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**Prediction of S&P 500 using technical indicators in conjunction with random forest classification: Adjustment of risk and expected return to maximize profitability**

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**Abstract**

This study investigated the effectiveness of technical indicators in conjunction with machine learning model to predict stock price movement from the S&P 500. We began our trading strategy by first calculating two Exponential Moving Averages (EMA) – 10-day versus 30-day EMA. The crossover between the two EMAs confirmed an up- or downtrend signal. Meanwhile, a buy signal would be triggered if Moving Average Convergence Divergence (MACD) and/or Relative Strength Index (RSI) flagged an oversold condition in conjunction with the EMA crossover signal; likewise, a sell signal would be triggered if MACD and/or RSI flagged an overbought condition in addition to the crossover signal. The combination of EMA and either MACD or RSI was to reduce the number of false positives. Furthermore, we calculated risk (beta) and change of expected return (week-over-week) and then passed these features along with the signals generated by above mentioned indicators into an algorithm of building a Random Forest (RF) model. We compared the actual return (alpha) of each set of trading strategies across the eleven industry sectors. The result indicated that the random forest classification outperformed the other strategies. We discussed whether this study questioned the prevailing view in the financial economic literature that the financial markets were generally efficient. Overall, technical analysis in conjunction with machine learning can substantially enhance the profitability of investment.

**Introduction**

Investors are always driven to maximize profits by reducing uncertainty in the decision-making process. The profitability of investing in financial asset heavily relies on the success of making correct prediction of future movement of the market prices of financial asset. Therefore, the goal of investing is always about making as many correct predictions and decisions as possible to maximizing returns. However, there is a strong academic opposition to making profits from prediction of stock market prices, and the rationale is that asset prices already reflect all available information. The Efficient Market Hypothesis (EMH) argues that markets are efficient, and therefore there is no room left to generate excess profits by investing since everything is already fairly and accurately priced (Fama, 1970). It is simply impossible to “beat the market” consistently on a risk-adjusted basis since market prices should only react to new information. The EMH strongly argues that prices already reflect all available, relevant information about the actual value of the underlying assets in an efficient market. Thus, the idea of generating profits from prediction of stock price movement based on existing trading data is futile.

If we were to assume that the markets are effective, we would not be able to create any model or trading strategy that can “beat the market” and provide excess returns to investors. However, investors do realize that excess return can be generated by applying various prediction methods. These excess returns are usually come from signals generated by various technical analyses, which have been practiced and applied effectively in a variety of asset markets in many decades. Technical analysis is sometimes seen as more art than science. There is a strong assumption that prices move in patterns that can be detected and taken advantages of by investors, and that the durations of these patterns sometimes can last long enough to compensate for any transactional costs and losses that could be incurred due to false positives. This assumption reinforces the belief and innovative use of technical analysis across different financial markets.

Obviously, this assumption of technical analysis is at odds with the widely accepted EMH proposed by Fama and others in academic circles. Many studies have shown that trading strategies generated by technical analysis have not made any significant or acceptable level of profitability, not to mention that considerable portfolio turnover generated by noises that resulted in additional transaction cost that could offset any profit accumulated during the investing period. In short, researchers were reasonably skeptical about the effectiveness and application of these trading strategies generated by technical analysis (Fama & Blume, 1966; Jensen & Benington, 1970). Technical analysis has had its ups and downs over the past few decades, depending on the extent of the prevalence of EMH in academic circles. This represents a challenge for behavioral science both in terms of the choice of investment strategy as well as in terms of the theoretical basis of its application.

Park and Irwin (2007) conducted a comprehensive literature review of the performance of technical trading strategies. Their detailed analysis included a total of 137 studies which covered the stock markets, foreign exchange markets and future markets during the period between 1960 and 2004. All the studied material was divided into two groups: early studies (1960-1987) and modern studies (1988-2004). The early studies analyzed application of only several simple trading rules and in most cases the trading strategies were not implemented and tested in appropriate way. In general, this group of studies disproved the efficacy and application of technical trading strategies. At least, the early studies indicated that technical analysis only seemed to be profitable in foreign exchange and futures markets, but not in stock markets in general.

On the other hand, modern studies demonstrated significantly more mature and flexible use of trading strategies adopted across various technical indicators. This group of studies mostly applied appropriate way of back testing and they were able to offer suggestion about enhancing accuracy of trading signals, strategies in general. In most cases (about 60%) of the modern studies, Park and Irwin were able to summarize and confirm the profitability of various trading strategies based on technical analysis. The rest of modern studies showed either mixed or negative results. By and large, the modern studies indicated the effectiveness and consistency of generating profitable returns in a variety of speculative markets at least until the early 1990s. Despite some positive evidence on the profitability of technical analysis, Park and Irwin concluded that majority of these empirical studies lacked appropriate way of estimating and controlling risk and transaction cost in their trading strategies. As a result, researchers remained skeptical about the use of technical indicators.

More recent studies in the past decade, however, have neither strongly supported nor opposed the effectiveness and application of trading strategies based on technical indicators. Instead, success and decision of technical trading is now considered to be adaptive and responsive to the market (or environment) – in accordance with the Adaptive Market Hypothesis (AMH) proposed by Andrew Lo in the early 2000s. Under this new paradigm, traditional models of modern financial economics can now coexist with behavioral models (Todea, Ulici & Silaghi, 2009; Todea, Zoicas-Ienciu & Filip, 2009). The AMH argues that investors are capable of optimal dynamic allocation and many behaviors previously seen as irrational and impractical can now be explained as adaptive and consistent with an evolutionary perspective, i.e., individuals are striven to adapt and respond to environment (market) using simple heuristics for enhancing, maximizing the chance of survival (profitability). Economic irrationality is therefore seen as basic instinct driven by evolutionary forces. The AMH can be seen as an alternative to EMH. This theory can be characterized as link between EMH and behavioral finance. There is an assumption that the dynamic of the financial market, the chance for arbitrage and the irrationality of investors all point to an unstable relationship between risk and returns. Therefore, Lo (2004) stated that investment strategies "wax and wane, performing well in certain environments and performing poorly in other environments".

As a result, opposing and ambivalent attitudes on the performance and application of technical analyses can now be considered relative, depending on the time and the market which is being studied. Nowadays, many investors would agree that success in technical trading rules largely depends on the conditions on the financial market, primarily (non)liquidity, and to a lesser extent macroeconomic (in)stability, including the ability to short-sell stocks (Taylor, 2014). Although the existing literature on this topic of technical analysis is still quite controversial, technical analysis is widely used and communicated in academic and professional circles. Many studies have been conducted to find optimization of trading strategies (Gehrig & Menkhoff, 2006; Menkhoff, 1997). For example, Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI) are two of the most popular technical indicators for developing trading strategy. They are found consistently effective in optimizing investors’ portfolio in the financial markets (Rosillo, de la Fuente & Brugos, 2013; Stankovic et al., 2015; Wu & Diao, 2015). In addition, trading strategies based on crossover signal generated by moving averages could significantly reduce investment risk and confirm trading signal (Anghel, 2013).

More recent studies suggest that, if the information obtained from stock prices is carefully pre-processed and then run by complex machine learning algorithms, the trend or stock price index movement can be highly predictable (Patel, Shah, Thakkar & Kotecha, 2015). The advance of machine learning and more cost efficient of big data technology have made significant contribution to investment strategy, e.g., from quantitative to sentiment analysis using Natural Language Processing (NLP). Not surprisingly, machine learning is gaining tremendous attention in the financial market. Concepts such as support vector machines, genetic algorithms, artificial neural networks, fuzzy logic, and chaos theory have become new buzzwords in Wall Street. Many studies have demonstrated the application of various machine learning algorithms in the successful prediction of stock price movement and thus significantly contributed to the increase in profitability and reducing the risk involved in trading. Some of the most sophisticated algorithms in the market include but not limited to Artificial Neural Networks (ANNs) (Boyacioglu, Kara & Baykan, 2009), linear and multi-linear regression (LR, MLR) (Atsalakis & Valavanis, 2009), genetic algorithm (GA) (Atsalakis & Valavanis, 2009), and Support Vector Machine (SVM) (Stankovic, Markovic & Stojanovic, 2015). The methods most widely used for predicting stock market trend are the approaches based on Support Vector Machine (SVM) and Random Forest (RF) (Chen, Chen & Liu, 2020; Lohrmann & Luukka, 2019).

On one hand, technical analyses alone seem to have become obsolete and replaceable in the advanced age of machine learning. However, some have found evidence that machine learning is not always applicable or reliable in terms of outperforming simple technical trading strategies. For example, Jian and Jakubowicz (2017) applied four classic classification algorithms: random forest, gradient boosted trees, artificial neural network, and logistic regression in predicting 463 stocks of the S&P 500. They carried several experiments thoroughly to study the predictability of these stocks using the mentioned algorithms. Furthermore, they validated each prediction algorithm by applying standard cross validation, sequential validation, and single validation. Surprisingly, they were not able to predict stocks future prices from their past using any of these algorithms. Although the financial sector was relatively easier to predict, none of these algorithms was able to predict, generate meaningful signals that could be profitable. Similarly, Qian and Rasheed (2007) investigated the predictability of the Dow Jones Industrial Average Index using artificial neural network, decision tree, and k-nearest neighbor. They concluded that none of these algorithms could achieve more than sixty-five percent accuracy. Their work seemingly supported the argument proposed by the Efficient Market Hypothesis, i.e., stock prices should follow a random walk pattern and trading strategies solely based on prediction of stock price movement would fail to generate any considerable profit in the long run.

On the other hand, there are still overwhelmingly strong evidence in favoring the use of machine learning in predicting stock price movement. Chen and colleagues (2020) explored the application of machine learning in prediction of S&P 500 stock price movement between 2014 and 2018. They compared three machine learning models: Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF). They concluded that all three models outperformed benchmark market index, and that RF generated the best performance by risk-adjusted measures, followed by SVM and ANN. Others found similar and positive evidence in support of the application of machine learning in stock price prediction, Random Forest in particular (Lohrmann & Luukka, 2019; Thakur & Kumar, 2018).

Prediction of stock market is rewarding but extremely challenging due to its highly volatile nature. Stock market can be influenced by any change and impact from foreign commodities like emotional behavior of investors, geopolitical, psychological, and various economic factors. Investors sell out at the wrong time and often fail to gain or maintain any profit. Successful investing is therefore based on timing, i.e., whether it is time to buy, hold, or sell an asset. Mistakes can be minimized by making accurate prediction of the market movement based on analysis of historical data. Although it is clearly not possible to predict stock market movement with full accuracy, losses from selling stocks at wrong time can still be minimized to greater extent using machine learning. Some of the most effective trading strategies powered by machine learning models is simply built by effective feature engineering. The features are extracted from signals generated by technical indicators, such as moving average crossover. Machine learning and traditional technical indicators effectively supplement each other to come up with simpler but more efficient trading strategies that can generate less noisy buy and sell signals. The predictability of a stock market and the profitability of model-based trading strategies are based on the maturity of the market, the sophistication of algorithm(s) employed, and the technical feasibility for generating accurate and timely prediction in real-time trading. There is already compelling evidence against the stand-alone application of technical indicators from the field of technical analysis and financial economic driven by the Efficient Market Hypothesis (Hsu, Lessmann, Sung, Ma, & Johnson, 2016). The emphasis has long been shifted from disputing whether those financial markets are generally efficient, or which specific technical indicator(s) or machine learning algorithm(s) are most effective; instead, researchers and practitioners focus on the wide application of technical indicators in conjunction with machine learning in mature market.

Recently, researchers have become very interested in exploring emerging markets, since these markets are now being recognized as important alternative of investment opportunities; however, studies on these markets showed mixed results (Stankovic et al., 2015). Unlike these emerging markets, many studies have demonstrated the ease of access to the historical data and consistent profitability generated by technical indicators in the case of developed markets. As a result, the present study focused on the application of technical indicators and machine learning algorithm to evalutate profitable return from a mature market, i.e., S&P 500. The S&P 500 is widely considered a significant representation for the overall US economy as it includes some of the biggest corporations from the NYSE and the NASDAQ stock exchanges. Basically, the list of S&P 500 includes some of the largest (in terms of capitalization) and most influential global companies across eleven industry sectors. Any efficient prediction of the S&P 500 is of great importance to investors and policy makers in general, since their decisions may trigger large scale buying or selling opportunities that can bring significant impact to the global market and overall economy. There is already compelling evidence in favor of the use and experiment (back testing) of trading strategies using historical data from mature market, e.g., NASDAQ, Dow Jones or S&P 500 (Chen, et al., 2020; Jian & Jakubowicz, 2017; Lohrmann & Luukka, 2019; Thakur & Kumar, 2018). Studies in EU or other emerging markets showed that predictive power of technical analysis or machine learning model was only effective in small and medium sized capitalization markets (Metghalchi, Marcucci & Chang, 2012). Others found mixed evidence in the world’s emerging markets (Fifield, Power & Donald, 2005; McKenzie, 2007). Overall, there is still a lack of consensus about the profitability of technical trading strategies in European frontier markets (Stankovic et al., 2015). Therefore, we focused on the S&P 500 and applied a specific machine learning algorithm, i.e., Random Forest (RF), to investigate the effectiveness of trading strategies based on historical data between 2010 and 2022.

This study built a set of simple trading strategies based on signal generated from Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI). Signals extracted from these indicators were used as inputs to build a classification model that would signal a market trend for each security on the S&P 500 based on daily historical data in above mentioned period. This study would compare the effectiveness of each trading strategy by measuring the actual return. In addition, we would compare the result of each strategy against the traditional “Buy & Hold” strategy and use it as a benchmark index. Furthermore, we would evaluate beta and its impact on trading strategies across the eleven sectors. To the best of our knowledge, there’s no conclusive study to date that has looked at beta of each security across the eleven sectors from the S&P 500, and then subsequently evaluated alpha based on various trading strategies generated by technical indicators versus machine learning model.

**Method**

Technical analysis applies various qualitative and quantitative methods to evaluate asset price trends. The simplest qualitative method is based on charting asset prices along with trading volume to discern any pattern that signals optimal instant for entry or exit strategy. Technical indicators are quantitative methods in which they represent simple mathematical expression of price and volume changes. Investors usually use a combination of both methods, in conjunction with fundamental and sentiment analyses, to provide a more precise overview of market trends.

In this study, we extracted 490 stocks from the current list of S&P 500 and looked at period between January 2010 and February 2022. We employed the most common technical indicators, i.e., Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD), and the Relative Strength Index (RSI). Technical trading rules were based on the combination of crossover indicated by the EMA and signals generated from MACD and/or RSI. In addition, beta was measured as it represented the relative volatility of an investment. Beta represented risk and we also calculated the expected return along the way, and then subsequently passed them in the machine learning model for generating entry and exit signals.

*Exponential Moving Average (EMA)*

A running moving average or simply Moving Average (MA) represents the average of the price of a financial asset over a certain period. This is a frequently used indicator, and usually the first step in time series analysis when investors look at the trend of a financial asset. The purpose of calculating MA is to smooth the trend of asset prices by removing noise in the time series. This method, however, is not particularly useful in generating signal since the trend of market prices is extremely volatile and highly correlated to the most recent events/changes in prices. Therefore, investors tend to apply the Exponential Moving Average (EMA) for generating insight (and confirmation) of market trend. The EMA is still a type of MA, but it places a greater weight, e.g., a smoothing constant, on the most recent data points when calculating an average over a certain period. MA or EMA is considered a lagging indicator as it triggers or displays signal of a trend that is already in place. Thus, a trading strategy solely based on the signals triggered by MA or EMA tend to miss the optimal buying or selling window. Instead, we should use it as confirmation of buying/selling opportunity in conjunction with the signals triggered by MACD and/or RSI.

In this study, we adapted a trading system that involved the calculation of two EMAs. That was, we calculated the EMA for the past 10-day versus the past 30-day. When there was a crossover between the two EMAs, that would trigger a signal of market uptrend (10-day EMA > 30-day EMA) or downtrend (10-day EMA < 30-day EMA). This crossover strategy served as a confirmation of buy/sell signals generated by the MACD or RSI.

*Moving Average Convergence Divergence (MACD)*

The Moving Average Convergence-Divergence (MACD) is a commonly used indicator for trend monitoring as well as tracking changes in the trend. It is a popular momentum indicator that can visually display the relationship between two EMAs of a financial asset price. The MACD is simply calculated by subtracting the 26-period EMA from the 12-period EMA. The result of that calculation is the "MACD line". Subsequently, we calculate a nine-day EMA of the MACD line and that is referred to the "signal line". A buy signal is triggered when the MACD line crosses above its signal line; conversely, a sell signal is triggered when the signal line crosses above the MACD line. MACD is a trend-following indicator that can allow investors to anticipate the optimal time of buying and selling a security. In addition, investors pay attention to the speed of crossover as it can reveal whether the security is overbought or oversold. MACD helps investors to understand and anticipate whether the bullish or bearish movement in the price is strengthening or diminishing. In this study, the buy signal was only triggered when the MACD instantaneously crossed above the signal line (meaning the MACD line from the day prior must still be below the signal line, whereas the present day the MACD line just barely crossed it to trigger a buy signal); likewise, the same condition applied to the sell signal (meaning the signal line from the day prior was still above the MACD line and then it crossed below it). That was to reduce false positives.

*Relative Strength Index (RSI)*

Another popular indicator is the Relative Strength Index (RSI), which is also a momentum indicator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions of an asset. The RSI is sometimes referred to as an oscillator as it can be visually displayed as a line between two extremes of 0 and 100. The interpretation is quite simple as the RSI goes above the value of 70 would indicate an overbought condition; on the other hand, if the value of RSI goes below 30, it would indicate an oversold condition. The overbought/oversold condition alarmed by the RSI would indicate a trend reversal or corrective pullback of an asset price in near future. Like the above MACD trigger, the RSI from this study would only trigger a buy signal when the RSI from the day prior was still above the threshold (30), and then crossed below it in the present day to trigger an oversold condition; similar condition applied to the overbought condition, i.e., RSI remained below the threshold (<70) the day prior until it went above in order to trigger a sell signal.

*Random Forest (RF)*

Random Forest (RF) is a very popular classification algorithm that is made up by numerous decision trees. It consists of many individual decision trees that operate as an ensemble. The algorithm applies randomness from a set of independent variables to build each individual tree in random to promote uncorrelated forest. Subsequently, each tree in the random forest spits out a class prediction and then the class with the most votes becomes the model's prediction, aka majority vote.

In this study, we split the data into two for model validation. We used 80% of the data for training and 20% for testing purposes. We defined our dependent variable as a flag for either up, down, or flat based on the moving average of the proceeding 5 trading days, i.e. if 80% or more (at least 4 out of 5) of the following trading days that we observed that the adjusted close price for each associated day was above the corresponding 5-day MA, it signaled an uptrend condition (up); conversely, if 80% or more of the time, the adjusted close price fell below the corresponding 5-day MA, it signaled a downtrend condition (down); other than these, that was a flat condition.

In addition to passing the features extracted from above EMA, MACD and RSI into building a classification model, we also calculated the expected risk (beta) and expected return for each security. We would include the risk and change of expected return (percent change of return week over week) into the RF model. The prediction of the flag generated by the model in conjunction with the confirmation triggered by the EMA would generate the buy, sell signal.

Eventually, we calculated the actual return (alpha) for these 490 stocks across different trading strategies, i.e., MACD plus EMA, RSI plus EMA, RF plus EMA, and Buy-and-Hold. We applied the Analysis of Variance (ANOVA) to measure any statistically significant difference in means across these trading strategies and eleven sectors.

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