

Bull flag pattern recognition: Evidence from the BOVESPA index.

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Abstract

This paper studies the predictive power of technical analysis using bull flag patterns based on a template matching technique. This method is applied to the Brazilian stock market (BOVESPA) over the period from February 1st 1995 to December 30th 2021. The empirical results demonstrate that bull flag trading rules can correctly predict the direction of the index price movements. Technical analysis achieved positive and statistically significant annualized excess profits compared with the buy everyday strategy, even when considering transaction costs. Moreover, shorter fitting windows and better quality of price fit values are associated with better performance for shorter holding periods.

Keywords: Technical analysis, Trading rule, Template matching technique, Bull flag pattern, BOVESPA index.

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1. Introduction

The concept of Weak Form efficiency portrayed in the study by Fama (1970) states that historical values and trends can not predict future prices. This means that advocates of this form of efficiency believe that the use of technical analysis is limited and does not bring significant benefits. Yet, 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. The relevance of technical analysis can also be attested by its users (called technicians). According to a study published by Menkhoff (2010), a survey was conducted with “692 fund managers in five markets, namely the US, Germany, Switzerland, Italy and Thailand”, where 87 per cent of them recognized the importance of technical analysis and 18 per cent even stated that it is their favourite way of processing information. In addition, the importance of technical analysis in the field of finance can also be demonstrated by the number of studies published recently, as is the case of Ayala et al. (2021), Detzel et al. (2021), Ma and Yu (2021) and Masuku and Gopane (2022).

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 present study is based on the use of a qualitative indicator as a prediction variable, where a template matching technique is applied 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 article’s methodology, is relatively recent and, above all, still little explored in the literature.

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Moreover, existing studies using this technique are generally focused on more developed markets such as the Nasdaq Composite Index (NASDAQ), the New York Stock Exchange Composite Index (NYSE) and the Dow Jones Industrial Average Index (DJIA) (Leigh, Purvis, & Ragusa, 2002; Leigh, Paz, & Purvis, 2002; Leigh et al. 2002; Leigh et al., 2004; Wang & Chan, 2007; Leigh et al., 2008; Arévalo et al., 2017). Hence, this paper contributes to the expansion of the literature in this field by examining the Brazilian stock market, an emerging market, and by investigating the profitability of technical trading rules conditioned on bull flag patterns using a template matching technique. More specifically, the study evaluates whether these rules can generate returns above the average market performance and examines how their performance varies according to the fitting window, holding period, and threshold defining the quality of the template price fit. To the best of our knowledge, this is the first time that the Brazilian stock market has been examined in this context.

Against this background, the main objective of this study is to investigate whether bull flag technical trading rules, identified through a template matching technique, can generate returns that outperform the average market performance of the Brazilian stock market. More specifically, the study examines whether the profitability of these trading rules varies according to the fitting window, the holding period, and the threshold used to define the quality of the bull flag pattern.

To address this objective, the following section briefly reviews the most relevant literature on the subject. Section 3 describes in greater detail the purposes of this research, the data collection and treatment processes, and the methods implemented for this purpose. Section 4 presents and descriptively examines the empirical results obtained for each of the strategies

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under study. Finally, the last section presents the conclusions and suggestions for possible future research.

2. Literature Review

One of the most famous and well-known concepts 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. 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.

Park and Irwin (2004), in a review of 92 studies, found that 58 reported significant evidence supporting the profitability of technical analysis. Similarly, Nazário et al. (2017), reviewing 89 studies, found evidence of profitability and predictability in 79, while noting that technical analysis may be particularly relevant in less efficient markets. This literature suggests that the potential effectiveness of technical analysis may vary across market environments, with emerging markets providing an important context for further investigation.

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).

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,

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2007; Agrawal et al., 2010). Indeed, methodologies that use quantitative indicators build forecasts and provide trading signals through a quantitative investigation of time series data.

Although there are many quantitative techniques with numerous variations, perhaps the most popular are the moving average convergence/divergence model developed by Appel (1979), the relative strength index created by Wilder (1978), and the bollinger bands technique designed by Bollinger (1992). Concerning studies aimed at different developed markets, several authors evidenced the possibility to obtain abnormal returns using quantitative technical indicators (e.g., Wong et al., 2003; Chong & Ng, 2008; Gebka et al., 2015; Butler & Kazakov, 2010; García et al., 2018). 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 studies conducted by Stanković et al. (2015) and de Souza et al. (2018) evidenced, respectively, the profitability of technical analysis in the Bulgarian, Serbian, Romanian and Croatian markets and in the BRICS countries (Brazil, Russia, India, China and South Africa). Also, Vidotto et al. (2009), evidenced that the use of the moving average technique was a good tool to help investors obtain abnormal returns in the Brazilian stock market through stock buy and sell signals.

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

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(Roberts, 1959; Fama, 1970; Neftci, 1991; Lo et al., 2000; Dawson & Steeley, 2003; Wang & Chan, 2007; Friesen et al., 2009; Zapranis & Tsinaslanidis, 2012).

Neftci (1991) and Lo et al. (2000) provide evidence in favour of the predictive ability of technical patterns in US markets, while Dawson and Steeley (2003) obtain similar evidence for the UK market. Wang and Chan (2009) and Zapranis and Tsinaslanidis (2012) further examine chart-pattern trading rules in US stocks, with results supporting their predictive potential.

Among the most popular visual patterns of traditional technical analysis, there is 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). 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, Purvis, and Ragusa (2002), Leigh, Paz, and Purvis (2002), Leigh et al. (2002), Leigh et al. (2004), and Leigh et al. (2008), the results evidence that 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 addition to the above cited studies, there is a paper that is central to the present work. Wang and Chan (2007) used a template matching technique to identify bull flag patterns as a technical trading rule for the NASDAQ and Taiwan Weighted Index (hereafter TAIEX), the

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former being a highly developed market and the latter an emerging market. This study was applied to daily NASDAQ index values ranging from April 3rd 1985 to March 20th 2004, corresponding to about 4,785 trading days, and to TAIEX price data ranging from June 1st 1971 to March 24th 2004, corresponding to 9,284 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 concluded that the better the bull flag template price fit, the higher the average return and, thus, that 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 per cent for the NASDAQ and 46.49 per cent for the TAIEX when the holding period was minimal. Under the same conditions, the market-based strategy of buying every day only obtained returns of 12.77 and 15.22 per cent, respectively. Lastly, there is the paper by Arévalo et al. (2017), in which 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.

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3. Data and Methodology

The empirical analysis aims to assess the profitability of bull flag technical trading rules, identified through a template matching technique, by comparing their performance with the average market returns of the Brazilian stock market, represented by the Brazil Stock Market Index (hereafter BOVESPA).

From the statistical and financial database *Thomson Reuters Eikon Datastream* platform, a series of daily index values for the BOVESPA index was collected, ranging from February 1st 1995 to December 30th 2021, covering a period of 27 years and totalling 6,620 valid trading days. In addition to the index values, it is also necessary to obtain information about the weights used in the template that defines the bull flag pattern, which can be easily found in Wang and Chan (2007) and is explained below.

As mentioned earlier, the methodology used replicates that of Wang and Chan (2007), applying a pattern recognition technique to identify the bull flag. 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, whereas the latter uses a template to detect patterns through a pictographic image, since both techniques constitute the first steps to be taken in this process (Wang & Chan, 2007). *Figure 1* presents the template used by Wang and Chan (2007):

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-.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 1: 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 template are weights that permit the definition of the bull flag pattern in the grey marked squares. The calculation of these weights is performed 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. As can be seen in *Figure 1*, Wang and Chan (2007) first categorize a bull flag pattern transcribed in a template by an upward trend, which can be identified in the first five columns, followed by a horizontal consolidation between columns six and nine and, in the last column, the representation of an ascending breakout. According to the authors this methodology manages to stably detect price increases, which are essential for the process of identifying a bull flag

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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 BOVESPA index for several p trading day windows, $p = \{20, 40, 60, 80, 100 \text{ and } 120\}$, 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, 1998). 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 (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:

$$I_{t,i} = 1 \text{ if } (i - 1) \cdot \frac{p}{10} < \text{Rank (Trading day)} \leq i \cdot \frac{p}{10}$$
$$I_{t,i} = 0, \text{ otherwise}$$

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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 j th column, then $J_{t,j} = J$; otherwise, $J_{t,j} = 0$ as shown in the formula below:

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

$$J_{t,j} = 0, \text{ otherwise}$$

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

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

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:

$$p \cdot I \cdot J = 10$$

therefore,

$$I = 1$$

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

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 1* and the “scale values of the image grid for each cell in row i and column j ”, shown below (Wang & Chan, 2007, p. 307):

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

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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:

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

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

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

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,

$\sum_{k=m}^n B_k$ 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:

$$\text{Excess Profit} = \text{Trading Rule Average Return} - \text{Market Average Return}$$

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4. Empirical results and data analysis

4.1. Average return

Table 1 presents the average returns from the BOVESPA 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 1995 to December 30th 2021.

Table 1: Performance of the market-based and trading rules strategies implemented in the BOVESPA index for the period ranging from 01/02/1995 to 30/12/2021.

Market		Bull Flag								
p	q	Average Return (%)	T=0		T=1		T=2		T=3	
			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

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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. $N(\text{buys})$ 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 Bovespa 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, $q = \{20, 40, 60, 80, \text{ and } 100\}$. 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 2.37 per cent 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 6.35 per cent for a $t = 3$, which corresponds to the best template price fit of this study. This specific trading rule ($\text{Fit}_k \geq 3$) delivered 970 buy signals in a total of 6620 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.

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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 subsection 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 $T = \{0, 1, 2 \text{ and } 3\}$. 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 2.37, 3.58, 4.95 and 6.35 per cent for respectively increasing T values. These outcomes are in agreement with other studies performed on emerging markets, such as the Taiwanese stock market (Wang & Chan, 2007). 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,

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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 occurs because each trading day is associated with a value of Fit_k , and the purchase of the index is decided based on the quality of Fit_k on that trading day relative to the threshold. Therefore, the number of days for which the investment is held has no impact on the number of signals captured by the trading rules. Moreover, an increase in the value assigned to the threshold causes the number of buy signals to decrease, since higher Fit_k volumes are required; on the other hand, as previously mentioned, it improves the performance of the bull flag. In sum, the results presented in *Table 1* illustrate that bull flag conditional trading rules can validly predict changes in the direction of BOVESPA index values, regardless of the fitting window. It is important to note that, although in most observations there is a positive relationship between the threshold and the average return, there are some exceptions in which the return decreases. This occurs more intensively for strategies that combine the largest fitting windows, with $p = \{60, 80, 100 \text{ and } 120\}$, with the shortest holding period, which is twenty days. For example, when $p = 80$ and $q = 20$, bull flag average returns range from 0.46 to 1.32 per cent, depending on the threshold, and are well below the market average return of 1.40 per cent for the BOVESPA. This finding is consistent with the results reported by Wang and Chan (2007) in their examination of the NASDAQ index, a developed market. Furthermore, it is evident that, in most cases, bull flag conditional trading rules can outperform the daily buying strategy, with

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returns superior to those "offered" by the market. However, as noted in the previous paragraph, there are some cases in which technical analysis leads to underperformance relative to the market strategy. This pattern becomes more pronounced as the number of p-trading days used in the fitting windows increases and the length of time for which assets are held decreases.

Overall, the results based on average returns indicate better performance for shorter fitting windows. *Table 2* summarizes some descriptive statistics about the returns generated by bull flag strategies.

Table 2: Descriptive statistics of bull flag patterns.

Descriptive Statistics	p	Bull Flag
Average returns per fitting window	20	8.82
	40	10.47
	60	7.75
	80	8.29
	100	5.53
	120	5.42
Median of average returns per fitting window	20	9.02
	40	9.67
	60	7.05
	80	7.26
	100	4.29
	120	4.80
Standard deviation of average returns per fitting window	20	3.44
	40	6.41
	60	6.43
	80	6.69
	100	5.01
	120	4.19
Maximum return of a trading operation		122.74
Maximum return date		14/01/1999
Minimum return of a trading operation		-59.48
Minimum return date		30/03/1998
Number of observations (index values)		6620

Source: Own calculations. The mean, median and standard deviation are calculations performed on the results shown in *Table 1* 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

Table 3 reports the annualized returns and excess profits obtained from the bull flag strategy and the market strategy under the different combinations of fitting windows, holding periods, and threshold values.

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

p	q	Market			Bull Flag (T = 3)					
		Average Return (%)	Annualized Return (%)	Standard Deviation	N(buys)	Average Return (%)	Transaction Cost (%)	Annualized Return (%)	Standard Deviation	Annualized Excess Profit (%)
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: $Transaction\ Cost = \frac{Average\ Return}{2}$.

^x 5% significance level assigned to t-tests.

Both the average daily return and the annualized return are measures commonly employed when assessing 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. Nonetheless, if one wants to draw conclusions about the performance of trading rules with different holding periods, it is important to rely on estimates expressed as annualized returns rather than average returns. Indeed, this study is applied to a emerging market that has been expanding over the years. Thus, if one analyzes merely the average of the generated returns, it is quite natural for them to be higher for longer holding periods. In this way, the annualized return calculates the average amount of money earned by a given investment on an annual basis, comprising 254 trading days, and is dependent on the holding period of the assets. As a result, this measure allows for 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 estimates of annualized returns.

The results in *Table 3* 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, regardless of the holding period or threshold value. Besides, the observations are constrained to the maximum threshold for the reason already clarified in subsection 4.1. where, 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.

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 3* 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 3.18 per cent. Thus, considering reasonable transaction costs⁴, the bull flag approach continues to be profitable and with better results than the buy everyday strategy, since the theoretical costs indicated in *Table 3* are shown to be very high.

Moreover, contrary to the average return, *Table 3* 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 instance, the bull flag annualized excess return when $q = 20$ was 62.84 per cent, while for a $q = 100$ it was only 19.38 per cent. 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 from Wang and Chan (2007) for the NASDAQ and TAIEX Indices. Nevertheless, according to Leigh et al. (2004), this investment policy is only viable when the market presents a positive window price change because if it is falling (a bear market), the opposite was true for the NYSE index.

⁴ 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/

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According to the figures available in *Table 3*, the 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). 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 4* (Reed et al., 2002).

Table 4: Representation of the coefficient of variation for each trading strategy.

p	q	Coefficient of variation	
		Market	Bull Flag
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: $CV = \frac{\text{Standard Deviation}}{\text{Average Return}}$.

4.3. Market timing

The empirical results presented in *Table 3* 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 $\text{Fit}_k \geq 3$. Interestingly, among the displayed data, this is the observation in which the annualized excess profit is maximum and, at the same time, the standard deviation is minimum. As in the previous subsection, this subsection intends to provide additional detailed

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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 5*.

Table 5: Buy signals success.

P	q	Market			Bull Flag (T = 3)		
		N (buys)	N (r > 0)	Ratio (%)	N (buys)	N (r > 0)	Ratio (%)
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 $N(\text{buys})$.

The statistics in *Table 5*, 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 the index values, that is, if the market will continue to rise or, instead, will have a decline in the future. The Ratio indicates the proportion of buy signals followed by positive returns. For the bull flag strategy, this ratio ranges from 80.41% to 88.25%, compared with 57.85% to 63.91% for the market strategy. These results provide evidence of the predictive ability of the bull flag rules in identifying subsequent positive price movements.

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

To assess the robustness of the results reported in *Table 3*, the overall sample is divided into five non-overlapping subperiods: 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. The bull

flag strategy with $p = 20$, $q = 20$, and the maximum threshold considered generates positive average and annualized returns across the five subperiods, while the market strategy also produces positive returns but generally at lower levels.

Table 6 reports positive and statistically significant annualized excess profits for the five subperiods, providing evidence that the main findings are not restricted to the full-sample period. In the fourth subperiod, for example, the market strategy produces an average return of 0.03%, compared with 5.34% for the bull flag strategy, corresponding to an annualized return of 67.79%. At the same time, the standard deviation decreases from 6.58% for the market strategy to 5.89% for the bull flag strategy.

4.5. Performance of the "buying run" approach

According to Leigh et al. (2004), the type of empirical results presented in *Tables 3* and *6* may be incorrect. The authors argue that the statistical computation of the significance tests applied is more likely to produce probabilities that represent lower bounds rather than the values that they might actually take. To this end, the authors identify two assumptions in the decision-making process that involve inconsistent dependencies regarding the use of the t-test as a mechanism for calculating the significance of the difference between the average returns of the two strategies for all trading rules. Firstly, the commitment to buy at the beginning of the next trading day is established after the market has closed on the previous. Secondly, the price change over any p -day fitting window following a trading day is closely related to the corresponding price change on the following trading day.

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Table 6: Performance of the market-based and trading rules strategies, when $p = 20$, $q = 20$ and $T = 3$, for several non-overlapping sub-periods.

p	q	Sub-period	Market				Bull Flag ($T = 3$)				
			N(buys)	Average Return (%)	Annualized Return (%)	Standard Deviation	N(buys)	Average Return (%)	Annualized Return (%)	Standard Deviation	Annualized Excess Profit (%)
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 five sub-periods defined for the BOVESPA index 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. 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.

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 7 reveals the bull flag performance adjusted to the concept of buying runs for a twenty-day fitting window and $\text{Fit}_k \geq 3$. 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. The results identify 96 buying runs, with an average length of approximately nine days. Positive returns are observed for most holding periods, except for $q = 20$. Annualized returns are generally higher for shorter holding periods, while statistically significant excess profits are obtained in three of the five holding periods considered. For $q = 80$, the excess profit of 8.91% is not statistically significant, while for $q = 20$ the excess profit is negative and statistically insignificant at -5.50% . Overall, the buying-run analysis provides broadly consistent evidence with the results reported in Tables 3 and 6.

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Table 7: Buying runs performance for a $T = 3$.

p	q	N(runs)	First day of run only				Excess profit
			Average run length	Average Return (%)	Annualized Return (%)		
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.

5. Conclusions and research suggestions

This paper presents empirical evidence on the performance of technical analysis, using bull flag trading rules based on template matching techniques, as opposed to market average returns. The research was conducted on the emerging Brazilian stock market (BOVESPA), over a period of 27 years. Moreover, this is the first time that this method has been applied to this market, which also represents an important contribution to the literature. Methodologically, this study also acknowledges the effects that data snooping bias can have on the validity of the final results, in particular, the possibility of non-synchronous trading effects. Hence, all 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 the BOVESPA index values for almost all trading rules. In comparison with the buy everyday strategy, the bull flag

achieved statistically significant annualized excess profits of greater magnitude for shorter fitting windows combined with shorter holding periods, even when considering transaction costs. Furthermore, the application of the bull flag pattern to 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 exposure to the risk associated with the investment. Moreover, the excess profit associated with the bull flag remains 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 shorter holding periods.

Nevertheless, some limitations of the present study should be acknowledged. According to Zapanis and Tsinaslanidis (2012), the implementation of a template matching technique commonly involves a certain degree of subjectivity, as the identification of a pattern requires the prior definition of the weights contained in the template grid, a process that may involve a certain degree of arbitrariness. In addition, the results may depend on the specific choices of fitting window, holding period, and threshold used in the trading rules. Although these parameters allow the performance of the bull flag strategy to be examined under different conditions, they may also affect the magnitude and statistical significance of the observed returns. Finally, the analysis is restricted to the Brazilian stock market and to the period under consideration, which limits the extent to which the findings can be generalized to other markets and periods.

These limitations provide several opportunities for future research. First, future studies could examine alternative templates or variations of the bull flag pattern and investigate whether similar results are obtained using different pattern specifications. Second, the

methodology could be applied to other emerging markets and to developed markets, allowing the robustness and generalizability of the findings to be assessed across different market environments. Third, future research could employ additional out-of-sample or rolling-window procedures to examine the stability of the results over time. Finally, it would be relevant to investigate whether combining bull flag pattern recognition with other technical indicators or trading rules can improve the robustness of the observed performance.

Ultimately, the results achieved in this paper provide evidence that price movements in the BOVESPA may contain information that can be exploited by bull flag-based technical trading rules. Therefore, the findings suggest that technical analysis can identify potentially relevant investment opportunities within an investor's asset allocation process, providing evidence that is not fully consistent with the weak-form version of the EMH. Nevertheless, the results should be interpreted in light of the methodological limitations discussed above and should not be generalized beyond the market and period analyzed without further empirical evidence.

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