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Stock market trading rule discovery using technical analysis and a template matching technique for pattern recognition -
Evidence from two emerging markets

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Abstract

The major purpose of technical analysis is to predict future evolution of the price movement of securities. The existing literature has been debating the usefulness of this technique as opposed to the ideals defended by the Efficient Market Hypothesis (EMH) initially proposed by Fama (1970). Over time, this theme has invited many academics to the centre of the debate. Yet, the amount of experiments conducted with quantitative indicators represents the majority of published studies.

This study aims at investigating the predictive power of technical analysis using bull flag patterns based on a template matching technique, being this a qualitative indicator. This method is applied to the emerging stock markets of Brazil (BOVESPA) and China (SSE) as opposed to the buy everyday strategy advocated by the EMH. Additionally, the methodology used by Wang and Chan (2007) is replicated on the BOVESPA for the interval from February 1st 1995 to December 30th 2021 (about 6620 trading days) and in the SSE from February 1st 1991 to December 31st 2021 (about 7549 trading days). Moreover, this particular test has never been applied in these markets, which represents an important contribution to the literature.

The empirical results demonstrate that bull flag trading rules can correctly predict the price movement direction of both indices. Technical analysis achieved positive and significant annualized excess profits compared to the buy everyday approach, even when considering transaction costs. Moreover, shorter fitting windows and better quality of price fit values for lower holding periods are associated with better performance. In particular, for a twenty-day fitting window and holding period, the bull flag generates an annualized excess profit of 62.84% for the BOVESPA and 103.83% for the SSE in contrast to the standard approach for the best quality of fit. Consequently, this research may have relevant practical implications for investors who opt for this investment support route, fundamentally as an instrument for the asset allocation process.

Keywords: Technical analysis; Trading rule; Template matching technique; Bull flag pattern; Emerging markets.

Resumo

O principal objetivo da análise técnica é prever a evolução futura do movimento dos preços dos títulos. A literatura existente vem debatendo a utilidade desta técnica em contraposição aos ideais defendidos pela Hipótese do Mercado Eficiente (HME) proposta inicialmente por Fama (1970). Ao longo do tempo, este tema tem convidado muitos académicos para o centro do debate. Ainda assim, a quantidade de experimentos realizados com indicadores quantitativos representa a maioria dos estudos publicados.

Este estudo tem como objetivo investigar o poder de previsão da análise técnica utilizando padrões de bull flag com base numa técnica de correspondência de modelos, sendo esta um indicador qualitativo. Este método é aplicado aos mercados de ações emergentes do Brasil (BOVESPA) e China (SSE) em oposição à estratégia de compra diária defendida pela HEM. Adicionalmente, a metodologia utilizada por Wang e Chan (2007) é replicada sobre a BOVESPA para o intervalo de 1 de fevereiro de 1995 a 30 de dezembro de 2021 (cerca de 6620 dias de negociação) e sobre a SSE de 1 de fevereiro de 1991 a 31 de dezembro de 2021 (cerca de 7549 dias de negociação). Além disso, este teste em específico nunca foi aplicado nestes mercados, o que representa uma importante contribuição para a literatura.

Os resultados empíricos demonstram que as regras de negociação de bull flag conseguem prever corretamente a direção do movimento dos preços de ambos os índices. A análise técnica obteve lucros excedentes anualizados positivos e significativos em comparação com a abordagem de compra diária, mesmo considerando os custos de transação. Além disso, janelas de ajuste mais curtas e valores com uma maior qualidade no ajuste de preço para períodos de espera mais baixos estão associados a um melhor desempenho. Em particular, para uma janela de ajuste e período de espera de vinte dias, a bull flag gera um lucro excedente anualizado de 62,84% para a BOVESPA e 103,83% para o SSE em contraste com a abordagem padrão para a melhor qualidade de ajuste. Consequentemente, esta pesquisa pode ter implicações práticas relevantes para investidores que optem por esta via de apoio ao investimento, fundamentalmente como instrumento para o processo de alocação de ativos.

Keywords: Análise técnica; Regra de negociação; Técnica de correspondência de modelos; Padrão de bull flag; Mercados emergentes.

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1. Introduction

Technical analysis is of enormous relevance in the financial world since it can provide important insights into future security price movements by observing market trends. Indeed, the study of this scientific area is important for its theoretical implications, as it is the example of the concept of weak form of efficiency portrayed in the study by Fama (1970), which states that historical values and trends can not predict future prices. This means that advocates of this form of efficiency think that the use of technical analysis is limiting and does not bring great benefits. Additionally, the relevance of technical analysis can also be attested by its users (called technicians). Indeed, according to a study published by Menkhoff (2010), it was conducted a survey with "692 fund managers in five markets, namely the US, Germany, Switzerland, Italy and Thailand", where 87% of them recognize the importance of technical analysis and 18% even stated that it is their favourite way of information processing. In addition, the importance of technical analysis in the area of finance can still be translated by the number of studies published recently, as is the case of Masuku and Gopane (2022), Ayala et al. (2021), Detzel et al. (2021) and Ma and Yu (2021), which shows the liveliness of the topic.

Just to clarify, technical analysis is a trading discipline that involves exploring patterns and finding trading opportunities based on historical trading data, such as trading volume and past prices (Brown & Jennings, 1989). Regarding the academic study of technical analysis, the existing literature focuses mostly on predicting stock price movements using quantitative indicators (e.g., relative strength index, stochastics and moving average among others). On the contrary, the study we conduct is based on the usage of a qualitative indicator as a prediction variable, where it is applied a template matching technique to discover the bull flag pattern, that is, a method of calculating fit values by using a chart for pattern recognition. This technique, which is used as an integral part of the dissertation's methodology, is relatively recent and, above all, still little explored in the literature.

Moreover, existing studies using this technique are generally focused on more developed markets such as the Nasdaq Composite Index (hereafter NASDAQ), New York Stock Exchange Composite Index (hereafter NYSE) and the Dow Jones Industrial Average Index (hereafter DJIA) (Arévalo et al., 2017; Wang & Chan, 2007; Leigh, Frohlich et al., 2008; Leigh, Modani, & Hightower, 2004; Leigh, Purvis, & Ragusa, 2002; Leigh, Paz, &

Purvis, 2002; Leigh, Modani, Purvis, & Roberts, 2002). Hence, this dissertation makes an important contribution to the expansion of the literature in this field due to the innovation presented regarding the markets under investigation, namely, the Brazilian and Chinese stock markets. Indeed, this is the first time that these markets have been examined concerning the profitability extracted from technical trading rules conditioned on bull flag patterns, using a template matching technique. Also, considering the results and conclusions drawn from this research, it can become a relevant study for traders and investors focused on short-term investments.

To this end, the dissertation tries to answer the question "what will be the potential profit that an investor can obtain by exploiting bull flag technical trading rules using a template matching technique, in contrast to the buy everyday approach for the Brazilian and Chinese stock markets?". Accordingly, the method in question is implemented on the Brazilian Index for the interval that goes from February 1st 1995 to December 30th 2021, around 6620 trading days, and on the Chinese Index for the interval that goes from February 1st 1991 to December 31st 2021, around 7549 trading days. Furthermore, we find that a trading approach based on the bull flag pattern is capable of producing positive and significant annualized returns greater than those obtained with a buy everyday strategy, especially for lower holding periods, even when considering transaction costs. For instance, for a twenty-day fitting window and holding period, the bull flag produces an annualized excess profit of 62.84% over the standard market approach for the BOVESPA and of 103.83% for the SSE when the quality of fit is the best. Also, in both markets, we find that bull flag trading rules have a buy signal success rate of around 80% for the various fitting windows, in contrast to rates arising from the market-based strategy, which vary between 51% and 63%. These evidences highlight the superior predictive power of technical analysis and the possibility of obtaining abnormal returns.

The following chapter of this document briefly reviews the most relevant literature about the subject. In chapter 3, it is disclosed in greater detail not only the purposes of this research but also an explanation of the data collection and treatment processes and a description of the methods implemented for that intent. Chapter 4 exhibits and descriptively examines the empirical results obtained for each of the strategies under study. Finally, the last chapter is dedicated to the presentation of the conclusions and suggestions for possible future works to be developed on this topic.

2. Literature Review

As previously discussed, the concept of technical analysis refers to a set of charts or trading rules (i.e., technical indicators) that serve to predict future movements in security prices using only historical data (Nazário et al., 2017; Park & Irwin, 2004). This is possible since a technical analyst, who owns a portfolio of assets, intends to maximize its returns by evaluating the market based on the idea that information collected, such as trading volume and securities prices, already intrinsically includes all the fundamentals that may somehow affect the market price (Gorgulho et al., 2011). Moreover, it is also assumed that investors generally present a consistent level of information and "tend to repeat past behaviour" (Oliveira et al., 2013, p.7597). Although there are several studies in the literature on this topic, it is important to note that opinions on the effectiveness of technical analysis as a forecasting mechanism are not unanimous. Moreover, despite the density of studies, these fall mainly on quantitative forecasting techniques. Whereby, gaps in the literature on qualitative techniques need to be highlighted.

2.1. Efficient Market Hypothesis and technical analysis

One of the most famous and well-known studies in the world of finance was defined by Fama (1970) with the creation of the Efficient Market Hypothesis (hereafter EMH), which serves as a fundamental pillar for modern financial theory. Its main idea is that markets operate all of the time efficiently and, therefore, it is impossible to beat them systematically. Nonetheless, it can be distinguished three levels of market efficiency as scrutinized in the study by Jensen (1978): 1) Weak Form of the EMH states that past prices are irrelevant because the price, at this moment, has imbedded all the past information; 2) Semi-Strong Form of the EMH that suggests that all public information connected to expectations is linked to the stock price, that is, current security prices immediately and fully reflect all public information which, perceptibly, also includes past data; and 3) Strong Form of the EMH says that security prices immediately and fully reflect all known information, including private data (i.e., insider information). Due to the motivation of this dissertation, a special focus will be given to the Weak Form of efficiency as a result of the theoretical implications that it entails on technical analysis.

In addition to what has already been explained in the paragraph above, it should be noted that the Weak Form of EMH has as one of its main assumptions the concept that stock prices follow a random walk. This means that successive changes in prices are not only independent of each other but are also compliant for some probability distribution (successive returns are identically distributed). As a result, it is impossible to know what the future movement of a given security will be (Fama, 1970). Additionally, because security prices instantly and fully reflect all available information, the appearance of new data will thus be quickly incorporated into market prices, making them quoted at a fair price at all times. In consequence, it is not expected that someone will be able to obtain an economic profit (i.e., net risk-adjusted return) over a long period. Since this is a trading strategy that is based on prices whose nature is random and unpredictable, this causes the investment alphas to also be random and unpredictable (Fama & Blume, 1966; Jensen, 1978). This set of assumptions about capital market efficiency is commonly defended in many of the articles that compose the classical theories of finance, such as the EMH, and whose authors are often known as rationalists. Indeed, according to Fama (1965), a capital market is comprised of a large number of market participants who act rationally and consider all available information in the decision-making process in order to maximize their wealth. Due to competition, any new public information is instantly reflected in the security's actual price, which eradicates opportunities for abnormal returns.

Ultimately, with the information presented, it is possible to conclude that for the Weak Form of EMH to be verified, it is necessary that the use of technical analysis as a trading strategy proves to be an approach incapable of producing abnormal returns when compared to a buy and hold strategy. The latter being a long-term passive strategy. Moreover, this conjecture must remain valid whatever the sampling period, the market examined or the technique used. In the next section, it is analysed whether the use of technical analysis is capable of generating returns for its users.

2.2. Technical analysis profitability

Following the ideas defended in the EMH, the use of technical analysis will not be able to provide any excess return when considering a certain risk-return of an investment and its transaction costs. In this regard, Menkhoff and Taylor (2007) identify three relevant methodological conditions that should be approached carefully in studies whose objective is to assess the potential profitability of technical analysis: 1) Any study conducted on this matter must make it clear what are the investment alternatives, i.e. on the one hand, it is essential to detail the technical analysis strategy that is being used and, on the other hand, make a diagnosis on a strategy that is defended by the EMH. In addition, the comparison between these two alternatives should preferably include "transaction costs and interest rate carry costs" (p. 10); 2) Both strategies should explore time series features for any particular sample, addressing the significance of the results obtained and not the profitability of the strategy itself; and 3) studies must have an appropriate understanding on the form of risk, with an ex-ante outlook.

With this, it becomes imperative to highlight the study by Brock et al. (1992), as it is one of the pioneers in the use of the bootstrap technique. This is a statistical inference model for determining the probability of technical trading rules, which computes average estimates from several small samples of data. In their research, two of the most used trading rules, the moving average and the trading range break, were analyzed in the DJIA Index in a time horizon ranging from 1897 to 1986, a data collection process that contains 90 years of daily data. The empirical results show that technical analysis has predictive power and that investments guided by trading rules outperform null models such as the random walk. Although this methodology does not include trading costs, this study was replicated by Bessembinder and Chan (1998) with adjustments to the payment of dividends and trading costs. The authors conclude that before the introduction of these parameters there is statistical evidence of abnormal returns with the use of non-fundamental strategies, however introducing these costs into the equation, profits are neutralised.

The report by Park and Irwin (2004) reviews 92 studies, published between 1988 and 2004, on evidence of potential profit arising from technical analysis strategies in the stock, futures and foreign exchange markets. The authors state that 58 of these studies obtained results with significance in favour of technical analysis. In a more recent report by Nazário et al. (2017), it is made a review of the most relevant studies in the area of technical analysis, with articles published between 1959 and 2016. Surprisingly, of a total of 89 studies collected, 79 of them obtained results that corroborate the use of technical analysis for the *profitability* and *predictability* categories.

Additionally, the lower the efficiency level of a given market, the greater the probability that technical analysis strategies will obtain statistically significant abnormal returns. Indeed, empirical evidence shows that trading rules can perform better in emerging markets than in developed markets, where the level of efficiency in the latter is higher (Marshall et al., 2010).

2.3. Quantitative and qualitative indicators in technical analysis

In practice, it is possible to divide the different methods of technical analysis into two large groups according to the indicators used - quantitative and qualitative techniques, whose objective is to guide investors to make a decision based on the captured signals (Wang & Chan, 2007; Agrawal, 2010). Indeed, methodologies that use quantitative indicators build forecasts and provide trading signals through a quantitative investigation of time series data. This imposes some strictness on the technician, since he has to comply with the rules inherent to the mathematical function that comes from the indicator (Menkhoff & Taylor, 2007).

Although there are many quantitative techniques with numerous variations, perhaps the most popular, as they are also the most used, the moving average convergence/divergence model developed by Appel (1979). His model works both as an indicator of trend and momentum through a relationship between two moving averages of prices for a given security. Also, the relative strength index created by Wilder (1978), classified as a momentum indicator capable of measuring the magnitude and speed of price changes. And, lastly, the bollinger bands technique designed by Bollinger (1992), where the key variable of this indicator is the security's volatility.

Concerning studies aimed at developed markets, Wong et al. (2003) analysed the Singapore Stock Exchange for a period between 1974 and 1994. Its empirical results show that the moving average and relative strength index indicators are capable of producing positive returns with statistical significance. The same results were obtained with the applicability of these indicators on the London Stock Exchange, as opposed to a buy-and-hold strategy, reinforcing the idea that technical analysis has significant predictive power (Chong & Ng, 2008). Additionally, Gebka, Hudson and Atanasova (2015) concluded that an investment approach that combines seasonal anomalies and certain trading rules, such as the moving average, can significantly predict returns for the S&P500 and DJIA indices with a low level of transaction costs, more suitable for portfolios with low diversification. Other studies, more specifically that of Butler and Kazakov (2010), in the DJIA from 1990 to 2009, show that quantitative trading rules, such as the bollinger band model, can generate significant abnormal returns and outperform a buy and hold strategy even in situations where transaction costs are included in the equation. The report by García et al. (2018) focusing on the German Dax-35 Stock Index, argues that active strategies, that resort to the use of stock market trends, can statistically predict the direction of price movement and make a profit. Nonetheless, implementing strategies that apply many different quantitative indicators can generate a lot of noise and affect the predictive level of the model.

On the other hand, regarding emerging markets, the study conducted by de Souza et al. (2018) examines the profitability of technical analysis through the application of moving average trading rules to the stock exchanges of BRICS member countries (Brazil, Russia, India, China and South Africa). It is concluded that the returns obtained are higher than the initial amounts invested and significantly superior to the buy and hold benchmark, with emphasis on India and Russia, where the results were stronger. Also, Stanković et al. (2015) selected the moving average and relative strength index as quantitative indicators and inputs for a machine learning model. Their empirical results for the Bulgarian, Serbian, Romanian and Croatian stock markets are in favour of the use of technical analysis as opposed to the Weak Form of market efficiency. Along the same line, Hrušová (2011) shows that the application of quantitative indicators in seven Central and Eastern European stock markets provides significant abnormal returns in almost all of them. The author also argues that technical trading rules are easier to enforce in markets characterized by having a lower level of efficiency, liquidity and development. To conclude, according to Vidotto, Migliato and Zambon (2009), the use of the moving average technique is a good tool to help investors obtain an abnormal return, superior to the return of the Ibovespa (Brazilian Stock Market) through stock buy and sell signals. Yet, the author recommends not using the moving average as a stand-alone tool, but rather with the complementarity of other techniques such as stochastics or the relative strength index.

In addition to the widely used techniques that are expressed algebraically, there is another category of technical analysis defined by qualitative indicators that help to identify certain visual patterns (Chang & Osler, 1995). The latter are techniques that can assist investors in the decision-making process when managing a portfolio through signals obtained with the recognition of non-linear visual patterns and removal of noisy data for the considered time horizon (Omrane & VanOppens, 2006). These techniques lead practitioners and academics to rely on something that goes beyond numbers and that ends up telling much more because "a picture is worth a thousand numbers" (Anand et al., 2001, para. 3). Among the most popular visual patterns of traditional technical analysis, it is important to highlight three of them: 1) the *head-and-shoulder*, whose chart pattern is composed of three peaks, the two ends very close in height, called *shoulders,* and the peak in the middle, bigger than the previous ones, called *head*; 2) the *rounded tops and bottoms*, where the *rounded top* is a bearish long-term pattern that shows the approach of the end of a positive trend and, conversely, the *rounded bottom* is a bullish long-term pattern that indicates the approach of the end of a downward trend; and 3) the *flag* in which there is a fluctuation in a countertrend between two parallel lines until a breakout occurs (Chang & Osler, 1995; Lo et al., 2000; Caginalp & Balevonich, 2003). *Figure 1* illustrates a hypothetical example of a bull flag, a charting pattern that is explained in more detail in the next subchapter.

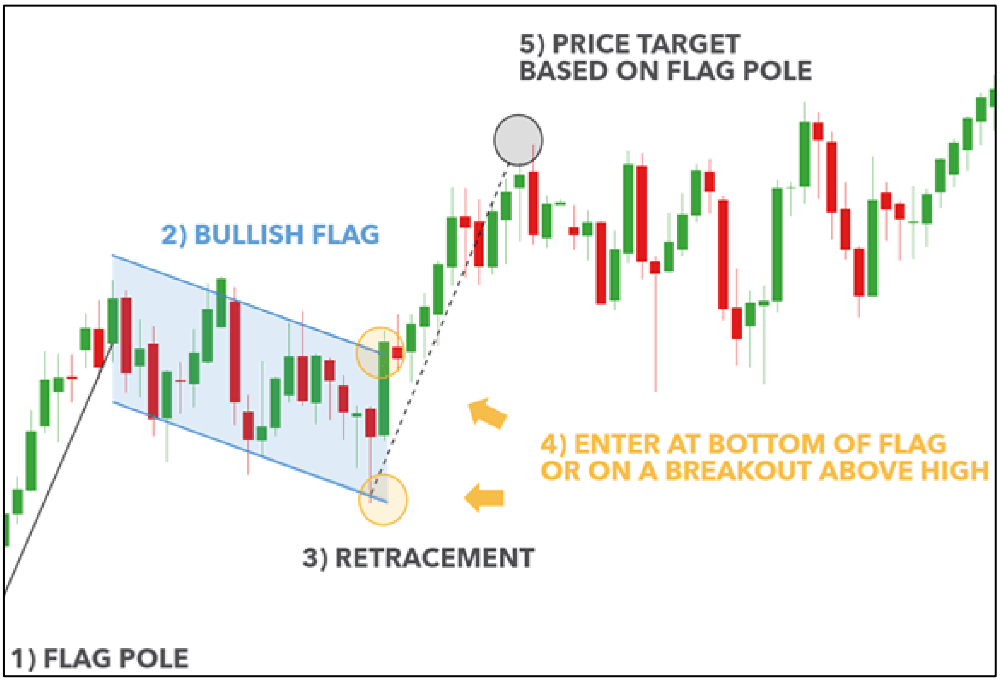

Figure 1: Illustration of a bull flag pattern (Venketas, 2019).

Considering the breadth of existing studies on technical analysis, there is an excess of experiments that use quantitative indicators rather than pattern charting techniques, which are "comparatively rare" (Wang & Chan, 2007, p. 305). In the most recent review of studies performed in the field of technical analysis by Nazário et al. (2017), in a total of 85 relevant studies admitted to the category *methodology*, the chart pattern is used in only eight of them (Roberts, 1959; Fama, 1970; Neftci, 1991; Lo et al., 2000; Dawson & Steeley, 2003; Wang & Chan, 2007; Friesen, Weller, & Dunham, 2009; Zapranis & Tsinaslanidis, 2012). These and other articles are covered more prominently in the next subchapter.

2.4. Charting patterns in technical analysis

One of the first published studies on this type of indicator is that of Roberts (1959). In his article, the author makes a comparison between a time series of random numbers and the current price series from the DJIA Index, where he found that price changes are caused by an accumulated random number. Despite having still found some patterns in stock prices, Roberts (1959) argues that these trends arise by chance and that they can mislead investors if they believe they have any predictive power. Moreover, Fama (1970) reviews the literature on market efficiency, including some studies based on price chart patterns, further formulating the EMH. According to the author, the evidence to date is favourable to the market efficiency model however "much remains to be done" (p. 416).

In turn, the study by Neftci (1991) on the DJIA Index for the sample period from 1792 to 1976, presents empirical evidence in favour of technical analysis as a tool for forecasting future movements in stock prices with significant results for the period from 1911 to 1976. In particular, the author uses a trading strategy guided by signals generated by a 150-day moving average rule in conjunction with head-and-shoulders and triangle patterns.

Additionally, Lo et al. (2000) used a nonparametric kernel regression on US stocks of the main indices to identify ten popular patterns, which include head-and-shoulders, triangle tops and bottoms, and rectangle tops and bottoms, among others. The authors argue that while this is not a guarantee for all markets and time horizons, technical analysis has predictive power and constitutes an important factor in the investment process. Subsequently, Dawson and Steeley (2003) applied the methodology used by Lo et al. (2000) in the UK stock market and the conclusions remained the same, mentioning only that technical analysis in the UK yielded stronger predictability results.

Another pattern also analyzed in the literature is the *volume spike* characterized by an exponential increase in trading volume in a short period, usually associated with the beginning or end of a trend (Leigh et al., 2005). According to Leigh et al. (2005), the use of volume spike patterns identified through a template matching technique can robustly predict price changes of shares listed on the NYSE Index. Also, Leigh and Purvis (2008) show that the implementation of a stock purchase strategy when a spike in its transaction volume is identified, presents statistically significant positive results for long time horizons for the main market indices such as the DJIA and S&P500. Also, according to the authors, this trading strategy is closely linked to the phenomenon of market momentum, which refers to the ability of an extended trend to sustain itself in the market into the future.

Alternatively, Friesen, Weller, and Dunham (2009) developed a theoretical model that explains the success of trading rules based on head-and-shoulders and double-top patterns. Their model also incorporates the phenomenon of confirmation bias, capable of generating price momentum. This bias can be described as the search for evidence or the interpretation of information in a manner that supports one's expectations or beliefs.

The report by Wang and Chan (2009) examines the predictability of the rounding top and bottom patterns that signal the optimal timing of purchases of several U.S. tech stocks. The empirical data obtained suggest that trading rules, where these patterns are applied, can positively predict stock price movements, compared to the alternative strategy of buying every day indicated as an optimal approach by the EMH. Similarly, in the research made by Zapranis and Tsinaslanidis (2012), for the same data collected, the authors chose to add a short-term rolling window to reduce problems of data mining by identifying non-continuous patterns. With this new methodology, although it reached the same major conclusion as the study by Wang and Chan (2009), it was also observed that abnormal returns from the technical strategy were being diluted over time as one progressed to more recent years.

Ultimately, the bull flag pattern is considered a downward or horizontal continuation of the technical flag chart pattern, followed by a breakout expressed by a sudden positive increase and consequent extension of the trend (Leigh, Purvis, & Ragusa, 2002; Pring, 1991). In the literature dedicated to the analysis of this pattern, namely that of Leigh, Frohlich et al. (2008), Leigh, Modani, and Hightower (2004), Leigh, Purvis, and Ragusa (2002), Leigh, Paz, and Purvis (2002) and Leigh, Modani, Purvis, and Roberts (2002), the conclusions are all homogeneous and around the failure of the EMH to correctly describe the way markets operate. This happens because investors can systematically beat the market using simple bull flag pattern recognition models. Yet, although methodologically there are minor changes in the way in which the bull flag pattern is discovered and analyzed, both in terms of trading window fit values and in terms of the templates used, and differences in the period of analysis, all these studies focus on the NYSE Index. In particular, Leigh, Modani, Purvis, and Roberts (2002) study two variations of the bull flag which fall over the period from August 6^{th} 1980 to June 9^{th} 1999. At a confidence level of 95%, bull flag 1 and bull flag 2 recorded a significant average excess return of 6.70% and 5.12% over a buy everyday approach with 100-day holding periods. Likewise, the research by Leigh, Modani, and Hightower (2004) is applied over the period from January 28^{th} 1981 to September 15^{th} 1999, approximately 4697 trading days. The authors conclude that the bull flag strategy generates a significant annualized excess return of 45.9% over buying the NYSE everyday for a holding period of twenty days with the best price fit and positive window price change.

In addition to these studies, there is a paper that is central to this dissertation, which is the article published by Wang and Chan (2007) because we have replicated the methodology presented in it, but now for a couple of different markets that were never tested before for this purpose. These authors use a template matching technique to find bull flag patterns as a technical trading rule, for the NASDAQ and Taiwan Weighted Index (hereafter TAIEX), the former being a highly developed market and the latter an emerging market. This study is applied to daily NASDAQ Index values ranging from April 3^{rd} 1985 to March 20^{th} 2004, about 4785 trading days, and to TAIEX price data ranging from June 1^{st} 1971 to March 24^{th} 2004, which corresponds to 9284 trading days. The empirical results obtained confirm that it is possible to use technical trading rules to correctly predict changes in price direction for both markets. Furthermore, the authors conclude that the better the bull flag template price fit, the higher the average return and thus, using bull flag conditional trading rules is significantly better than the strategy of buying every day for the study period. Additionally, the empirical data obtained for the TAIEX were somewhat better than those obtained for the NASDAQ, which confirms the premise already defended in other studies that emerging markets, being less efficient, allow a better performance of technical analysis as a forecasting tool (Marshall et al., 2010). For instance, for a twenty-day fitting window in conjunction with the best template price fit, the bull flag was able to produce annualized returns of 20.93% for the NASDAQ and 46.49% for the TAIEX when the holding period is minimal. Under the same conditions, the market-based strategy of buying every day only obtained returns of 12.77% and 15.22%, respectively. Moreover, the ratio of the number of buy signals sent by the bull flag that translated into positive returns varies between 62.03% and 68.92% for the NASDAQ and between 52.97% and 57.78% for the TAIEX. Since these figures are superior to those obtained by the strategy defended by the EMH, the authors also argue that bull flag trading rules have greater predictive power. Indeed, the uniqueness of this dissertation resides in the fact that the study by Wang and Chan (2007), among others, has only been implemented in developed markets, or at most, in less significant emerging markets such as the TAIEX.

Besides, the template matching technique, although not widely explored in the literature, is also used in some more recent studies such as the one presented by Chen and Chen (2016). The authors suggest a hybrid model that combines template matching with the Perceptually Important Points (PIP) identification matching method to recognize a bull-flag stock pattern. The PIP method consists of reducing the number of data points in a time series while maintaining the relevant ones. Through their empirical results, it is possible to conclude that the proposed model outperforms popular algorithms like the *rough set theory* (RST) and *genetic algorithms* (GAs) when comparing returns for TAIEX and NASDAQ.

Lastly, there is also the paper by Arévalo et al. (2017), where the authors present a new dynamic mechanism that incorporates flag pattern recognition using a template matching based on the study by Cervelló-Royo et al. (2015) that introduced two new parameters, stop loss and take profit. According to the results obtained for the DJIA Index, their method outperforms the base approach of Cervelló-Royo et al. (2015) and the buy and hold strategy for factors such as profitability and risk.

3. Research Question and Methodology

In this section, although already briefly discussed in the *Introduction*, it is addressed in greater detail the major research question of this dissertation. Additionally, to obtain empirical evidence on the subject, it is also presented a brief portrayal of the collection and treatment processes of all the data used in this research. To conclude, the last subchapter reveals the methodological steps to be followed within the framework of the markets under analysis.

3.1. Research question

The research we conduct aims at investigating the potential profit of bull flag technical trading rules, using a template matching technique, in contrast to the market average returns for the emerging stock markets of Brazil and China - Brazil Stock Market Index (hereafter BOVESPA) and the Shanghai Stock Exchange Composite Index (hereafter SSE), respectively. In other words, this analysis tries to assess whether trading success can be achieved with charting patterns, which helps to fill a double gap in the literature on the topic of technical analysis. Indeed, the amount of experiments conducted with quantitative indicators represents a large part of the published studies and, therefore, as the model involved in our investigation only incorporates qualitative indicators, this contributes to balance the literature. Additionally, this methodology has never been tested in emerging markets, at least the most important ones since there are studies available on the Taiwanese stock market (Wang & Chan, 2007; Chen & Chen, 2016).

Furthermore, this study can add relevant evidence to the literary debate about the effectiveness of technical analysis, and can also contribute to the discussion of the premise that technical analysis has a better performance in emerging markets than in developed markets.

3.2. Data

Regarding the data collection process, this study essentially focuses on the exploration and comparison of strategies returns that are based on technical analysis as opposed to the returns "offered" by the emerging markets of Brazil and China. Hence, by accessing the statistical and financial database *Thomson Reuters Eikon Datastream* platform, it was only required to collect a set of daily index values for each of the markets - a data series ranging from February 1st 1995 to December 30th 2021, a time interval of 27 years, and February 1st 1991 to December 31st 2021, a time interval of 31 years, for the BOVESPA and SEE Indeces respectively. It should be noted that the difference of four years in the starting date of the Brazilian sample period compared to the Chinese one is attributable to the lack of sufficiently robust data from the digital platform. Indeed, the time horizon implemented in this analysis is quite similar to that found in most of the relevant literature. Some studies scrutinize indices over 16-year periods (Chen & Chen, 2016), 19-year periods (Leigh, Modani, & Hightower, 2004; Leigh, Paz, & Purvis, 2002), 33-year periods (Wang & Chan, 2007) and 35-year periods (Leigh, Frohlich et al., 2008). It is also important to highlight that the index values are expressed in the currency of the country they represent. Yet, for the purposes of comparing returns, and the number of buys, among other variables, this is something that does not cause any blunder since all empirical data are expressed in the same units.

Even before implementing any type of method, the collected values first underwent a treatment process that consisted of removing duplicates. This is related to the fact that the platform on which they were gathered was counting every day of the week, including holidays, as a trading day (i.e., when a stock exchange is open for investors to trade). In numerical terms, this procedure made it possible to eliminate 425 days on the BOVESPA Index and 539 days on the SSE Index, totalling 6620 and 7549 valid trading days for the considered time horizons, respectively.

In addition to the index values, it is also mandatory to obtain information about the weights used in the template that define the bull flag pattern, something that can be easily found in the article published by Wang and Chan (2007) and shown in *Figure 3* of the next subchapter.

3.3. Methodology

As mentioned earlier, the methodology presented next is a replica of the study developed by Wang and Chan (2007), that applies a pattern recognition technique to identify the bull flag, which is a charting pattern used to detect buy signals. In reality, it is necessary to make a distinction between a template matching technique and a pattern recognition technique. The former uses price data as fitting values, and and the latter uses a template to detect patterns through a pictographic image, since both these techniques constitute the first steps to be taken in this process (Duda & Hart, 1973, as cited in Wang & Chan, 2007).

By way of comparison, *Figure 2* presents the template created by Leigh, Purvis, and Ragusa (2002) and *Figure 3* the template used by Wang and Chan (2007):

0.5	0	-1	-1	-1	-1	-1	-1	-1	0
1	0.5	0	-0.5	-1	-1	-1	-1	-0.5	0
1	1	0.5	0	-0.5	-0.5	-0.5	-0.5	0	0.5
0.5	1	1	0.5	0	-0.5	-0.5	-0.5	0	1
0	0.5	1	1	0.5	0	0	0	0.5	1
0	0	0.5	1	1	0.5	0	0	1	1
-0.5	0	0	0.5	1	1	-0.5	0.5	1	1
-0.5	-1	0	0	0.5	1	1	1	1	0
-1	-1	-1	-0.5	0	0.5	1	1	0	-2
-1	-1	-1	-1	-1	0	0.5	0.5	-2	-2.5

Figure 3: A 10 x 10 grid of weights ranging from -2.5 to 1.00 used in Leigh, Purvis, and Ragusa (2002) to display the bull flag charting pattern.

-.25	-.4	-.45	-.7	-1.5	-1.6	-1.6	-1.6	-1.6	-.7
-.25	-.4	-.45	-.6	-.75	-1.4	-1.4	-1.4	-.8	1
-.25	-.4	-.45	-.55	-.5	-.75	-.75	-.5	-.5	.4
-.25	-.4	-.45	-.55	-.25	.9	.9	.9	-.15	-.35
-.25	-.5	-.6	-.25	.9	1	1	1	1	-.55
-.3	-.6	-.25	.8	1	.9	.9	.9	.8	-.45
-.35	.1	.8	1	.65	.6	.6	.4	.75	-.15
.1	.8	1	.5	.3	.5	.5	.3	0	.1
.8	1	.5	.35	.15	0	0	0	.3	.35
1	.8	.35	0	0	0	0	.1	.25	.3

Figure 2: A 10 x 10 grid of weights ranging from -1.65 to 1.00 used in Wang and Chan (2007) to display the bull flag charting pattern.

The numbers contained in the templates are weights that permit to define the bull flag pattern in the grey marked squares. The calculation of these weights is done using a machine learning method based on artificial neural networks (Leigh, Paz, & Purvis, 2002). Nevertheless, this is a process that involves a certain degree of arbitrariness as it depends on how the user conceives the image he wants to represent in the template (Zapranis & Tsinaslanidis, 2012). In turn, the numbers that constitute the weights are extracted from the network and can be used for image characterization purposes. Also, the higher the value assigned to a weight, the closer that template pixel is to the optimal representation of a bull flag. For example, in *Figure 3*, Wang and Chan (2007) first categorize a bull flag pattern transcribed in a template by an upward trend, as is possible to identify in the first five columns, then between columns six and nine a horizontal consolidation and, in the last column, the representation of an ascending breakout. Although the research of these authors focuses on the same topic, the constitution of their templates is different because for Leigh, Purvis, and Ragusa (2002) the bull flag pattern is primarily defined as a downtrend followed by an upward breakout, using prices and trading volumes as fitting values. Instead, for Wang and Chan (2007) this pattern is described as a horizontal flag of consolidation followed by a positive trend where prices are the only fitted values. Ultimately, according to Wang and Chan (2007), the way the weights are predisposed in the template presented in *Figure 2* can make the fitting process unreliable. This happens because "the rising flag template fit" may be "lower than that of the declining flag", which can negatively affect the robustness of the forecasts (p. 306). On the contrary, the template in *Figure 3* manages to stably detect price increases, being these essential for the process of identifying a bull flag pattern. For this reason, we will use the template created by Wang Chan (2007) as one of the integral tools of the forecasting procedure.

With the template defined, it must then be combined with the information collected on the daily prices of the SSE and BOVESPA Indeces for several p trading day windows, p = {20, 40, 60, 80, 100 and 120}, to obtain fitting values (hereafter Fit_K). These latter ones will serve as inputs for the application of conditional trading rules.

Moreover, this type of analysis is subject to the possibility of non-synchronous trading results, which is a measurement error that can cause overestimation in the returns of securities that are being assessed using observed data (Scholes & Williams, 1977; Bessembinder & Chan, 1995). Nevertheless, this occurrence can easily be counteracted by adding one day lag to the time the transaction is made relative to the buy signal, that is, the buy signal is followed by a day of delay before the transaction takes place (Ratner & Leal, 1999, as cited in Wang & Chan, 2007). In consequence, the calculation of Fit_K, which evaluates the quality of fit between the bull flag matching template and the various trading windows with p trading days, will infer that each of the trading days is defined as K-1 in the sample period.

However, even before calculating the Fit_K results, it is first essential to rank the p-days daily index values in descending order of quality by dividing them into 10 portions. Therefore, concerning the image grid $I_{t,i}$, the values of each cell in row i are determined through a combination between each cell and the ten intervals of time series as shown in the following formula:

$$\mathrm{It,i} = 1 \text{ if } (i-1).\frac{p}{10} < Rank\ (Trading\ day) \leq i.\frac{p}{10},$$

$$\mathrm{It,i} = 0, \text{otherwise.}$$

For each Index, this process needs to be replicated six times as there are six different fitting windows. Subsequently, for each cell in a J column, it is adopted the same procedure as the one applied to rows so that this price matching technique can map all the cells of a template. In particular, if the index value for the trading day t matches with the jth column, then $J_{t,j} = J$; otherwise, $J_{t,j} = 0$ as shown in the formula below:

$$\mathrm{Jt,j} = \frac{1}{\frac{p}{10}} \text{ if } (j - 1).\ \frac{p}{10} < t\ (time\ series)\ \leq j\ .\frac{p}{10},$$

$$\mathrm{Jt,j} = 0, \text{otherwise.}$$

Hence, $I_{t,I}$ and $J_{t,j}$ must satisfy the following condition:

$$\sum_{t=1}^{p}\sum_{i=1}^{10}\sum_{j=1}^{10}\left(I_{t,i} \cdot J_{t,j}\right) = 10\ ,$$

where for a certain day t, there is only one $I_{t,I}$ and $J_{t,j}$ defined as I and J, respectively, and the others are equal to zero. Accordingly, the above equation can be rewritten as:

$$p\ .I\ .J\ =\ 10\ ,$$

therefore,

$$I = 1\ ,$$

$$J = \frac{10}{p}\ .$$

By way of example, *Table 1* and *Table 2* displayed below represent the mapping of each trading day, in this case for a fitting window of twenty tradable days, incident on the SSE Index, since each day under the series is correlated with a certain value of I and J that can range from 1 to 10:

Table 1*:* The image grid's values of $I_{t,i}$ for the first trading days of the SSE Index in a 20-day fitting window.

Date	Index values	Rank	i (row)									
			1	2	3	4	5	6	7	8	9	10
01/02/1991	128.84	20	0	0	0	0	0	0	0	0	0	1
01/03/1991	130.14	18	0	0	0	0	0	0	0	0	1	0
01/04/1991	131.44	15	0	0	0	0	0	0	0	1	0	0
01/07/1991	132.06	12	0	0	0	0	0	1	0	0	0	0
01/08/1991	132.68	10	0	0	0	0	1	0	0	0	0	0
01/09/1991	133.34	8	0	0	0	1	0	0	0	0	0	0
01/10/1991	133.97	6	0	0	1	0	0	0	0	0	0	0
01/11/1991	134.6	3	0	1	0	0	0	0	0	0	0	0
01/14/1991	134.67	2	1	0	0	0	0	0	0	0	0	0
01/15/1991	134.74	1	1	0	0	0	0	0	0	0	0	0
01/16/1991	134.24	5	0	0	1	0	0	0	0	0	0	0
01/17/1991	134.25	4	0	1	0	0	0	0	0	0	0	0
01/22/1991	133.72	7	0	0	0	1	0	0	0	0	0	0
01/23/1991	133.17	9	0	0	0	0	1	0	0	0	0	0
01/24/1991	132.61	11	0	0	0	0	0	1	0	0	0	0
01/25/1991	132.05	13	0	0	0	0	0	0	1	0	0	0
01/28/1991	131.46	14	0	0	0	0	0	0	1	0	0	0
01/29/1991	130.95	16	0	0	0	0	0	0	0	1	0	0
01/30/1991	130.44	17	0	0	0	0	0	0	0	0	1	0
01/31/1991	129.97	19	0	0	0	0	0	0	0	0	0	1

Source: own calculations. These dates correspond to the first twenty trading days of the entire horizon under analysis, in this case, it goes from 01/02/1991 to 01/31/1991. The numbers of the variable *Rank* are defined from the index values for the trading days belonging to the fitting window and organized in descending order (i.e., the higher the index value, the better the corresponding rank). The values of $I_{t,I}$ are presented for each cell in a row *i*, matching each of the rows to one of the ten columns identified by index values.

Table 2: The image grid's values of $J_{t,j}$ for the first trading days of the SSE Index in a 20-day fitting window.

Date	Index values	t	J (column)									
			1	2	3	4	5	6	7	8	9	10
01/02/1991	128.84	1	0.5	0	0	0	0	0	0	0	0	0
01/03/1991	130.14	2	0.5	0	0	0	0	0	0	0	0	0
01/04/1991	131.44	3	0	0.5	0	0	0	0	0	0	0	0
01/07/1991	132.06	4	0	0.5	0	0	0	0	0	0	0	0
01/08/1991	132.68	5	0	0	0.5	0	0	0	0	0	0	0
01/09/1991	133.34	6	0	0	0.5	0	0	0	0	0	0	0
01/10/1991	133.97	7	0	0	0	0.5	0	0	0	0	0	0
01/11/1991	134.6	8	0	0	0	0.5	0	0	0	0	0	0
01/14/1991	134.67	9	0	0	0	0	0.5	0	0	0	0	0
01/15/1991	134.74	10	0	0	0	0	0.5	0	0	0	0	0
01/16/1991	134.24	11	0	0	0	0	0	0.5	0	0	0	0
01/17/1991	134.25	12	0	0	0	0	0	0.5	0	0	0	0
01/22/1991	133.72	13	0	0	0	0	0	0	0.5	0	0	0
01/23/1991	133.17	14	0	0	0	0	0	0	0.5	0	0	0
01/24/1991	132.61	15	0	0	0	0	0	0	0	0.5	0	0
01/25/1991	132.05	16	0	0	0	0	0	0	0	0.5	0	0
01/28/1991	131.46	17	0	0	0	0	0	0	0	0	0.5	0
01/29/1991	130.95	18	0	0	0	0	0	0	0	0	0.5	0
01/30/1991	130.44	19	0	0	0	0	0	0	0	0	0	0.5
01/31/1991	129.97	20	0	0	0	0	0	0	0	0	0	0.5

Source: own calculations. These dates correspond to the first twenty trading days of the entire horizon under analysis, in this case, it goes from 01/02/1991 to 01/31/1991. The numbers of the variable t are defined from time series. The values of $J_{t,j}$ are presented for each cell in a column j, matching each of the dates to one of the ten columns identified by time series.

Finally, the Fit_K value for trading day k can be determined, knowing that the higher the Fit_K values, the better the bull flag template price fit. Fit_K's equation is a cross-multiplication between "the template grid's weight" presented in *Figure 3* and the "scale values of the image grid for each cell in row i and column j", shown below (Wang & Chan, 2007, p. 307):

$$Fit_k = \sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{t=1}^{p}\left(w_{i,j} \cdot I_{t,i} \cdot J_{t,j}\right).$$

For a given trading day k, in case the Fit_K is higher than a trading threshold (T), the investor must buy on that same day, since the method already incorporates the one-day lag, then hold the securities for q number of days, and only afterwards sell.

In opposition, to determine whether a charting approach, using the bull flag pattern, is better than certain trading policies considered optimal for the EMH, such as buying every day or at random, the market average return should be calculated as follows:

$$Market\ Average\ Return = \frac{\sum_{k=m}^{n}\left[\left(X_{k+q} - X_k\right)/X_k\right]}{n-m+1},$$

next, the average return from the strategy of technical analysis is computed with the subsequent formula:

$$Trading\ Rule\ Average\ Return = \frac{\sum_{k=m}^{n}\left[\left(X_{k+q} - X_k\right).\ B_k/X_k\right]}{\sum_{k=m}^{n} B_k} \quad \text{where,}$$

$\mathbf{X_k}$ is the index value on trading day k,

q represents the holding period, where q = 20, 40, 60, 80 and 100,

m the first trading day in a sub-period of comparison,

n the last trading day in a sub-period of comparison,

$\boldsymbol{\sum_{k=m}^{n} B_k}$ signifies the number of buys with, $B_k = 1$, if $Fit_K \geq T$,

$B_k = 0$, otherwise.

Ultimately, it is verified whether technical analysis can generate significant abnormal returns compared to the benchmark returns defended by the EMH through the formula:

$$Excess\ Profit = Trading\ Rule\ Average\ Return - Market\ Average\ Return\,.$$

Alternatively, it can be found in *Appendix 1* a complementary note with a simpler explanation of the methodology applied in this study with hypothetical illustrative examples.

4. Empirical results and data analysis

This chapter is divided into five subchapters, namely: section 4.1 which displays the average returns inherent to each investment strategy; section 4.2 exposes the excess profit that one approach has over another, deepening and providing more insights into the performance of implemented investment policies; section 4.3 presents empirical results about the market timing of each strategy; section 4.4 expresses the outcome of statistical tests performed on the robustness of empirical data across various non-overlapping sub-periods; and, finally, section 4.5 which tests the performance of a third possible approach entitled "buying run".

4.1. Average return

Firstly, a rate of return can be defined as a gain or loss on an investment made over a particular period, usually specified as a percentage of the investment expense. Likewise, the average return is a mathematical and financial statistic that can help an investor in the process of measuring and judging the past performance of a given security or a portfolio. Additionally, the analysis of this aspect also becomes important especially with regard to the investment decision process in the search for the strategy that will ensure a higher level of return (Brandão, 2014).

To recapitulate, this study confronts two investment strategies based on divergent ideals using two samples of very long data series of emerging market index values, the first of which is shown in *Table 3*. This table presents a set of average returns from the SEE Index, more specifically market average returns and bull flag trading rule average returns. These are dependent on the available modalities, that is, for the various fitting windows (*p*), holding periods (*q*) and threshold values (*T*) for the entire period under analysis, from February 1st 1991 to December 31st 2021.

Table 3: Performance of the market-based and trading rules strategies implemented in the SSE Index for the period ranging from 01/02/1991 to 12/31/2021.

Market			Bull Flag							
			T=0		T=1		T=2		T=3	
p	q	Average Return (%)	N(buys)	Average Return (%)	N(buys)	Average Return (%)	N(buys)	Average Return (%)	N(buys)	Average Return (%)
20	20	1.58	5167	2.60	3785	3.75	2326	6.87	1381	9.76
20	40	3.33	5167	5.56	3785	7.80	2326	12.73	1381	16.66
20	60	5.13	5167	8.17	3785	10.65	2326	15.90	1381	21.27
20	80	6.84	5167	10.47	3785	13.57	2326	19.43	1381	27.18
20	100	8.65	5167	12.77	3785	16.20	2326	23.23	1381	33.37
40	20	1.58	5213	0.56	3603	0.94	2238	1.93	1338	3.13
40	40	3.33	5213	4.01	3603	6.55	2238	10.38	1338	13.52
40	60	5.13	5213	7.78	3603	12.18	2238	18.29	1338	24.04
40	80	6.84	5213	10.05	3603	15.33	2238	23.22	1338	31.20
40	100	8.65	5213	12.48	3603	18.09	2238	26.16	1338	35.26
60	20	1.58	5210	0.53	3529	1.23	2177	2.15	1190	3.33
60	40	3.33	5210	3.12	3529	5.45	2177	8.72	1190	12.30
60	60	5.13	5210	6.91	3529	11.62	2177	18.95	1190	28.41
60	80	6.84	5210	10.44	3529	17.35	2177	27.05	1190	40.02
60	100	8.65	5210	13.22	3529	21.07	2177	30.99	1190	46.06
80	20	1.58	5386	0.39	3846	0.42	2141	0.27	1266	0.37
80	40	3.33	5386	2.28	3846	2.85	2141	3.36	1266	4.02
80	60	5.13	5386	5.38	3846	6.75	2141	8.38	1266	10.79
80	80	6.84	5386	8.94	3846	11.55	2141	18.21	1266	24.28
80	100	8.65	5386	12.26	3846	16.35	2141	27.05	1266	37.39
100	20	1.58	5140	0.67	3553	1.30	2057	0.90	1182	2.37
100	40	3.33	5140	2.84	3553	4.33	2057	3.29	1182	6.42
100	60	5.13	5140	5.75	3553	8.21	2057	7.03	1182	11.68
100	80	6.84	5140	9.02	3553	12.57	2057	12.51	1182	19.82
100	100	8.65	5140	12.92	3553	18.53	2057	22.93	1182	32.64
120	20	1.58	4746	0.39	3405	0.12	1950	0.58	978	2.01
120	40	3.33	4746	1.53	3405	2.07	1950	3.84	978	6.58
120	60	5.13	4746	3.62	3405	5.44	1950	9.19	978	12.64
120	80	6.84	4746	6.55	3405	9.46	1950	15.35	978	20.95
120	100	8.65	4746	10.15	3405	14.69	1950	24.06	978	35.91

Source: own calculations. p represents the number of days in the fitting window, which can range from 20 to 120 days. Both trading strategies buy and hold for a q number of trading days in the horizon period, which can range from 20 to 100 days. T refers to the threshold implicit in the trading rules. N(buys) symbolizes the number of buy signals indicated by the trading rules. The market average return is the average daily profit generated from buying on every day. The bull flag average return is the trading rule average profit generated from buying on the days indicated by the rules.

The investment plan shown in the first columns of the table can be portrayed as a strategy of buying the SSE Index for all tradable days, a trading policy advocated by the EMH. On the other hand, the remaining columns exhibit the results referring to a policy focused on technical analysis and driven by bull flag trading rules. For both strategies, it is possible to identify that each fitting window may have allocated five different holding periods, q = {20, 40, 60, 80, and 100}. Also, in general, the longer the holding period, regardless of the window, the greater is the average return assigned to a given strategy. For instance, with regard to the buy everyday strategy, it generates an average daily market return of 1.58% for a fitting window and a holding period of twenty days. On the other hand, under the same conditions, a trading policy based on the bull flag manages to generate an average return per buy signal of 9.76% for a $t = 3$, which corresponds to the best template price fit of this study. This specific trading rule ($Fit_k \geq 3$) delivered 1381 buy signals in a total of 7549 trading days.

Nevertheless, it is interesting to note that for the market-based strategy, each holding period corresponds to a single average return value, completely independent of the number of days chosen to compose the fitting window. This phenomenon can be explained by the intrinsic condition of the trading policy that is buy the index everyday, causing the fitting windows to be entirely composed of days in which an investment was made. Consequently, this neutralises any effect on the return caused by the variation in the number of days that each window encompasses. In contrast, this same phenomenon is not observed when implementing the method based on technical analysis, as the buy signals are not triggered daily, but rather through a system of trading rules that integrate bull flag patterns. In other words, bull flag returns are influenced by the quality of Fit_k, which naturally incorporates the value chosen as the p-trading day fitting window, as explained in the subchapter dedicated to the description of the methodology. Instead, the implementation of conditional trading rules is associated with another event, which is related to the empirical result that, commonly, for holding periods of shorter duration and small fitting windows, the greater the number of p-days in the fitting window, the lower the average returns.

In addition, bull flag average returns are categorized according to different threshold levels and can assume the values of T = {0, 1, 2 and 3}. A threshold value can be defined, in this case, as being a lower limit of a hypothetical Fit_k measure from which the conditional trading rules issue a buy signal, that is, $B_k = 1$ if $Fit_k \geq T$ and $B_k = 0$, otherwise. On this wise, the empirical findings show the existence of another event related to the fact that there is a direct and positive relationship between the values assumed as threshold and the obtained returns, so that the higher the value of *T*, the greater the average return. For example, for a $p = 20$ and $q = 20$, the bull flag average returns were 2.60%, 3.75%, 6.87% and 9.76% for respectively increasing *T* values. These outcomes are in agreement with other studies performed on emerging markets with the same purpose, such as the Taiwanese stock market (Wang & Chan, 2007). Under the same variables, trading rules generated average returns of 1.73%, 2.25%, 3.24% and 3.87% for increasing *T* levels in the TAIEX. In fact, increasing the threshold value makes the required level of Fit_k's quality also higher, which means that better degrees of template price fit lead trading rules to present better performance, reaching higher average returns. On the contrary, the approach of buying every day does not require the stipulation of any threshold as no condition prevents the purchase of the index on any trading day.

It is also worth noting that each fitting window has an immutable number of days on which there was a buy indication, regardless of the holding period that can be chosen. This event occurs because each trading day is associated with a value of Fit_k, and the purchase of the index is decided based on the relationship of Fit_k's quality, on that trading day, relative to the threshold. Therefore, the number of days the investment is held has no impact on the quantity of signals captured by trading rules. Moreover, the increase in the value assigned to the threshold causes the number of buy signals to decrease since higher Fit_k volumes are required, but on the other hand, as previously mentioned, it improves the performance of the bull flag. Meanwhile, if the method used is the one supported by the EMH, the methodological process is simpler because the number of trading days that compose the sample period is equal to the number of times the index is bought.

Empirically, above all, the results observed in *Table 3* illustrate that, in general, bull flag conditional trading rules can validly predict changes in the direction of the SSE Index values regardless of the fitting window, with the exception of a few remarks. Indeed, as the number of *p*-trading days increases, bull flag average returns tend to deteriorate, registering lower values than market returns on some occasions, mainly for shorter holding periods. As an example, this phenomenon occurs for a $p = 20$, $q = 100$ and $T = 0$, in which the return obtained by the bull flag was 0.67%, being lower than the associated market average return, which was 1.58%. Likewise, despite not indicating any observation of a worse performance of the bull flag in relation to the standard strategy, this trend is also verified in the TAIEX (Wang & Chan, 2007). For instance, with a p = 20, q = 20 and T = 0, the average return of the bull flag was very similar to that of the buy everyday strategy (1.28% and 1.27%, respectively), while for a q = 100 the difference between these results is higher (7.21% and 6.91%, respectively). In reality, flag charts are often classified as "trend-following patterns" and are of enormous relevance to investors because they are labelled as a period in which it is conceivable to obtain abnormal profits with little risk in rising markets (Arévalo et al., 2017, p. 2; Wang & Chan, 2007). This is a conception that can be demonstrated by the results achieved in this study.

These outcomes are similar to those obtained by Wang and Chan (2007) when testing TAIEX, although, in this case, there was no indication of observations with worse performance than the market. As a consequence of these empirical findings and only considering average returns, an investor who is interested in buying the Chinese Index should follow strategies focused on searching for investment opportunities based on short fitting windows. Similarly, in the article published by Leigh, Modani, and Hightower (2004), bull flag strategies applied on the NYSE Index with the shortest fitting windows are those that record the highest average returns for positive window price changes during the period from 1981 to 1999. Also, Wang and Chan (2007) hold that an approach that uses shorter fitting windows can magnify the performance of technical analysis when applied to both the NASDAQ and TAIEX Indeces.

In parallel, *Table 4* presents the average returns obtained according to the different modalities for the strategies under analysis implemented in the Brazilian Index, from February 1st 1995 to December 30th 2021.

Table 4: Performance of the market-based and trading rules strategies implemented in the BOVESPA Index for the period ranging from 01/02/1995 to 12/30/2021.

Market			Bull Flag							
			T=0		T=1		T=2		T=3	
p	q	Average Return (%)	N(buys)	Average Return (%)	N(buys)	Average Return (%)	N(buys)	Average Return (%)	N(buys)	Average Return (%)
20	20	1.40	4366	2.37	2954	3.58	1756	4.95	970	6.35
20	40	2.91	4366	4.98	2954	7.36	1756	9.49	970	11.54
20	60	4.39	4366	6.14	2954	8.47	1756	10.36	970	13.04
20	80	5.83	4366	7.15	2954	9.11	1756	10.75	970	13.24
20	100	7.28	4366	8.92	2954	11.07	1756	12.65	970	14.91
40	20	1.40	4736	0.86	3411	1.40	1993	2.81	1085	3.73
40	40	2.91	4736	4.12	3411	5.79	1993	9.52	1085	12.52
40	60	4.39	4736	6.86	3411	9.46	1993	15.13	1085	19.26
40	80	5.83	4736	8.45	3411	11.04	1993	16.97	1085	21.02
40	100	7.28	4736	9.82	3411	12.24	1993	17.63	1085	20.84
60	20	1.40	4786	0.33	3467	-0.22	2244	0.04	1251	0.07
60	40	2.91	4786	1.79	3467	2.03	2244	3.66	1251	5.31
60	60	4.39	4786	4.91	3467	6.38	2244	9.42	1251	12.98
60	80	5.83	4786	7.72	3467	9.87	2244	14.09	1251	18.53
60	100	7.28	4786	9.35	3467	11.82	2244	16.34	1251	20.56
80	20	1.40	4535	0.77	3379	0.46	2038	0.85	1181	1.32
80	40	2.91	4535	2.45	3379	2.68	2038	3.85	1181	5.27
80	60	4.39	4535	5.30	3379	6.31	2038	8.21	1181	11.15
80	80	5.83	4535	8.37	3379	10.08	2038	13.76	1181	18.32
80	100	7.28	4535	10.97	3379	13.28	2038	18.43	1181	23.92
100	20	1.40	4528	0.44	3132	0.19	1980	0.38	1036	-0.75
100	40	2.91	4528	1.73	3132	1.75	1980	2.67	1036	0.97
100	60	4.39	4528	3.79	3132	4.16	1980	5.56	1036	4.42
100	80	5.83	4528	6.32	3132	7.52	1980	9.26	1036	9.68
100	100	7.28	4528	9.48	3132	12.00	1980	14.70	1036	16.24
120	20	1.40	4583	0.75	3249	0.81	1971	0.22	1172	0.62
120	40	2.91	4583	2.10	3249	2.36	1971	2.55	1172	3.56
120	60	4.39	4583	3.75	3249	4.11	1971	5.49	1172	6.19
120	80	5.83	4583	5.64	3249	6.30	1971	8.24	1172	9.87
120	100	7.28	4583	8.16	3249	9.61	1971	12.86	1172	15.14

Source: own calculations. *p* represents the number of days in the fitting window, which can range from 20 to 120 days. Both trading strategies buy and hold for a *q* number of trading days in the horizon period, which can range from 20 to 100 days. *T* refers to the threshold implicit in the trading rules. N(buys) symbolizes the number of buy signals indicated by the trading rules. The market average return is the average daily profit generated from buying on every day. The bull flag average return is the trading rule average profit generated from buying on the days indicated by the rules.

To facilitate the inspection of analogies between indices of different physical spaces, both *Table 3* and *Table 4* present the results achieved for the same categories of variables and over a similar time perspective. Indeed, contemplating the two tables, each phenomenon and trend documented for the SSE Index are also broadly verified, albeit with other magnitudes, for the BOVESPA. Despite the high degree of similarity between the two indices, it is perhaps important to note that although in most observations there is a positive connection between the threshold and the average return, there are some exceptions where the return decreases. This happens more intensively for strategies that combine the largest fitting windows with p = {60, 80, 100 and 120} with the shortest holding period, which is twenty days. For example, in the situation where $p = 80$ and $q = 20$, bull flag average returns range from 0.46% to 1.32% (depending on the threshold), being far below than the market average return of 1.40% for the BOVESPA. This episode is in line with the results published in the study by Wang and Chan (2007) from the examination of the NASDAQ Index, a developed market. Under these same conditions, the bull flag average returns range from 0.91% to 1.10% (depending on the threshold), with the exception of the observation characterized by a $T = 2$ where the return was 1.10%. Even though, for the remaining observations of the NASDAQ, the direct and positive relationship between T and average returns is not always true and explicit or even to the same extent as that reflected in the BOVESPA Index.

Furthermore, it is possible to testify in the BOVESPA that, for most of the figures, bull flag conditional trading rules can overcome the daily buying strategy with returns superior to those "offered" by the market. However, as attested in the previous paragraph, there are some cases where technical analysis leads to underperformance relative to the market strategy, a pattern that thickens as the number of p-trading days used in the fitting windows increases and the time in which assets are held is reduced. As an example, when $p = 120$ and $T = 0$, the bull flag can only outperform the base strategy when the holding period is maximum ($q = 100$). In this case, the trading rule average return was 8.16%, being higher than the market's 7.28%. By comparison, under these circumstances, it was registered as an underperformance of the bull flag regardless of any q for the NASDAQ Index, and the exact opposite was true for the TAIEX (Wang & Chan, 2007). Particularly, for a $q = 100$, the bull flag average return was 4.48% for the NASDAQ and 7.81% for the TAIEX, as opposed to the returns generated by the buy everyday strategies of 5.44% and 6.91%, respectively.

Accordingly, the experiment reveals that the Chinese Index presents a higher success rate of strategies based on the bull flag pattern relative to the Brazilian one, reinforcing the idea that the BOVESPA Index has a superior level of efficiency (Marshall et al., 2010). According to PwC (2017), even though both markets are considered emergent they can be at different stages of maturity, given that in some observations of *Table 4* not even with the best quality of Fit_k (T = 3) it is possible to assure that technical analysis surpasses the EMH's approach.

Ultimately, as a curiosity, *Table 5* presents some descriptive statistics about the returns generated by bull flag strategies for each of the indices.

Table 5: Descriptive statistics of bull flag returns.

Descriptive Statistics	p	BOVESPA	SSE
		Bull Flag	Bull Flag
Average returns per fitting window	20	8.82	13.90
	40	10.47	13.76
	60	7.75	15.45
	80	8.29	11.37
	100	5.53	9.79
	120	5.42	9.26
Median of average returns per fitting window	20	9.02	12.75
	40	9.67	12.33
	60	7.05	11.96
	80	7.26	7.57
	100	4.29	7.62
	120	4.80	6.56
Standard deviation of average returns per fitting window	20	3.44	7.97
	40	6.41	10.16
	60	6.43	13.19
	80	6.69	10.15
	100	5.01	8.42
	120	4.19	9.28
Maximum return of a trading operation		122.74	387.32
Maximum return date		01/14/1999	12/30/1991
Minimum return of a trading operation		-59.48	-66.51
Minimum return date		30/03/1998	06/30/1992
Number of observations (index values)		6620	7549

Source: Own calculations. The mean, median and standard deviation are calculations performed on the results shown in *Table 3* and *Table 4* for the different fitting windows. The maximum and minimum return of a trading operation refer to the bull flag maximum and minimum return of a single trade resulting from a buy signal generated by a given trading rule.

4.2. Excess profit

This subchapter is similar to the previous one as both portray the profitability of the investment strategies in question, but now for a set of particular circumstances in order to deepen the investigation of their performance. Hence, *Table 6* presents detailed evidence about other profitability indicators of both trading policies, in situations where the investor chooses to use a twenty-day fitting window and simultaneously the best available price fit values, which occur when $Fit_k \geq 3$.

Table 6: Performance of the market-based and trading rules strategies for both indices, when $p = 20$ and $T = 3$, for the sample period.

		Market			Bull Flag (T = 3)						
p	q	Average Return (%)	Annualized Return (%)	Standard Deviation	N(buys)	Average Return (%)	Transaction Cost (%)	Annualized Return (%)	Standard Deviation	Annualized Excess Profit (%)	
Panel A: SSE Composite Index											
20	20	1.58	20.09	13.63	1381	9.76	4.88	123.93	16.14	103.83	(0.0000) [x]
20	40	3.33	21.14	21.37	1381	16.66	8.33	105.80	27.03	84.66	(0.0000) [x]
20	60	5.13	21.71	27.35	1381	21.27	10.64	90.06	35.85	68.35	(0.0000) [x]
20	80	6.84	21.72	31.36	1381	27.18	13.59	86.30	46.64	64.58	(0.0000) [x]
20	100	8.65	21.98	35.32	1381	33.37	16.69	84.76	56.10	62.78	(0.0000) [x]
Panel B: BOVESPA Index											
20	20	1.40	17.78	8.75	970	6.35	3.18	80.62	8.33	62.84	(0.0000) [x]
20	40	2.91	18.45	12.83	970	11.54	5.77	73.29	11.07	54.85	(0.0000) [x]
20	60	4.39	18.57	15.45	970	13.04	6.52	55.20	14.11	36.63	(0.0000) [x]
20	80	5.83	18.52	17.62	970	13.24	6.62	42.03	16.76	23.50	(0.0000) [x]
20	100	7.28	18.50	19.97	970	14.91	7.46	37.87	19.06	19.38	(0.0000) [x]

Source: own calculations. p represents the number of days in the fitting window, in this case twenty days. Both trading strategies buy and hold for a q number of trading days in the horizon period, which can range from 20 to 100 days. The annualized excess profit is the difference between the annualized return achieved by the bull flag trading rules and the annualized return derived from the market strategy defined as buy on everyday. Both annualized returns and annualized excess profits are calculated based on the 254 trading days existing in a calendar year. The transaction cost corresponds to the theoretical value that the cost of an operation of a single transaction would need to have in order for it to be able to offset the gains generated by the bull flag trading strategy. The formula used for this purpose is as follows: $\textit{Transaction Cost} = \frac{Average\ Return}{2}$.

[x] 5% significance level assigned to t-tests.

Both the average daily return and annualized return are two measures commonly employed when inferring the performance of a financial portfolio, however, in this case, it is necessary to make a distinction between the two. On the one hand, the average return is methodologically computed using a simple arithmetic average of the daily returns on the days indicated by the trading rules (Brandão, 2014). Nonetheless, if one wants to retain some sort of conclusion regarding the performance of trading rules with different holding periods, it is important to resort to estimates expressed as annualized returns rather than average returns. Indeed, this study is applied to two emerging markets that have been expanding over the years. Thus, if one analyzes merely the average of the generated returns, it is quite natural that they are higher the longer the holding period. This way, the annualized return calculates the average amount of money earned by a given investment(s) on an annual basis that comprises 254 trading days and is dependent on the holding period of the assets. As a result, this measure allows the comparison of strategies based on trading rules with different holding periods (Wang & Chan, 2007). Henceforth, inferences about the performance of any trading approach are mainly supported by estimations of annualized returns.

The experimental results in *Table 6* are circumscribed by twenty-day fitting windows, as this is the only *p* capable of generating bull flag average returns that are higher than those from the buy everyday strategy for both Indices, regardless of the holding period or threshold value. Also, due to the empirical fact highlighted above of better results in terms of bull flag performance for fitting windows with shorter days. Besides, the observations are constrained to the maximum threshold for the reason already clarified in *subchapter 4.1.,* and that is common to both Indices, in which, generally, the higher the value attached to *T*, the higher the average returns deducted from technical analysis.

In addition, considering the whole time scope, the empirical results show a positive and statistically significant annualized excess profit for all holding periods in both indices. In other words, for a significance level of 5% and/or a confidence level of 95%, the execution of trading rules under the circumstances inherent to this experiment and based on the bull flag, can generate investments with a higher profit than that obtained by a market approach. In fact, these explanatory variables are associated with low *p*-values, making it necessary to reject the null hypothesis that surplus profits are not significant (Oliveira, Santos & Fortuna, 2018). Besides, these findings continue to be true even when considering the existence of transaction costs. This is an important aspect as it is a factor that makes the data analysis closer to reality. Indeed, the column in *Table 6* referring to *transaction cost* relates to the theoretical value that the cost of operating a single transaction would need to have so that, in their entirety, the costs involved in buying and selling a given index on the days indicated by the trading rules, were able to offset the bull flag average gains. For example, for the bull flag average return characterized by a trading rule that has a $p = 20$ and $q = 20$ to be offset by the associated transaction costs, the unit cost of a trading operation would have to be 4.88%. Thus, considering reasonable transaction costs[1], the bull flag approach continues to be profitable and with better results than the buy everyday strategy, since the theoretical costs indicated in *Table 6* are shown to be very high.

Moreover, contrary to the average return, *Table 6* glimpses an opposite event, which is related to the fact that an increase in the holding period is associated with a decrease in excess profit for both Indices. In the particular case of the BOVESPA, the bull flag annualized excess return when $q = 20$ was 62.84%, while for a $q = 100$ it was only 19.38%. Hence, based on this empirical observation, investors should hold index assets for as little time as possible to maximize their possible gains, in this case, twenty days. In the literature, this trend is in line with the study published by Wang and Chan (2007) for the NASDAQ and TAIEX Indices. For instance, the excess annualized return of the bull flag when $q = 20$ was 31.27% for the TAIEX, while for a $q = 100$ it was only 7.41%. Nevertheless, according to Leigh, Modani, and Hightower (2004), this investment policy is only viable when the market presents a positive window price change because if it is falling (usually connoted as a bear market), the opposite will be true for the NYSE Index. Indeed, for a negative window price change, the annualized excess profit of the bull flag was -25.4% for $q = 20$, which was lower than the excess recorded for $q = 100$ of around 10.8%.

In this context, the standard deviation can be seen as a measure of investment risk as it determines the dispersion of the securities yield around its average. Accordingly, the bigger the movement of index values, the greater the market volatility, which increases the standard deviation (Brandão, 2014). According to the figures available in *Table 6*, the

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[1] For more information about fees and taxes charged by the SSE, consult the following link: http://english.sse.com.cn/start/taxes/. The fees and taxes charged by the BOVESPA can be consulted at the following link: https://www.b3.com.br/en_us/products-and-services/fee-schedules/listed-equities-and-derivatives/equities/ibovespa-and-brazil-index-50-fees/options/. Additionally, according to Leippold, Wang, and Zhou (2022, p. 80), "25 bps might be a reasonable estimate of transaction cost in the Chinese stock market during normal times".

execution of conditional trading rules on the BOVESPA Index can not only significantly increase the return on investment, but at the same time reduce risk exposure, compared to the buy everyday strategy. This is a phenomenon that has also been supported in other similar studies (Leigh & Purvis, 2008; Wang & Chan, 2007; Leigh, Purvis, & Ragusa, 2002). Regarding the Chinese Index, the standard deviation associated with the bull flag is greater than that observed in the market for any *q*, but the average returns linked to trading rules are significantly higher. Thus, using the coefficient of variation that calculates an investment total risk per unit of return, it can be noticed that the underlying risk of the bull flag is lower than that of the buy everyday strategy, as shown in *Table 7* (Reed, Lynn, & Meade, 2002).

Table 7: Representation of the coefficient of variation for each trading strategy.

p	q	Coefficient of variation	
		Market	Bull Flag
Panel A: SSE Composite Index			
20	20	8.62	1.65
20	40	6.42	1.62
20	60	5.33	1.69
20	80	4.58	1.72
20	100	4.08	1.68
Panel B: BOVESPA Index			
20	20	6.25	1.31
20	40	4.42	0.96
20	60	3.52	1.08
20	80	3.02	1.27
20	100	2.74	1.28

Source: own calculations. p represents the number of days in the fitting window, in this case twenty days. Both trading strategies buy and hold for a q number of trading days in the horizon period, which can range from 20 to 100 days. The coefficient of variation (CV) can be calculated using the following formula: $CV = \frac{Standard\ Deviation}{Average\ Return}$.

Despite that, considering the variable referring to excess profits, the results show greater success in terms of technical analysis performance incident on the SSE Index than the BOVESPA. Yet, compared to other studies, both these indices achieved higher excess profits than the emerging market of Taiwan, although subject to very different experimental periods with the consequences that this entails in terms of the analogy's veracity with the study by Wang and Chan (2007).

4.3. Market timing

The empirical results presented in *Table 6* indicate that buy signals derived from bull flag patterns and captured by conditional trading rules generate the best performance when p = 20, q = 20, and $Fit_k \geq 3$. Interestingly, among the displayed data, this is the observation in which the annualize excess profit is maximum and, at the same time, the standard deviation is minimum for both indices. As in section *4.2. Excess profit*, this subchapter intends to provide additional detailed information about the performance of the aforementioned trading strategies, under the same conditions. In particular, it investigates the forecasting ability related to changes in the direction of the stock index series as shown in *Table 8*.

Table 8: Buy signals success.

p	q	Market			Bull Flag (T = 3)		
		N (buys)	N (r > 0)	Ratio (%)	N (buys)	N (r > 0)	Ratio (%)
Panel A: SSE Composite Index							
20	20	7549	3948	52.30	1381	1124	81.39
20	40	7549	3905	51.73	1381	1132	81.97
20	60	7549	3947	52.29	1381	1093	79.15
20	80	7549	4030	53.38	1381	1096	79.36
20	100	7549	4148	54.95	1381	1079	78.13
Panel B: BOVESPA Index							
20	20	6620	3830	57.85	970	810	83.51
20	40	6620	3963	59.86	970	856	88.25
20	60	6620	4148	62.66	970	841	86.70
20	80	6620	4231	63.91	970	784	80.82
20	100	6620	4213	63.64	970	780	80.41

Source: own calculations. p represents the number of days in the fitting window, in this case twenty days. Both trading strategies buy and hold for a q number of trading days in the horizon period, which can range from 20 to 100 days. N(r > 0) symbolizes the number of buy signals that subsequently translated into positive returns. *Ratio* corresponds to the fraction of N(r > 0) divided by N(buys).

Firstly, according to Nazário et al. (2017), articles belonging to the technical analysis literature can present at least one of two different approaches when it comes to examining empirical results. First, through an analogy in terms of achieved returns, where it is often considered a benchmark strategy that supports a contrasting view regarding technical analysis, in particular, a buy-and-hold portfolio strategy. Alternatively, by evaluating the degree of accuracy relative to the predictions made on market price movements, which is typically the least employed by the authors and that corresponds to this subchapter.

The statistics in *Table 8*, more specifically those assigned to the variable designated as *Ratio*, indicate the percentage of success allocated to the forecasting power of technical analysis by comparing predictions about changes in the direction of each index value, that is, if the market will continue to rise or, instead, will have a decline in the future. This indicator is thus expressed by the number of buy signals that resulted in positive returns, relative to subsequent actual changes in the market. Empirically, it is possible to observe that for the Chinese market this quotient varies between 78.13% and 81.97%, whereas for the Brazilian market it fluctuates between 80.41% and 88.25%. Hence, the holding period is a less relevant factor in the SSE than in the BOVESPA Index in terms of forecast accuracy. Moreover, all these values are greater than those registered by the buy everyday strategy, regardless of the holding period. In consequence, based on these results, the bull flag strategy can accurately predict the movement of market prices, promptly signalling opportunities for price increases. This mechanism, in turn, improves the return associated with its investments, outperforming the market strategy.

As already mentioned earlier, for a p = 20 and $Fit_k \geq 3$, the bull flag reaches its best performance when q = 20. In this case, regarding the fraction of buys that resulted in a return greater than zero, this quotient is maximum when q = 40 for both markets. Nonetheless, it should also be noted that the existing figures for q = 20 and q = 40 are very close, which reinforces the outcomes displayed in *Table 6*. Similarly, Wang and Chan (2007) argue that technical analysis structured in bull flag conditional trading rules has an effectively higher degree of prediction than a buy everyday approach. Furthermore, the ratio between the number of buys with a positive return and the total number of buys reaches its maximum (i.e., the minimum forecast error) at 66.02% for the emerging market of Taiwan when q = 20 and 73.27% for the NASDAQ when q = 100 (Wang & Chan, 2007).

4.4. Robustness of empirical results for several non-overlapping sub-periods

The main purpose of this subchapter is to test the robustness of the results expressed in *Table 6*, particularly, the trading rule that had the best performance. To this end, the overall sample period is divided into five non-overlapping sub-periods of equivalent duration for the BOVESPA and SSE Indices, as illustrated in *Figure 4* and *Figure 5*, respectively. Subsequently, in *Table 9*, these time horizons are investigated individually in terms of their average and annualized returns. In consequence, this information makes it possible to assess whether the bull flag's performance is due to the good results of a specific sub-period or if, on the contrary, it is explained by a generalized trend.

Figure 4: Historical movement representation of the BOVESPA Index prices for several non-overlapping sub-periods (02/01/1995 to 12/30/2021).

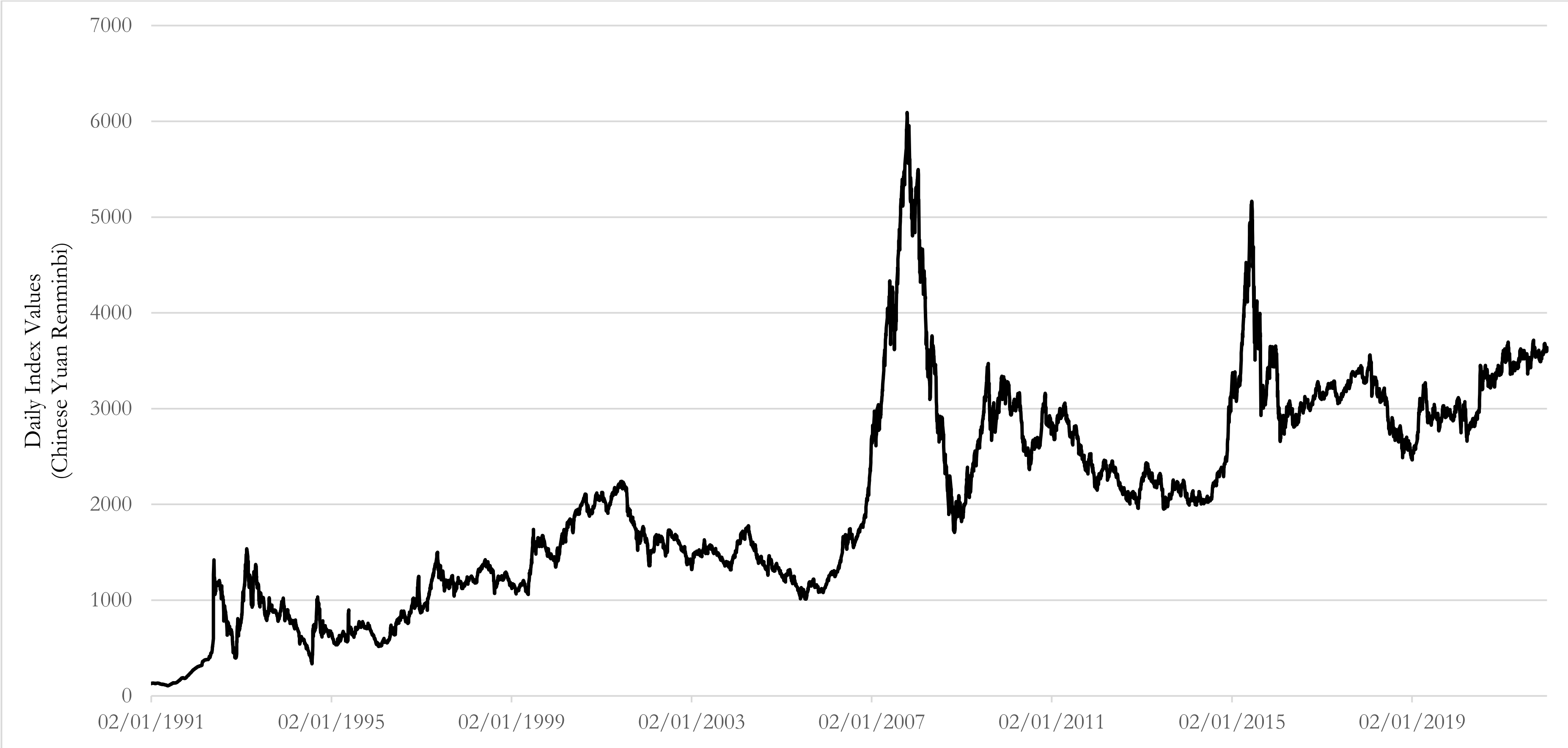

Figure 5: Historical movement representation of the SSE Composite Index prices for several non-overlapping sub-periods (02/01/1991 to 12/31/2021).

Table 9: Performance of the market-based and trading rules strategies for both indices, when $p = 20$, $q = 20$ and $T = 3$, for several non-overlapping sub-periods.

			Market				Bull Flag (T = 3)					
p	q	Sub-period	N(buys)	Average Return (%)	Annualized Return (%)	Standard Deviation	N(buys)	Average Return (%)	Annualized Return (%)	Standard Deviation	Annualized Excess Profit (%)	
Panel A: SSE Composite Index												
20	20	1	1510	5.01	63.61	26.24	375	19.33	245.50	25.57	181.90	(0.0000) [x]
20	20	2	1510	0.96	12.24	7.63	253	6.16	78.20	8.73	65.96	(0.0000) [x]
20	20	3	1510	1.45	18.45	9.39	305	9.50	120.68	8.14	102.24	(0.0000) [x]
20	20	4	1510	0.32	4.00	7.41	220	5.86	74.45	8.79	70.45	(0.0000) [x]
20	20	5	1509	0.23	2.98	6.78	228	2.11	26.78	4.33	23.80	(0.0000) [x]
Panel B: BOVESPA Index												
20	20	1	1324	3.06	38.88	12.44	241	8.44	107.23	11.20	68.35	(0.0000) [x]
20	20	2	1324	1.37	17.34	8.53	155	6.21	78.88	8.03	61.55	(0.0000) [x]
20	20	3	1324	1.35	17.18	7.55	185	5.18	65.81	6.09	48.62	(0.0000) [x]
20	20	4	1324	0.03	0.44	6.58	148	5.34	67.79	5.89	67.35	(0.0000) [x]
20	20	5	1324	1.18	14.99	7.11	241	5.86	74.37	7.57	59.37	(0.0000) [x]

Source: own calculations. p represents the number of days in the fitting window, in this case twenty days. Both trading strategies buy and hold for a q number of trading days in the horizon period, in this case twenty days. The annualized excess profit is the difference between the annualized return achieved by the bull flag trading rules and the annualized return derived from the market strategy defined as buy on everyday. Both annualized returns and annualized excess profits are calculated based on the 254 trading days existing in a calendar year.

[x] 5% significance level assigned to t-tests.

Descriptively, the five sub-periods defined for the SSE are 01/02/1991 to 12/30/1996, 12/31/1996 to 04/24/2003, 04/25/2003 to 07/17/2009, 07/20 /2009 to 12/10/2015, and 13/10/2015 to 31/12/2021. Regarding the BOVESPA Index, the sub-periods are 02/01/1995 to 26/07/2000, 27/07/2000 to 25/11/2005, 28/11/2005 to 08/04/2011, 11/04/2011 to 15/08/2016, and 16/08/2016 to 30/12/2021. For all these sub-periods, the empirical results inherent to the bull flag trading rule, characterized by a twenty-day fitting window, twenty-day holding period and maximum threshold, show positive average and annualized returns. It is also noteworthy that the returns of the buy everyday strategy are positive for all time intervals but on a much smaller scale. In specific, there are some observations in which the market average return is almost zero, as is the case of the 4th sub-period of the Brazilian Index.

Moreover, according to *Table 9*, technical analysis reaches positive and significant annualized excess profits for the five sub-periods of each index, relative to the market's trading strategy. Therefore, these results are statistically consistent with the data presented in *Table 6*, reinforcing its robustness. Indeed, the excess profit found for this trading rule is the result of a greater predictive power translated during the entire sample period, an outcome that does not change when the investigation is performed considering non-overlapping sub-periods.

In addition, it is possible to detect in *Figure 4* that during the 4th sub-period of the BOVESPA, which until then had been displaying an upward trend, suffers a slight drop that lasts throughout the entire interval. As a result of this event, the buy everyday strategy performed its worst average return among all observations, corresponding to 0.03%. In turn, the empirical results from the bull flag show that for this sub-period, technical analysis not only managed to achieve a higher average return and annualized return, approximately 5.34% and 67.79%, respectively but at the same time reduced the risk associated with the investment from 6.58% to 5.89%. Also, for the SSE, it is noted that sub-periods with a better level of performance, related to higher annualized returns, are connected with a greater number of buy signals detected by trading rules. Similarly, according to Wang and Chan (2007), the everyday buy market approach recorded its worst performance in the 5$_{th}$ sub-period of the TAIEX Index with an annualized return of 1.85% and standard deviation of 8.36%. The exploitation of the bull flag pattern in this market was able to generate an annualized return of 20.42% and a standard deviation of 7.74% for the same time interval.

Lastly, the experimental results reveal that the SSE has a higher degree of volatility than the BOVESPA, even though both are classified as emerging markets which, in general, are associated with high volatility values. Indeed, the immanent volatility of emerging markets is typically characterized by sudden changes in variance, mainly linked to their usual low inclusion in the world market (Shin, 2005) and also due to "country-specific political, social and economic events" (Aggarwal, Inclan, & Leal, 1999, p. 14).

4.5. Performance of the "buying run" approach

According to Leigh, Modani, and Hightower (2004), the empirical results presented in *Table 6* and *Table 9* may be incorrect. It is argued that the statistical computation of the applied significance tests is more likely to calculate probabilities that represent lower bounds rather than what those values might truly be. To this end, the authors identify two assumptions in the decision-making process with inconsistent dependencies regarding the use of the t-test as a mechanism to calculate the significance of the difference between the average returns of both strategies for all trading rules. Firstly, the fact that the commitment to buy at the beginning of the next trading day is established after the market has closed on the previous day and, finally, the circumstance that the price change to any fitting window of *p*-days after a trading day is intimately related to that same change for the following trading day. Consequently, to establish an upper bound, this article also suggests the usage of probabilities measured through t-tests that only incorporate the first trading day of each buying run. This means that the remaining buy signals arising from the bull flag-conditioned trading rules are completely ignored. In fact, buy recommendations normally occur during consecutive days, which generates a concept termed *buying runs*.

Table 10: Buying runs performance for a $T = 3$.

p	q	N(runs)	First day of run only: Average run length	Average Return (%)	Annualized Return (%)	Excess profit	
Panel A: SSE Composite Index							
20	20	111	11.01	0.95	12.10	-7.99	(0.5344)
20	40	111	11.01	9.73	61.77	40.63	(0.0190) [x]
20	60	111	11.01	11.29	47.80	26.09	(0.0423) [x]
20	80	111	11.01	12.88	40.89	19.17	(0.0297) [x]
20	100	111	11.01	14.72	37.40	15.42	(0.0306) [x]
Panel B: BOVESPA Index							
20	20	96	8.73	0.97	12.28	-5.50	(0.6484)
20	40	96	8.73	7.67	48.74	30.29	(0.0002) [x]
20	60	96	8.73	9.08	38.45	19.87	(0.0033) [x]
20	80	96	8.73	8.64	27.44	8.91	(0.0851)
20	100	96	8.73	10.91	27.70	9.20	(0.0442) [x]

Source: own calculations. The statistics referring to the *first day of run only* are calculated considering just the first day of each run, completely ignoring the remaining trading days. N(runs) corresponds to the number of runs. The annualized excess profit is the difference between the *First day of run only* annualized return achieved by the bull flag trading rules and the annualized return derived from the market strategy defined as buy on everyday. Both annualized returns and annualized excess profits are calculated based on the 254 trading days existing in a calendar year.

[x] 5% significance level assigned to t-tests.

Therefore, *Table 10* reveals the bull flag performance adjusted to the concept of buying runs for a twenty-day fitting window and $Fit_k \geq 3$. At this point, instead of the quantity of buy signals, it is only measured the number of buying runs that can be identified during the whole period under analysis. For instance, in the case of the SSE there were one hundred and eleven trading days that culminated in consecutive index purchases. It is also noted that the average run length is roughly 11 days for the SSE and 9 days for the BOVESPA. Moreover, except for the twenty-day holding period, trading rules are capable of generating positive average returns for both indices and, in particular, it appears that the annualized return is greater the smaller the holding period associated with it. In turn, when compared with a market approach, the bull flag manages to produce significant annualized excess profits in seven out of ten observations. Notably, for a q = 80, it is documented a non-significant statistical excess of profit in the Brazilian market of 8.91%. Also, for a q = 20, it is recorded an insignificant loss of performance of technical analysis relative to the buy everyday strategy for both indices of -7.99% for the SSE and -5.50% for the BOVESPA. Accordingly, in general the empirical results shown in this subchapter support the outcome expressed in *Table 6* and *Table 9*, where trading rules appear to have a better performance than the market strategy for both the SSE and the BOVESPA, even in situations where buying runs are considered.

In the literature, when bull flag trading rules are conditioned to situations of buying runs on the Taiwanese stock market, technical analysis proved to be an instrument with "great forecasting power" (Wang & Chan, 2007, p. 314). For instance, considering buying runs with an average run length of roughly 4 days, the excess return from the bull flag when q = 20 was 22.74% and with q = 40 it was 13.93% for the TAIEX. On the contrary, for both the NASDAQ and the NYSE, bull flag trading rules generally produce insignificant excess profits when only buying runs are considered (Wang & Chan, 2007; Leigh, Modani, & Hightower, 2004). Additionally, *Table 11* exhibits a literary summary of the main results related to the performance of buying runs based on the bull flag pattern.

Table 11: Summary of the main results found in the literature about the performance of buying runs for a $T = 3$.

Source	Period analyzed	Number of trading days	Index	p	q	N(runs)	First day of run only		
							Average run length	Annualized Excess profit	
This study	02/01/1991 to 12/31/2021	7549	SSE	20	20	111	11.01	-7.99	(0.5344)
					60	111	11.01	26.09	(0.0423) x x
					100	111	11.01	15.42	(0.0306) x x
This study	02/01/1995 to 12/30/2021	6620	BOVESPA	20	20	96	8.73	-5.50	(0.6484)
					60	96	8.73	19.87	(0.0033) x x
					100	96	8.73	9.20	(0.0442) x x
Wang and Chan (2007)	04/03/1985 to 03/20/2004	4785	NASDAQ	20	20	182	4.13	5.22	(0.1451)
					60	182	4.13	0.50	(0.4478)
					100	182	4.13	-0.90	(0.3745)
Wang and Chan (2007)	06/01/1971 to 03/24/2004	9284	TAIEX	20	20	307	4.01	22.74	(0.0004) x
					60	307	4.01	9.89	(0.0099) x
					100	307	4.01	6.83	(0.0176) x x
Leigh, Modani and Hightower (2004)	01/28/1981 to 09/15/1999	4697	NYSE	120	20	10	15.30	36.83	(0.0546)
					60	10	15.30	22.01	(0.0379) x x
					100	10	15.30	12.95	(0.0674)

The statistics referring to the *first day of run only* are calculated considering just the first day of each run, completely ignoring the remaining trading days. N(runs) corresponds to the number of runs. The annualized excess profit is the difference between the *First day of run only* annualized return achieved by the bull flag trading rules and the annualized return derived from the market strategy defined as buy on everyday. The annualized excess profits are calculated based on the 254 trading days existing in a calendar year. In the article by Leigh, Modani, and Hightower (2004) the results are originally expressed in the form of average excess returns, having been transformed into annualized excess returns.

[x] 1% significance level assigned to t-tests. [x x] 5% significance level assigned to t-tests.

5. Conclusions and research suggestions

According to Menkhoff (2010), academics generally have a sceptical view regarding the use of technical analysis by stock traders as an investment aid tool. This is perhaps more explicit in the article published by Fama (1970) where the author states that financial markets characterized by being efficient in their weak form, have security prices that only incorporate all publicly available information in the market. As a result, historical values and trends can not predict future prices or produce abnormal profit-generating forecasts.

To this extent, this dissertation enriches the debate on this topic by presenting empirical evidence about the performance of technical analysis, using bull flag trading rules from template matching techniques, as opposed to market average returns. This research was implemented on the emerging stock markets of Brazil (BOVESPA) and China (SSE), over a period of 27 years and 31 years, respectively. Moreover, this is the first time that this method has been applied to these two markets, which also represents an important contribution to the literature. Methodologically, this study also acknowledges the effects that can be caused by data snooping bias on the veracity of the final results, in particular, by the possibility of non-synchronous trading solutions. Hence, all the tests are conducted by methods that minimize these measurement errors.

The experimental results support the idea that technical analysis based on the bull flag pattern has the ability to correctly predict changes in the direction of both the SSE and BOVESPA Index values for almost all trading rules. Indeed, in comparison with the buy everyday strategy used as a trading policy that illustrates the ideas defended by rationalists, the bull flag achieved statistically significant annualized excess profits of greater magnitude for smaller fitting windows in conjunction with holding periods of shorter duration, even when considering transaction costs. Further, the exploration of the bull flag pattern on the BOVESPA proves to be particularly rewarding in relation to the market strategy, as it is not only capable of increasing the financial return, but also, at the same time, of reducing the exposure to the risk associated with the investment. Instead, investments in the SSE are subjected to a higher level of risk, but since the returns achieved are also higher than those in the market, their coefficient of variation is lower. Moreover, the excess profit connected to the bull flag is still dependent on the value assigned to the threshold. Indeed, the higher the quality of the template price fit, the better the strategy's performance for lower holding periods.

Additionally, although trading rules conditioned on bull flags seem to have a great ability to predict the direction of both the Chinese and Brazilian stock markets, it is still possible to detect a slightly better performance in the SSE. This can be justified by a higher success rate of its trading rules with greater excess profits and more significant empirical results (also considering buying runs). This outcome is consistent with the ideas presented in the study by Marshall et al. (2010), where the author argues that technical analysis has a greater potential for obtaining statistically significant abnormal returns in markets with a lower level of efficiency. Besides, in the literature on this subject, there are studies with empirical evidence that bull flag trading rules implemented on the TAIEX performed better than those on the NASDAQ (Wang & Chan, 2007). Others report that this method "has some forecasting ability" on the NYSE (Leigh, Modani, & Hightower, 2004 p. 529). Finally, there is still evidence that the use of this flag pattern can considerably improve the returns on the DJIA Index relative to a buy and hold strategy (Arévalo et al., 2017).

Nevertheless, according to Zapranis and Tsinaslanidis (2012), the execution of a template matching technique commonly involves a certain degree of subjectivity. This occurs because in order to identify any pattern it is necessary to previously define each of the weights contained in the template grid, a process that is often done arbitrarily. Yet, these authors also argue that despite the unavoidable nature of technical analysis, to assess its predictive ability it is necessary to start from scratch and look for descriptions of the patterns that are under analysis in the most varied technical manuals.

Ultimately, the results achieved in this dissertation under the conditions studied indicate that, in fact, price has memory. Therefore, technical analysis can be seen as an investment evaluation tool available to any investor, which provides additional relevant information based on patterns or price movements resulting from past trading activity. Indeed, these methods can identify investment opportunities that may prove to be important in terms of an investor's asset allocation process, jeopardizing the line of thought advocated by the EMH.

Considering the smaller number of academic articles that focus on the performance of technical analysis based on qualitative indicators, it may be interesting for future research to emerge on this topic. Notably, using other templates or variations of the bull flag pattern and investigating markets that have not yet been explored in this scope, as is the case of one of the most relevant emerging markets - the National Stock Exchange of India.

Moreover, there is still the possibility of expanding the methodology used in this dissertation. For instance, in addition to using price data to produce technical trading rules, these can also be generated from trading volume data. In the end, one could compare the profitability of these different trading rules and discover which one has a greater predictive power ability.

Appendix

Appendix 1 – Methodology

Generally, without going into detail regarding formulas as they are already properly displayed and clarified in *subchapter 3.3.*, the method covered by this study can be divided into five main steps:

- Step number 1: Rank the trading days belonging to each of the fitting windows in descending order of associated index value, that is, assign better ranks to days whose prices are higher. For instance, attribute rank 1 to the day with the highest index value.

- Step number 2: Calculate $I_{t,i}$ for each of the trading days belonging to the fitting windows. After applying the respective formula, each day corresponds to a single value of $I_{t,I}$ that can range from 1 to 10.

- Step number 3: Calculate $J_{t,j}$ for each of the trading days belonging to the fitting windows. This time, trading days are organized by time series, regardless of their index values. After applying the respective formula, each day corresponds to a single value of $J_{t,j}$ that can range from 1 to 10.

- Step number 4: Each of the *p*-trading days, which refers to the number of days that constitute each fitting window, has associated three different tables with weights. In specific, two grids of weights ($I_{t,I}$ and $J_{t,j}$) and a template that identifies the bull flag pattern already defined in the article by Wang and Chan (2007). Thus, through a cross-multiplication of these three tables, it is possible to calculate the price fit value (Fit_k) of each of the trading days. In reality, this mathematical operation corresponds to the mapping of trading days within the template where $I_{t,I}$ correspond to the rows and $J_{t,j}$ to the columns. For instance, regarding the first trading day belonging to a window, its Fit_k value can be calculated through the sum of the cross multiplication of the template weights over all the days that are part of that same fitting window. Below is a hypothetical example of a two-day fitting window (to be easier in terms of computations) and the subsequent Fit_k calculation.

Date	$I_{t,i}$	
	1	2
01/01/2022	1	0
01/02/2022	0	1

t	$J_{t,j}$	
	1	2
1	0	1
2	1	0

Template	
0.2	1
0.7	0.5

Figure 6: Representation of a hypothetical template and grid of weights with a two-day fitting window.

Fit_k calculation for 01/01/2022: (Row: 1; Column: 2) + (Row: 2; Column: 1) = 1 + 0.7 = 1.7.

As a result, if a threshold of 1 is admitted, the trading rule will generate a buy signal for this date. On the other hand, Fit_k's calculation for 01/02/2022 incorporates the weights contained in the template for that trading day and for the first day of the time interval that follows, which corresponds to 01/03/2022.

- Step number 5: Fit_k values serve as inputs for bull flag trading rules as if $Fit_k \geq$ Threshold, a buy signal is generated. After collecting the information about the buy signals, all that remains is to calculate the performance of each of the strategies and compare them.

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