Financial Forecasting and Trading Strategies: A Survey

Chapter · March 2014
DOI: 10.4324/9780203084984

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FINANCIAL FORECASTING AND TRADING STRATEGIES: A SURVEY*

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** This chapter is accepted to be included in the forthcoming book:*

Computational Intelligence Techniques for Trading and Investment, Dunis, C., Likothanassis, S. Karathanasopoulos, A., Sermpinis, G. & Theofilatos K. (eds), Routledge: Taylor & Francis (ISBN-13: 978-0415636803)

The book is to be published in December 2013 and the following is provisionally the second chapter. For more detailed information on the book and its contents, please contact the corresponding author of this chapter and editor of the book, Dr. Georgios Sermpinis.

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INTRODUCTION

Forecasting the market behavior has always been in the centre of scientific research by academics, financial and government institutions, investors, market speculators and practitioners. This task has proven to be extremely challenging and controversial due to the noisy and non-stationary nature of financial time series, especially in periods of economic turmoil. In order to quantify the results of financial forecasts in practical market terms, the above mentioned parties combine their forecasting methods with sets of rules regarding trade orders and capital management. These rules are called *trading strategies*. This chapter attempts to present a general survey of the trading rules originating from the technical market approach and link them with their modern automated equivalents and trading systems.

1. TECHNICAL ANALYSIS OVERVIEW

Technical analysis is a financial market technique that focuses on studying and forecasting the 'market action', namely the price, volume and open interest future trends, using charts as primary tools. Charles Dow set the roots of technical analysis in late 18th century. The main principle of his Dow Theory is the trending nature of prices, as a result of all available information in the market. These trends are confirmed by volume and do persist despite the 'market noise', as long as there are not definitive signals to imply otherwise. Another interesting definition of technical analysis is given by Pring (2002, p.2). *'The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces.'* Furthermore he adds that *'the art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.'*.

In order to fully understand the concept of technical analysis, it is essential to clearly distinct it from the fundamental one. It is also important to discuss the Efficient Market Hypothesis and the Random Walk Theory.

1.1. Technical Analysis vs. Fundamental Analysis

In order to fully understand the concept of technical analysis, it is essential to clearly distinct it from the fundamental one. The premises of the technical approach are basically that market action discounts all available information, prices move in trends and history tends to repeat itself. On the other hand, fundamental analysis is based on information regarding supply and demand, the two major economic forces affecting the prices' direction change. Both approaches aim to solve the same problem, but *'the fundamentalist studies the cause of market movement, while the technician studies the effect'* (Murphy, (1996, p. 5)).

In reality the complete separation between the fundamentalist and the technician is not so easy to be made, although there is always basis of conflict. For example, institutions that need a long term assessment of their stock turn to fundamental analysis, while short-term traders use technical one. The company's financial health is evaluated with the technical approach, whereas its long-term potential is based on fundamental approximations. Such examples show that both techniques have advantages and disadvantages and one does not exclude the other. The greatest benefit derived from fundamental analysis is the ability to understand market dynamics and not panic in periods of extreme market volatility. On the other hand, technical analysis does not utilize any economic data or market event news, just simple tools that are easy to understand in comparison with fundamental indicators. The technicians are also able to adapt in any trading medium or time dimension and therefore they gain extra market flexibility compared to fundamentalists. In conclusion, technical analysis appears able to capture trends and extreme market events that the fundamental one discovers and explains, after they are already been well established.

1.2. Efficient Market Hypothesis and Random Walk Theory

Fama (1970) introduced the concept of capital market efficiency. This influential paper established the framework implied by the context of the term '*Efficient Market Hypothesis'.* According to Fama (1970), a market is efficient if the prices always reflect and rapidly adjust to the known and new information respectively. The basis of this hypothesis is the existence of rational investors in an uncertain environment. A rational investor is following the news and reacts immediately to all important news that affect directly or indirectly his investment, capital, security price etc. The Efficient Market Hypothesis is also connected with the *Random Walk Theory*, which suggests that the market price movements are random.

The assumptions of the Efficient Market Hypothesis can be summarized as:

- Prices reflect all relevant information available to investors.
- All investors are rational and informed.
- There are no transaction costs and no arbitrage opportunities (perfect operational and allocation efficiency).

Fama (1970) further classifies market efficiency into three forms, based on the information taken under consideration:

- *The weak form* applies when all past information is fully reflected in market prices. The weakly efficient markets are linked with the Random Walk Theory. If the current prices fully reflect all past information, then the next day's price changes would be the result of new information only. Since the new information arrives at random, the price changes must also be random.

- *The semi-strong form* requires all publicly available information to be reflected in market prices. This form is based on the competition among analysts, who attempt to take advantage of the new information constantly generating from market actions. If this competition is perfect and fair, then there would be no analyst who would be able to make abnormal profits.

- *The strong form* implication is that market prices should reflect all available information, including that available only to insiders. This form of market efficiency is the most demanding, because it concludes that profits cannot be achieved by inside information.

There is a general agreement that developed financial markets would meet the conditions of semi-strong efficiency, despite of some anomalies. These anomalies are related to abnormal returns that can be evident simultaneously with the release time of the new information. On the other hand, the concept of strongly efficient markets is not easily accepted. This is because most of the countries already have anti-insider-trading laws, in order to prevent excessive returns from inside information.

Accepting or not the Efficient Market Hypothesis is one of the core financial debates of our times. The relevant literature is voluminous (see amongst others Jensen (1978), LeRoy and Porter (1981) Malkiel (2003), Timmerman and Granger (2004), Yen and Lee (2008), Lim and Brooks (2011) and Guidi and Gupta (2013)). The empirical results of this extensive literature are ambiguous and controversial. Especially during the 1980s and 1990s, the Efficient Market Hypothesis was under siege. Recent case studies present more results in favor of the market efficiency, but the debate is still ongoing. In fact, the main question remains: *'Does market efficiency exist?'* The practical market experience shows that trends are 'somewhat' existent and predictable, so strictly speaking the Efficient Market Hypothesis can be stated as false (Abu-Mostafa and Atiya, 1996). There is also the opinion that science tries to find the best hypothesis. Therefore, criticism is of limited value, unless the hypothesis is replaced by a better one (Sewell, 2011).

1.3. Profitability of Technical Analysis and Criticism

From all the above, it is clear that technical analysis is in contrast with the idea of market efficiency. The main reason for this conflict is that technical analysis opposes the accepted view of what is profitability in an efficient capital market. Technical analysis is based on the principal that investors can achieve greater returns than those obtained by holding a randomly chosen investment with comparable risk for a long time. Hence, the market can be indeed beaten.

However, claiming that there is a direct link between profitability and technical trading rules is justified. For example, Brock *et al.* (1992) in their pioneering paper present evidence of profitability of several trading rules using bootstrap methodology, when applied to the task of forecasting the Dow Jones Industrial Average index. Bessembinder and Chan (1995) extend the use of those rules to predict Asian stock index returns with similar results. These studies created a research trend in technical analysis' efficiency and utility. Menkhoff and Schmidt (2005), Hsu and Kuan (2005) and Park and Irwin (2007) summarize relevant empirical evidence in surveys that focus on the profitability of the technical approach. Especially the latter provide an interesting separation of the corresponding literature into two periods: The early (1960– 1987) and modern (1988–2004) studies periods. This classification is based on the available tools, factors, models, tests and drawbacks that the researcher of period had to face (i.e. Transaction costs, Risk Factor Analysis, Data Mining and Pattern Recognition issues, Parameter Optimization, Out-of-sample verification processes, Bootstrap and White Reality Checks, Neural Networks and Genetic Programming architectures). Park and Irwin (2007) also note that most of the studies conducted in 1960s were more or less published during and after the 1990s. The main reasons for that is, firstly, the fact that the computational resources 'flourished' during that period. Secondly, the benefits of technical analysis also emerged through several seminal papers, which till that period were not well known to the scientific public.

Taken all the above under consideration, it is very logical to wonder why technical analysis remains under constant criticism. Especially academics have an extreme and attacking attitude towards the technical approach, which can be 'colourfully' described as follows. *'Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) the method is patently false; and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: it is your money we are trying to save.'* (Malkiel, (2007, pp. 127-128)).

The main reasoning for this critique can be summarized as:

- Technical analysis does not accept the Efficient Market Hypothesis.
- Widely cited academic studies conclude that technical rules are not useful (Fama and Blume (1966); Jensen and Benington (1970)).
- Traders use the well known charts and see the same signals. Their actions go in a way that the market complies with the overriding wisdom. Thus, technical analysis is a 'self-fulfilling prophecy'.
- Chart patterns tell us where the market has been, but cannot tell us where it is going. In other word the past cannot predict the future.
- The technical approach is 'trapped' between the psychology of the trader and the 'insensitivity' of an automatic computational system, where no human intervention is allowed in real time.

2. TECHNICAL TRADING RULES

There is a wide variety of technical trading rules applied everyday by market practitioners, trading experts and technical analysts. This section attempts to present an overview of the 'universe' of these rules and to classify them in some basic categories.

2.1. The benchmark 'Buy-and-Hold' Rule (BH)

The 'Buy-and-Hold' rule (BH) is a passive investment strategy, which is thought to be the benchmark of all trading rules in the market. BH aligns with the Efficient Market Hypothesis (see Section 1). Its principle is that investors buy stocks and hold them for a long period of time, without being concerned about short-term price movements, technical indicators and market volatility. Although 'Buying-and-Holding' is not a 'sophisticated' investment strategy, historical data show that it might be quite effective, especially with equities given a long timeline. Typical BH investors use passive elements, such as dollar-cost averaging and index funds, focusing on building a portfolio instead of security research. There is ground for criticism, especially from technical analysts, who after the Great Recession declared the death of BH rules. Corrado and Lee (1992), Jegadeesh and Titman (1993), Gençay (1998), Levis *et al.* (1999), Fernández-Rodríguez *et al.* (2000), O'Neil (2001), Barber *et al.* (2006) and recently Szafarz (2012) perform competitions of trading strategies, with BH being the main benchmark. Although in most cases BH strategies are being outperformed, there are cases of returns of more than 10% per annum.

2.2. Mechanical Trading Rules

Charting is subjective to the technician's interpretation of the historical price patterns. Such subjectivity allows emotions to affect the technical decisions and trading strategies. This class of mechanical rules attempts to constrain these personal intuitions of the traders by introducing a certain decision discipline, which is based on identifying and following trends.

2.2.1. Filter Rules (FRs)

Filter Rules (FRs) generate long (short) signals when the market price rises (drops) multiplied by the per cent above (below) the previous trough (peak). This means that *'if the stock market has moved up 'x' per cent, it is likely to move up more than 'x' per cent further before it moves down by 'x' per cent'* (Alexander, (1961, p.26)). A trader using FRs, assumes that in each transaction he/she could always buy at a price exactly equal to the low plus '*x*' per cent and sell at the high minus '*x*' per cent, where '*x*' is the size of the filter (threshold). Such mechanical rules attempt to exploit the market's momentum. Setting up a filter rule requires two decisions. The first is the specification of the threshold. The second is the determination of the window length, meaning how far back the rule should go in finding a recent minimum. These decisions are obviously connected with the subjective view of the trader on the historical data at hand and the relevant past experience. Common thresholds values fluctuate between 0.5 percent and 3 percent, while a typical window length is about five trading days.

FRs have a prominent place among the common tools in technical analysis, although the studies of the 1960s tend to understate their performance in comparison to the 'buy-and-hold' rule. Several examples in the literature show that filtering techniques are capable of exhibiting profits. Dooley and Shafer (1983) conduct one of the earliest studies that focus on applying FRs to trading in the foreign exchange market. Their results show substantial profitability for most thresholds implemented over the period 1973–1981 for the DEM, JPY and GBP currencies. Sweeney (1986) suggests that a filter of 0.5% is outperforming a BH of 4% per annum strategy, using daily USD/DEM data during late 1970s. The bootstrap technique first used by Brock *et al.* (1992) and later by Levich and Thomas (1993) address the issue of the significance of such FRs' returns in the context of the stock market. Qi and Wu (2006) report evidence on the profitability and statistical significance of over 2000 trading rules, including FRs with various threshold sizes. Dunis *et al.* (2006 and 2008) forecast feature spreads with neural networks and apply filter trading rules. In their approach, they experiment beyond the boundaries of the traditional threshold approaches by implementing correlation and transitive filters (see Guégan and Huck (2004) and Dunis *et al.* (2005) respectively). These FRs, especially the transitive one combined with a recurrent neural network, present impressive results in terms of annualized returns. FRs can be used also as technical indicators that measure the strength of the trend. Dunis et al. (2011) also apply filter strategies to the task of forecasting the EUR/USD exchange rate. In their application, their confirmation filter does not allow trades that will result in returns lower than the transaction costs. Finally, Kozyra and Lento (2011) compare filter trading rules with the contrarian approach (see Section 2.4) and note that the filter technique is less profitable in periods of high market volatility in particular.

2.2.2. Moving Average Rules (MAs)

Moving Average rules (MAs) are also common mechanical indicators and their applications are known for many decades in trading decisions and systems. In simple words, a MA is the mean of a time series, which is recalculated every trading day. Their main characteristic is the length window, namely the number of trading days that are going to be used to calculate the rolling mean of the high frequency data. MAs are identifiers of short- or long-term trends, so the window length can be short (short MAs – 1 to 5 lags) or long (long MAs- 10 to 100 lags). The intuition behind them is that buy (sell) signals are triggered when closing prices cross above (below) the *x* day MA. Another variation is to buy (sell) when *x* day MA crosses above (below) the *y* day MA.

Assuming that the length window is *n* days, the current period's *t* closing price $P_{t,}$ MAs can be further divided into three main categories:

- Simple MA (SMA): $SMA_{t+1} = (1/n)(P_t + P_{t-1} + ...P_{t-n+1})$ (1)
- Exponential MA (EMA): $EMA_{t+1} = EMA_t + \alpha(P_t - EMA_t)$ (2)
- Weighted MA (WMA): $WMA_{t+1} = \left[nP_t + (n-1)P_{t-1}... + 2P_{t-n+2} + P_{t-n+1})\right] / \left[n(n+1)/2\right]$ (3)

The SMA is an average of values recalculated every day. The EMA is adapting to the market price changes by smoothing constant parameter *α*. The smoothing parameter expresses how quickly the EMA reacts to price changes. If *α* is low, then there is little reaction to price differences and vice versa. The WMA give weights to the prices used a lags. These weights are higher in recent periods, giving higher importance in recent closing prices. All these MAs are using the closing price as the calculation parameter, but open, high and low prices could also be used.

MAs are also well documented in the literature. Brock *et al.* (1992) and Hudson *et al.* (1996) analyse the Dow Jones Industrial Average and Financial Times Industrial Ordinary Index respectively with MAs and conclude that they have predictive ability if sufficiently long series of data are considered. Especially from the first study, it is suggested the best rule is 50-day MA, which generates an annual mean return of 9.4%. Applications of artificial intelligence technologies, such as artificial neural networks and fuzzy logic controllers, have also uncovered technical trading signals in the data. For example, Gençay (1998 and 1999) investigates the non-linear predictability of foreign exchange and index returns by combining neural networks and MA rules. The forecast results indicate that the buy–sell signals of the MAs have market timing ability and provide statistically significant forecast improvements for the current returns over the random walk model of the foreign exchange returns. LeBaron (1999) finds that a 150-day MA generates Sharpe ratios of 0.60–0.98 after transaction costs in DEM and JPY markets during 1979–1992. LeBaron and Blake (2000) further examine their profitability and note that it would be interesting to determine more complex combinations of MAs that are able to project even higher returns. Gunasekarage and Power (2001) apply the variable length MA and fixed length MA in forecasting the Asian stock markets. The first rule examines whether the short-run MA is above (below) the long-run MA, implying that the general trend in prices is upward (downward). The second rule focuses on the crossover of the long-run MA by the short-run MA. Their results show that equity returns in these markets are predictable and that the variable length MA is very successful.

On the other hand, Fong and Wong (2005) attempt to evaluate the fluctuations of the internet stocks with a recursive MA strategy applied to over 800 MAs. Their empirical results show no significant trading profits and align the internet stocks with the Efficient Market Hypothesis. Chiarella *et al.* (2006) analyze the impact of long run MAs on the market dynamics. When examining the case of the impact between fundamentalists and chartists being unbalanced, they present evidence that the lag length of the MA rule can destabilize the market price. Zhu and Zhou (2009) analyze the efficiency of MAs from an asset selection perspective and based on the principle that existing studies do not provide guidance on optimal investment, even if trends can be signalled by MAs. For that reason, they combine MAs with fixed rules in order to identify market timing strategies that shift money between cash and risky assets. Their approach outperforms the simple rules and explains why both risk aversion and degree of predictability affect the optimal use of the MA. Milionis and Papanagiotou (2011) test the significance of the predictive power of the MAs on the New York Stock Exchange, Athens Stock Exchange and Vienna Stock Exchange. Their contribution is that the proposed MA performance is a function of the window length and that it outperforms BH strategies. This happens especially when the changes in the performance of the MA occur around a mean level, which is interpreted as a rejection of the weak-form efficiency. Finally, Bajgrowicz and Scaillet (2012) revisit the historical success of technical analysis on Dow

Jones Industrial Average index from 1897 to 2011 and use the false discovery rate for data snooping. In their review they present the profitability of MAs during these years, but call into serious question the economic value of technical trading rules that have been reported in the period under study.

2.2.3. Oscillators (OTs) and Momentum Rules (MTs)

The third class of mechanical trading rules consists of the Oscillators (OTs) and Momentum Rules (MTs). OTs are techniques that do not follow the trend. Actually, they try to identify when the trend is apparent for too long or 'dying'. Therefore they are also called *'non-trending market indicators'*. The main drawback of MAs is the inability to identify the quick and violent swifts in price direction, which lead to capital loss by generating wrong trading signals. This performance gap is filled from OT indices. Their basic intuition is that a reversal trend is eminent, when the prices move away from the average. Simple OT rules are based on the difference between two MAs and generate buy (sell) signals when prices are too low (have risen extremely). Nonetheless, being a difference of MA rules, OTs can also present buy and sell position, when the index crosses zero. The boundaries between OTs and MTs can be a bit vague depending on the case, because MTs can be applied to MAs and OTs. The main difference is that OTs are non-trend indicators, whereas MTs are capitalizing on the endurance of a trend in the market. A simple MT rule would be the difference between today's closing price and the closing price of x days ago. The trading signal is generated based on this momentum. To put it simply, the buy (sell) signal is given when today's closing price is higher than the closing price x days ago. Setting properly the x day's price that is going to be used is also a matter of trader intuition, market knowledge and historical experience (5 and 20 days are common).

There are many types of OTs and MTs used in trading applications. Some typical examples are summarized, interpreted in short and followed by relevant research applications below:

- *Moving Average Convergence/Divergence* (MACD): MACD is calculated as the difference between short- and long-term EMAs and identifies where crossovers and diverging trends to generate buy and sell signals.
- *Accumulation/Distribution* (A/D): A/D is a momentum indicator which measures if investors are generally buying (accumulation) or selling (distribution) base on the volume of price movement.
- *Chaikin Oscillator* (CHO): CHO is calculated as the MACD of A/D.
- *Relative Strength Index* (RSI): The RSI is calculated based on the average ‘up’ moves and average ‘down’ moves and is used to identify overbought (when its value is over 70 – sell signal) or oversold (when its value is under 30-buy)
- *Price Oscillator* (PO): PO is identifying the momentum between two EMAs.
- *Detrended Price Oscillator* (DPO): DPO eliminates long-term trends in order to easier identify cycles and measures the difference between closing price and SMA.
- *Bollinger bands* (BB): BB are based on the difference of closing prices and SMAs and determine if securities are overbought or oversold.
- *Stochastic Oscillator* (SO): SO is based on the assumptions that as prices rise, the closing price tends to reach the high prices in the previous period.
- *Triple EMA* (TRIX): TRIX is a momentum indicator between three EMAs and triggers buying and selling signals base on zero crossovers.

The exact specifications and formulas of the abovementioned indicators can be found in Gifford (1995), Chang *et al.* (1996) and Edwards and Magee (1997) or in any common textbook of technical analysis. Their utility though has been eminent years before that. The pioneering paper of Brock *et al.* (1992) presents evidence of profitability of MACD, as for MAs and FRs mentioned above. Kim and Han (2000) propose a hybrid genetic algorithm – neural network model that uses OTs, such as PO, SO, A/D and RSI, along with simple momentum rules to predict the stock market. Leung and Chong (2003) compare the profitability of MA envelopes and BBs. Their results suggest BBs do not outperform the MA envelopes, despite being able to capture sudden price fluctuations. Shen and Loh (2004) propose a trading system with rough sets to forecast S&P 500 index, which outperforms BH rules. In order to set up this hybrid trading system, they search for the most efficient rules based on the historical data from a pool of technical indicator, such as MACD, RSI and SO. Lento *et al.* (2007) also present empirical evidence that prove BBs' inability to achieve higher profits compared to a BH strategy, when tested on tested on the S&P/TSX 300 Index, the Dow Jones Industrial Average Index, NASDAQ Composite Index and the Canada/USD exchange rate. Chong and Ng (2008) examine the profitability of MACD and RSI using 60-year data of the London Stock Exchange and found that the RSI as well as the MACD rules can generate returns higher than the BH strategy in most cases.

Ye and Huang (2008) extends Frisch's (1993) damping OT with a non-classical OT. The non-classical OT introduces Quantum Mechanics in the market, which is treated as an apparatus that can measure the value and produces a price as a result. With the numerical simulations presented, the OT under study explains qualitatively the persistent fluctuations in stock markets. Aggarwal and Krishna (2011) explore Support Vector Machines and Decision Tree classifiers in the task of direction accuracy prediction. In their application, the company's stock value history is evaluated based on the daily high, open, close, low prices and volumes traded over the last 5-10 years. The performance of their techniques provides impressive forecasting accuracy of over 50% and is tested with several OTs and MTs (i.e. MACD, DPO, SO, A/D and RSI). Finally, Dunis *et al.* (2011) and more recently Sermpinis *et al.* (2012) forecast exchange rates with several neural networks. In those applications, MACD are used as benchmarks, but they do not present significant profitability.

2.3. Other Trading Rules

The rules presented above are the main market indicators of technical analysis, but their 'universe' is in a way limitless. Technical analysts and practitioners tend to create new trading rules, which in reality are small specification alternatives of the existing ones. Such offsprings are commonly cited in the literature with different and more appealing names, despite their direct correlation with the basic mechanical rules presented in the previous section.

2.3.1 Contrarian Rules (CTs)

One such example is the contrarian approach in trading, or in other words the *Contrarian Rules* (CTs). Their logic and specification is very simplistic. For every simple trading rule that triggers a sell signal, there is the corresponding CT that triggers a buy signal and vice versa. Technical analysts, that use the contrarian approach, believe that the price changes can be temporary and the market tends to return to its steady state. Typical handbooks that refer to CTs are LeBaron and Vaitilingam (1999) and Siegel (2000). Forner and Marhuenda (2003) explore the profitability of the momentum and contrarian in the Spanish stock market. They find that a 12-month momentum strategy and the five-year contrarian strategy yield significant positive returns, even after risk adjustments have been made. Menkhoff and Schmidt (2005) compare BH, MT and CT traders and suggest that the later are overconfident and willing to hold on against the market. In other words, contrarians are long-run arbitrageurs, but tend to perform worst than Buyers-and-Holders or MT traders. More recently, Park and Sabourian (2011) also compare the ‘herding’ and ‘contrarian’ psychology of trade agents. The ‘herding’ trader follows the trend, whereas a ‘contrarian’ goes against it. Their main conclusion is that herding and contrarianism lead to price volatility and lower liquidity. It is also noted that herding trades are self-enforcing, while contrarian trades are self-defeating.

2.3.2. Trading Range Break Rules (TRBs)

Trading Range Break Rules (TRBs) is also an evident class of technical rules in the literature. TRBs can be thought as MT indicators, since their main premise is that a positive or negative momentum is built, when a stock breaks through or falls below its trading range after several days of trading. Trading range is the spread between the recent minimum and maximum of the current price. TRBs generate buy positions, when the current price exceeds the recent maximum by at least a band. Similarly, they emit sell signals, when the current price falls below the recent minimum by at least the band. For example, Brock et al. (1992) and Bessembinder and Chan (1995) apply TRBs over the period 50, 150 and 200 days and use bands of 0 and 1%. Coutts and Cheung (2000) investigates the applicability and validity of trading rules in the Hang Seng Index on the Hong Kong Stock Exchange for the period January 1985 to June 1997. Although TRBs are by far the most common, in terms of implementation they fail to provide positive abnormal returns, net of transaction costs and opportunity costs of investing. Park and Irwin (2007) in their technical analysis survey also include TRBs in the pool of profitable trading rules. In a more recent application, Wang *et al.* (2012) present a weight reward strategy, which combines MAs and TRBs to create a pool of 140 component trading rules. The proposed hybrid trading system employs a Particle Swarm

Optimization algorithm and the optimized combinations of MAs and TRBs are found to outperform the best individual MA and TRB.

2.3.3. Breakout Rules

Another interesting category of trading rules is the *Channel Breakout* (CHB) and *Volatility Breakout* (VOLB) rules. The CHBs are originating from Richard Donchian, a pioneer in futures' trading (Kestner, 2003). The idea behind them is that a 'channel' of price changes is incorporated in the trading strategy. This '*x* days' channel' is created by the plot of the high and lows of the price during *x* days and is also a measure of market volatility. Trading entries happen when prices remain into the channel. A buy (sell) position is taken when today's close is higher (lower) than the previous *x* day's closes. The VOLBs entries are decided in a similar logic, but based on the three following parameters:

- The reference value gives a measurement value to the price move.
- The volatility measure is a computational calculation of the market volatility and it is used to identify significant movements from random prices.
- The volatility multiplier specifies how sensitive the price move is.

The combination of these parameters results in a high and low trigger point. This allows the trader to buy (sell) when the closing price is above the upper (below the lower) trigger. Levitt (1998) compared two trend following trading systems employing CHB and VOLB strategies using standard and Daily Market Time Data from 1987 to1996. Both rules are profitable but especially VOLB presents average annual returns of more than 10%. Qi and Wu (2006) in their extensive search of profitable trading rules suggest that the best rule for trading the JPY and CHF exchange rate is the CHB rule. Marshall et al. (2008) examine the profitability of intraday technical analysis in US equity market and compare FRs, MAs, TRBs and VOLBs. Their findings show that VOLBs are the most profitable family of trading indicators.

2.3.4. Pattern Rules

Head-and-Shoulders (HSs), *Double-Tops-and-Double-Bottoms* (DTBs), *Triangles-and-Rectangles* (TRs) and *Flags-and-Pennants* (FPs) are types of rules that attempt to identify and establish pattern on pricing charts. They can also be thought as classes of MAs, OTs or MTs, and their short descriptions are given below:

- HS is a trading rule based on the tops of 'up-trends' and bottoms of 'down-trends'. In each period, the higher price peak (head), the two higher picks before (left shoulder) and after the head (right shoulder) are identified. The two lowest prices (points) during this period create a line, called HS 'neckline'. In an 'up-trend', a HSs rule will act as a reversal point, only when the price succeeds to break down the HS 'neckline'. Alternatively, it will go up and may retest the HS 'neckline' in the future. HSs are commonly used by daily currency traders.
- DTBs are also frequently used as reversal pattern indicators by the FOREX market participants. A 'double top' is formed by two price peaks at approximately the same level and the 'neckline' is similarly formed as in HSs. This pattern is completed, when a price closes below the lowest price that has been reached between the two peaks.
- TRs are formed by two converging trendlines (triangles) or pairs of horizontal trendlines (rectangles), one connecting highest peaks and one connecting lower peaks. A triangle is completed when the closing price goes outside one of its trendlines (similar to the CHBs). The vertical line (called base) connecting the initial point of the converging trendline is

called ‘base’ and the point of convergence is called ‘apex of the triangle’. The ‘base’ and the ‘apex’ are used to identify prices breakouts and moves respectively. Similarly, a rectangle is completed when the prices closes out of the horizontal trendlines. In the rectangles there is no ‘base’ or ‘apex’, but the distance between the horizontal lines is always recalculated, if a rectangle is completed.

- FPs are indicators of pattern continuation. The ‘flag’ is a rectangle that slopes against the eminent trend, while ‘pennants’ are formed a symmetrical triangles (see TRs). The FP patterns are completed, when the closing price breaks through one of their trendlines.

The applications of the above pattern rules are quite extensive in the literature too. Clyde and Osler (1998) examine how graphical technical modeling methods may be viewed as equivalent to nonlinear prediction methods. Evidence in support of this hypothesis is presented by applying HS algorithm to high-dimension nonlinear data and they suggest that HSs can be successful in pattern identification and prediction. Lo *et al.* (2000) develop a pattern detection algorithm based on kernel regressions. Their methodology is able to identify price patterns, including HSs in the US stock market over the period 1962–1996. Lucke (2003) also explores if HSs are profitable technical indicators in FOREX markets. In the study many HS combination are implemented, but the results present not significant or even negative returns. Hsu and Kuan (2005) reexamine the utility of technical analysis and in their survey pattern rules like, HSs, DTBs, TRs and FPs, have a prominent place in the ‘universe’ of the trading rules under study. Friesen *et al.* (2009) develop a theoretical framework that confirms the apparent success of both trend-following and pattern-based technical trading rules, as HSs and DBTs. Finally, extensive applications and specifications for the above pattern rules can also be found in Murphy (2012).

3. AUTOMATED TRADING STRATEGIES AND SYSTEMS

Many issues and variables have to be taken under consideration by managers and market practitioners, in order to reach the final specification and implementation phase of a trading strategy. These can be summarized as follows:

- Identifying trading opportunities
- Trading schedule and timing
- Trading costs
- Price appreciation and market impact
- Risk evaluation of alternative strategies
- Ability of execution of each strategy

All the above can be evaluated through fundamental or technical approaches. Nonetheless, the modern market practice has a tendency to turn to market technical indicators, whose variety and computational demands are increasing exponentially. This is the main reason that technical analysis and computing appear to be linked now more than ever before. Charting software are applied everyday to actual or virtual financial markets. Optimization algorithms are automatically integrated in trading platforms, such as Bloomberg, and make the life of the intraday trader much easier. Consequently, modern trading projects aim to develop automated decision support systems based on technical market technology and evolutionary computing. Fuzzy logic, artificial neural networks, genetic algorithms and programming are already established as the core of the automated trading approach (Deboeck, 1994).

Allen and Karjalainen (1999) present an automated decision tree that selects the optimal technical rules by genetic algorithms. Dempster and Jones (2001) also try to emulate successful trade agents by developing a rule system based on combinations of different indicators at different frequencies and lags, which are selected with genetic programming optimization process. Shapiro (2002) notes that merging technologies, such us neural networks, evolutionary algorithms and fuzzy logic can provided alternatives to a strictly knowledge-driven reasoning decision system or a purely data-driven one and lead to more accurate and robust solutions. Thawornwong *et al.* (2003) evaluate the use neural networks as a decision maker to uncover the underlying nonlinear pattern of these indicators. The overall results indicate that the proportion of correct predictions and the profitability of stock trading guided by these neural networks are higher than those guided by their benchmarks. Dempster and Leemans (2006) propose the use of adaptive reinforcement learning as the basis for a fully automated trading system application. The system is designed to trade foreign exchange (FX) markets relying on a layered structure consisting of a machine learning algorithm, a risk management overlay and a dynamic utility optimization layer. Their approach allows for a risk-return trade-off to be made by the user within the system, while the trading system is able to make consistent gains and avoid large draw-downs out-of-sample. Izumi *et al.* (2009) construct an artificial-market system based on support vector machines and genetic programming. Their system evaluates the risks and returns of the strategies in various market environments and tests the market impact of automated trading. Their results reveal that the market impact of the strategies may not only depend on their rule content but also on the way they are combined with other strategies.

The above cited applications prove that automated trading is and will be dominant in financial markets and forecasting tasks, although its academic philosophy appears to be ambiguous. The utility of trading systems is usually criticized in the traditional financial literature, because of their dependence on strict engineering and computational rules. The modern market reality, though, shows that returns are driven by trading systems' results, rather than the human trading behavior. On the other hand, automated trading applications and algorithms present practical drawbacks associated mainly with their parameter calibration. Therefore, financial researchers and computer engineers need to shed more light in this demanding and complex optimization problem.

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