review of recent artificial market simulation studies for financial market regulations and/or rules. *SSRN Electronic Journal*, 1-5Available at SSRN.

Moon, Y.-S., & Kim, J. (2007). Efficient moving average transform-based subsequence matching algorithms in time-series databases. *Information Sciences*, *177*(December (23)), 5415–5431.

Neely, C. J. (2003 Spring). Risk-adjusted, ex ante, optimal technical trading rules in equity markets. *International Review of Economics & Finance*, *12*(1), 69–87.

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the Equity Risk Premium: The Role of Technical Indicators. *Management Science*, *60*(July (7)), 1772–1791.

Neftci, S. N. (1991). Naive trading rules in financial markets and Wiener-Kolmogorov prediction theory: A study of "Technical Analysis". *The Journal of Business*, *64*(October (4)), 549–571.

Ni, L.-P., Ni, Z.-W., & Gao, Y.-Z. (2011). Stock trend prediction based on fractal feature selection and support vector machine. *Expert Systems with Applications*, *38*(May (5)), 5569–5576.

Northcott, A. (2009). *The complete guide to using candlestick charting: How to earn high rates of return-safely*. Ocala: Atlantic Publishing Group Inc. No. 1601382944.

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, *103*(March (3)), 429–453.

Oliveira, F. A. d., Nobre, C. N., & Zárate, L. E. (2013). Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index – Case study of PETR4, Petrobras, Brazil. *Expert Systems with Applications*, *40*(December (18)), 7596–7606.

Omrane, W. B., & Van Oppens, H. (2006). The performance analysis of chart patterns: Monte Carlo simulation and evidence from the euro/dollar foreign exchange market. *Empirical Economics*, *30*(4), 947–971.

Oppenheimer, H. R., & Schlarbaum, G. G. (1981). Investing with Ben Graham: An Ex Ante test of the efficient markets hypothesis. *Journal of Financial and Quantitative Analysis*, *16*(September (3)), 341–360.

Osler, C. L., & Chang, P. H. K. (1995). *Head and shoulders: Not just a flaky pattern. Staff reports*. Federal Reserve Bank of New York.

Pérez-Cruz, F., Afonso-Rodríguez, J. A., & Giner, J. (2003). Estimating GARCH models using support vector machines. *Quantitative Finance*, *3*(June (3)), 163–172.

Parisi, F., & Vasquez, A. (2000). Simple technical trading rules of stock returns: evidence from 1987 to 1998 in Chile. *Emerging Markets Review*, *1*(September (2)), 152–164.

Park, C.-H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys*, *21*(September (4)), 786–826.

Park, C.-H., & Irwin, S. H. (2009). A reality check on technical trading rule profits in the U.S. futures markets. *Journal of Futures Markets*, *30*(July (7)), 633–659.

Pavlov, V., & Hurn, S. (2012). Testing the profitability of moving-average rules as a portfolio selection strategy. *Pacific-Basin Finance Journal*, *20*(November (5)), 825–842.

Pemy, M. (2012). Optimal algorithms for trading large positions. *Automatica*, *48*(July (7)), 1353–1358.

Ratner, M., & Leal, R. P. (1999). Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. *Journal of Banking & Finance*, *23*(December (12)), 1887–1905.

Roberts, H. V. (1959). Stock-market patterns and financial analysis: Methodological suggestions. *The Journal of Finance*, *14*(March (1)), 1–10.

Rodríguez-González, A., García-Crespo, A., Colomo-Palacios, R., Iglesias, F. G., & Gómez-Berbís, J. M. (2011). CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator. *Expert Systems with Applications*, *38*(September (9)), 11489–11500.

Schredelseker, K., & Hauser, F. (Eds.). (2008). *Complexity and Artificial Markets.*. Berlin, Heidelberg: Springer. No. 978-3-540-70556-7.

Schulmeister, S. (2009). Profitability of technical stock trading: Has it moved from daily to intraday data? *Review of Financial Economics*, *18*(October (4)), 190–201.

Shen, K.-Y., & Tzeng, G.-H. (2015). Fuzzy inference-enhanced VC-DRSA model for technical analysis: Investment decision aid. *The International Journal of Fuzzy Systems*, *17*(July (3)), 375–389.

Shynkevich, A. (2012). Performance of technical analysis in growth and small cap segments of the US equity market. *Journal of Banking & Finance*, *36*(January (1)), 193–208.

Sullivan, R., Timmermann, A., & White, H. (1999). Data-snooping, technical trading rule performance, and the bootstrap. *The Journal of Finance*, *54*(October (5)), 1647–1691.

Töyli, J., Sysi-aho, M., & Kaski, K. (2004). Models of asset returns: Changes of pattern from high to low event frequency. *Quantitative Finance*, *4*(June (3)), 373–382.

Tan, Z., Quek, C., & Cheng, P. Y. K. (2011). Stock trading with cycles: A financial application of ANFIS and reinforcement learning. *Expert Systems with Applications*, *38*(May (5)), 4741–4755.

Taylor, N. (2014). The rise and fall of technical trading rule success. *Journal of Banking & Finance*, *40*(March), 286–302.

Teixeira, L. A., & Oliveira, A. L. I. D. (2010). A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Systems with Applications*, *37*(October (10)), 6885–6890.

Tharavanij, P., Siraprapasiri, V., & Rajchamaha, K. (2015). Performance of technical trading rules: Evidence from Southeast Asian stock markets. *SpringerPlus*, *4*(September (1)), 1–40.

Ticknor, J. L. (2013). A Bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications*, *40*(October (14)), 5501–5506.

Tung, W., & Quek, C. (2011). Financial volatility trading using a self-organising neural-fuzzy semantic network and option straddle-based approach. *Expert Systems with Applications*, *38*(May (5)), 4668–4688.

Ülkü, N., & Prodan, E. (2013). Drivers of technical trend-following rules' profitability in world stock markets. *International Review of Financial Analysis*, *30*(December), 214–229.

Vandewalle, N., Ausloos, M., & Boveroux, P. (1999). The moving averages demystified. *Physica A: Statistical Mechanics and its Applications*, *269*(July (1)), 170–176.

Vanstone, B., & Finnie, G. (2009). An empirical methodology for developing stockmarket trading systems using artificial neural networks. *Expert Systems with Applications*, *36*(April (3)), 6668–6680.

Vanstone, B., & Finnie, G. (2010). Enhancing stockmarket trading performance with ANNs. *Expert Systems with Applications*, *37*(September (9)), 6602–6610.

Vidotto, R. S., Migliato, A. L. T., & Zambon, A. C. (2009). O Moving Average Convergence-Divergence como ferramenta para a decisão de investimentos no mercado de ações. *Revista de Administração Contemporânea*, *13*(April/June (2)), 291–309.

Wang, L.-X. (2015). Dynamical models of stock prices based on technical trading rules–Part II: Analysis of the model. *The IEEE Transactions on Fuzzy Systems*, *23*(August (4)), 1127–1141.

Wang, J.-L., & Chan, S.-H. (2007). Stock market trading rule discovery using pattern recognition and technical analysis. *Expert Systems with Applications*, *33*(August (2)), 304–315.

Wang, Z.-M., Chiao, C., & Chang, Y.-T. (2012). Technical analyses and order submission behaviors: Evidence from an emerging market. *International Review of Economics & Finance*, *24*(October (1)), 109–128.

Wang, F., Dong, K., & Deng, X. (2009). Algorithmic trading system: Design and applications. *Frontiers of Computer Science in China*, *3*(May (2)), 235–246.

Warburton, A., & Zhang, Z. G. (2006). A simple computational model for analyzing the properties of stop-loss, take-profit, and price breakout trading strategies. *Computers & Operations Research*, *33*(January (1)), 32–42.

Wei, L.-Y., Chen, T.-L., & Ho, T.-H. (2011). A hybrid model based on adaptive-network-based fuzzy inference system to forecast Taiwan stock market. *Expert Systems with Applications*, *38*(May (11)), 13625–13631.

Yamamoto, R. (2012). Intraday technical analysis of individual stocks on the Tokyo Stock Exchange. *Journal of Banking & Finance*, *36*(November (11)), 3033–3047.

Yu, H., Nartea, G. V., Gan, C., & Yao, L. J. (2013). Predictive ability and profitability of simple technical trading rules: Recent evidence from Southeast Asian stock markets. *International Review of Economics & Finance*, *25*(January (1)), 356–371.

Zapranis, A., & Tsinaslanidis, P. E. (2012). A novel, rule-based technical pattern identification mechanism: Identifying and evaluating saucers and resistant levels in the US stock market. *Expert Systems with Applications*, *39*(June (7)), 6301–6308.

Zenobia, B., Weber, C., & Daim, T. (2009). Artificial markets: A review and assessment of a new venue for innovation research. *Technovation*, *29*(May (5)), 338–350.

Zhang, G., Eddy Patuwo, B., & Hu, Y. M. (1998). Forecasting with artificial neural networks. *International Journal of Forecasting*, *14*(March (1)), 35–62.

Zhu, H., Jiang, Z.-Q., Li, S.-P., & Zhou, W.-X. (2015). Profitability of simple technical trading rules of Chinese stock exchange indexes. *Physica A: Statistical Mechanics and its Applications*, *439*(December (1)), 75–84.

Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, *92*(June (3)), 519–544.

Zielonka, P. (2004). Technical analysis as the representation of typical cognitive biases. *International Review of Financial Analysis*, *13*(June (2)), 217–225.