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Stock market trading rule based on pattern recognition and technical analysis: Forecasting the DJIA index with intraday data

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ABSTRACT

This work presents empirical evidence which confronts the classical Efficient Market Hypothesis, which states that it is not possible to beat the market by developing a strategy based on a historical price series.

We propose a risk-adjusted profitable trading rule based on technical analysis and the use of a new definition of the flag pattern. This rule defines when to buy or sell, the profit pursued in each operation, and the maximum bearable loss. In order to untie the results from randomness, we used a database comprised of 91,307 intraday observations from the US Dow Jones index. We parameterized the trading rule by generating 96 different configurations and reported the results of the whole sample over 3 subperiods. In order to widen its validity we also replicated the analysis on two leading European indexes: the German DAX and the British FTSE. The returns provided by the proposed trading rule are higher for the European than for the US index, which highlights the greater inefficiency of the European markets.

1. Introduction

The possibility of predicting the future price of financial assets (stocks, ETFs, options, futures, etc.) from historical price series is one of the most important challenges both for individual investors and for companies linked to the financial environment.

Price prediction confronts the Efficient Market Hypothesis introduced by Fama (1970). According to this hypothesis, the efficient nature of the market makes it impossible to predict prices by means of historical series, which implies that it is not possible to develop an investment strategy that can beat the market under the classical criteria of risk and return. However, there is abundant evidence in the literature against this hypothesis, as we shall see later, much of which is based on the use of technical analysis.

As stated by Bagheri, Peyhani, and Akbari (2014), professional traders use two major types of analysis to make accurate decisions in financial markets: *fundamental* and *technical*. Fundamental analysis uses global economic, industrial and business indicators. The technical analysis makes its decisions on the basis of historical prices, under the assumption that past behaviors have an effect on the future evolution of prices. In technical analysis it is common to use indicators (Hu, Feng, Zhang, Ngai, & Liu, 2015; Patel, Shah, Thakkar, & Kotecha, 2015; Żbikowski, 2015), which are created by applying more or less complex formulas to historical prices. Together with these indicators, it is also common to use chart pattern analysis (Bagheri et al., 2014; Zapranis & Tsinaslanidis, 2012), which tries to predict the future behavior of prices from chart patterns which are constantly repeated in financial markets, regardless of the financial assets considered or the temporary window analyzed.

Those who have developed trading rules based on technical analysis use information based on indicators, chart patterns, or both of these. From a methodological point of view, these studies incorporate models from econometrics, statistics and artificial intelligence. In all cases trading rules are generated which allow investors to beat the market, confronting the Efficient Market Hypothesis.

Examples include the work of Hu et al. (2015), who propose a hybrid long- and short-term evolutionary trend-following algorithm that combines trend-following investment strategies with extended classifier systems (XCS). Through this methodology they introduce a trading rule which selects stocks by different indicators. Silva, Neves, and Horta (2015) apply a Multi-Objective Evolutionary Algorithms (MOEA) with two objectives, return and

Abbreviations: DAX, Deutscher Aktien index; DJIA, Dow Jones industrial index; FTSE, the FTSE 100 index; VAR, value at risk.

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risk, to optimize portfolio management. They conclude that to obtain stocks with high valuation potential, it is necessary to choose companies with a lower or average market capitalization, low PER, high rates of revenue growth and high operating leverage.

Bagheri et al. (2014) combine an Adaptive Network-based Fuzzy Inference System with a Quantum-behaved Particle Swarm Optimization to forecast a financial time series from the foreign exchange market (Forex), developing a prediction system by means of chart patterns. De Oliveira, Nobre, and Zárate (2013) use economic and financial theory, combining technical analysis, fundamental analysis and analysis of time series, to predict price behavior in the Brazilian stock market by an Artificial Neural Network.

Kao, Chiu, Lu, and Chang (2013) propose a new stock price forecasting model which integrates wavelet transform, multivariate adaptive regression splines (MARS), and support vector regression (SVR) to improve price forecasting accuracy. Patel et al. (2015) compare four prediction models to forecast the trend direction in financial markets: Artificial Neural Network (ANN), Support Vector Machine (SVM), random forest and Naive-Bayes. The results suggest random forest outperforms the three other prediction models on overall performance. Yu, Chen, and Zhang (2014) also use SVM to construct a stock selection model, which can classify stocks nonlinearly. Guresen, Kayakutlu, and Daim (2011) present an excellent compilation of studies which use neural networks in order to predict stock market indexes.

A hybrid stock trading system based on Genetic Network Programming (GNP) and Mean Conditional Value-at-Risk Model (GNP–CVaR) is proposed by Chen and Wang (2015). Dymova, Sevastianov, and Kaczmarek (2012) use fuzzy logic to build trading rules and develop a stock trading expert system based on the rule-base evidential reasoning. Ng, Liang, Li, Yeung, and Chan (2014) point that a major problem in machine learning based stock trading researches is the imbalance between *buy*, *hold* and *sell* decisions: the hold decision is in the majority in comparison to both buy and sell decisions. In order to solve this problem they propose the use of a genetic algorithm that minimizes the weighted localized generalization error (wL-GEM). Liao and Chou (2013) analyze co-movement in the Taiwan and China stock markets using association rules and cluster analysis.

Gottschlich and Hinz (2014) propose a decision support system (DSS) that enables investors to include the crowd's recommendations in their investment decisions and use it to manage a portfolio.

Booth, Gerding, and McGroarty (2014) propose an expert system based on machine learning techniques to predict the price return on seasonal events, and develop a profitable trading strategy. The technique applied is known as *random forest*, and the market in consideration is the German DAX. The authors consider not only return but also risk. As in our paper, Booth et al. (2014) measure risk by drawdown.

All the above studies analyze stocks, indexes or currencies. One of their limitations is the size of the sample from which the model is built. When working with daily data, it is difficult to build a database wide enough to rule out possible random results. In order to overcome this limitation, our work introduces intraday data, which widens the size of the sample in a very significant way.

In this context, the present study develops a chart pattern based trading rule using the flag pattern, which has received a lot of attention in academic circles. Leigh, Paz, and Purvis (2002), Leigh, Purvis, and Ragusa (2002), Leigh, Modani, and Hightower (2004) and Wang and Chan (2007), Wang and Chan (2009) have reported the positive performance of trading rules based on the flag pattern by employing different stock market indexes. The profits obtained from using this trading rule were greater than the index selected as a benchmark, even after including the transaction costs. However, the size of the sample used in these works is limited.

In order to test the statistical significance of these results, and to mitigate the effects of data snooping, attention should be paid to Brock, Lakonishok, and LeBaron (1992) advice: (1) to report results from all trading rules, (2) to use very long data series, and (3) to emphasize the robustness of results across various non-overlapping sub-periods.

The aim of the present work is to follow the line of research started with chart patterns, by proposing a new version of the flag pattern which includes similarities with the IF-THEN rule. To our knowledge, the last study which analyzed this pattern was the one carried out by Wang and Chan (2009).

The present work introduces significant contributions to the existing literature. Firstly, we introduce a new definition of the flag pattern. When empirically validating its return, we strengthen the statistical robustness of the pattern and its use in the design of the trading rule.

Secondly, the validation of the trading rule based on the flag pattern also presents important novelties with respect to previous works: (1) two new parameters are included, *stop loss* and *take profit*, which allow the dynamic modeling of the closing of operations; (2) intraday data are employed, which allows considerable width in the number of observations in the sample; (3) not only closing prices are considered, but also opening prices; thus, the information considered when deciding whether or not to start an operation is widened.

Thirdly, besides evaluating the performance of the trading rules through the profits they obtain, we also consider risk in the form of the maximum drawdown of the return curves, since the non normality of the returns prevents us from using the *t*-student.

The results confirm the positive performance of the flag pattern over the intraday data of the DJIA for a time horizon of more than 13 years.

Fourthly, the results provide empirical evidence which confronts the Efficient Market Hypothesis and show how it is possible to develop an investment strategy capable of beating the market in the mean–variance sense. This is obtained by applying the trading rule to 91,307 observations of the US DJIA index. Furthermore, we complete the analysis by including the results we obtained from the application of the trading rule to the two main European indexes: the German DAX and the British FTSE.

This paper is structured as follows: the next section presents the weight matrix that identifies the flag pattern, linking the rule IF-THEN. In the third section the trading rule is developed and the *stop loss* and *take profit* values are defined according to price range. In the fourth section we present the results obtained when applying the trading rule to the intraday data of the Dow Jones Industrial Average (DJIA). The fifth section presents the results of the 3 non-overlapped sub-periods, the sixth section presents two additional case studies on the DAX and FTSE indexes. Finally, the last section summarizes the findings and our conclusions are given.

2. A new version of the flag pattern

Charting analysis is based on the recognition of chart patterns in price changes and, eventually, in the volume of operations. This work focuses on price chart analysis, specifically on one of the most analyzed patterns in the literature: the flag. Downes and Goodman (1998) defined it thus: "Technical chart pattern resembling a flag shaped like a parallelogram with masts on either side, showing a consolidation within a trend. It results from price fluctuations within a narrow range, both preceded and followed by sharp rises or declines".

To the best of our knowledge, the works by Leigh, Modani, Purvis, and Roberts (2002), Leigh et al. (2002) and Leigh, Purvis, and Ragusa (2002) are the first to deal with the graphical