Research on Technical Trading and Market Efficiency

A Trader's Perspective

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Abstract

Research on the predictive power of technical analysis is a matter of controversy. The objective of this thesis is to look at the empirical research done on technical trading and see how the results can be used from a trader's perspective. Some results provide strong support for the technical trading and propose useful trading strategies. However, there are some limitations regarding transaction costs, risk adjustment, and statistical tests. Technical research has developed new methodology approaches and new trading rules. Technical analysis strategies alone provide incomplete background for modern trading. By integrating technical, fundamental, and psychological analysis into an investment or trading approach, one can handle increasingly complex contemporary markets.

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"Several times in the past, I have come to the conclusion after perfecting and testing a system that it was the 'ultimate' method. I would decide to stop searching and researching and be content to just trade the system…and then…as I did this morning, I will awake about 3 o'clock a.m., with another new concept to explore. It seems to be a never-ending search." (J. Welles Wilder, Jr. 1978)

1 Introduction

Brock et al. (1992) pointed out that technical analysis is dating back to 19th century. Therefore, it was used way before the fundamental analysis and the initiation of the efficient market hypothesis and the random walk theories. Many consider it to be *"the original form of investment analysis"*. Some of the modern technical trading techniques have been used for over 80 years. Despite that, most academics do not support this approach. Research on the predictive power of technical analysis is a matter of controversy.

According to the random walk and efficient market theories of security price behaviour, trading rules based only on the past price series cannot achieve greater profits than those generated by a buy-and-hold strategy. Technical analysts, however, have insisted that their rules are profitable and useful. Results, published by Fama and Blume (1966) in their article, convinced many academics that technical trading rules have no use. Nevertheless, recent research has provided accumulating evidence that technical trading can be profitable, especially over long time horizons, e.g. Brock, Lakonishok and LeBaron (1992). The results are mixed; however, it seems to be many problems with the validity of the efficient market hypothesis.

In 2007 Park and Irwin reviewed the evidence on the profitability of technical analysis. In their paper they looked at 137 technical trading studies published between 1960 and August 2004. Park and Irwin found that *modern studies indicate that technical trading strategies consistently generate economic profits in a variety of speculative markets at least until the early 1990s"*.

In this thesis, I review some of this evidence and discuss the practical applicability of the research results from a trader's perspective. I do not separate either among security classes or trading rules. Therefore, there are only few articles on each topic, and I could not give the same detailed attention to all of them. It is a general rather than in depth study.

Among most innovative proposals, I consider the Lo et al.'s (2000) automation of technical pattern recognition and the Duecker and Neely's (2005) Markov rule as a substitute for moving averages. Park and Irwin (2007), Kwon and Kish (2002) and Duecker and Neely (2005) found that the profitability of the technical trading rules disappears after 1990s. Maybe it is time for "old" trading rules to give place to the new ones, like the new Markov trading rule of Duecker and Neely (2005)?

As the research results show, technical analysis alone can be unreliable in the process of decision making. Old technical analysis strategies seem to provide incomplete background for modern trading and new trading rules emerge. By integrating technical, fundamental, and psychological analysis into an investment or trading approach, one can handle increasingly complex contemporary markets.

The remainder of this thesis is as follows. The next chapter starts with a description of random walk, efficient market hypothesis and technical analysis. The third chapter reviews studies conducted on technical analysis and efficient market hypothesis and discusses their results. Before looking at the research from a trader's perspective in chapter 5, I will introduce some estimation methods and econometric models. The chapter 6 looks at the limitations of this thesis and discussed further research.

The last chapter is devoted to conclusions. No financial theory is absolute, there are different ways to approach the markets. An understanding of the benefits and limitations of technical analysis can be a powerful tool in decision making for both traders and investors.

2 Technical Analysis vs. Efficient Market Hypothesis - Conceptual Framework

In order to put technical analysis into perspective, I review in this chapter existing theories on financial markets. There are two main approaches to identifying investment possibilities in financial markets: fundamental analysis and technical analysis (Bodie et al. 2002). The former focuses on examining the underlying economic factors while the latter, which is the focus of this thesis, looks at historical data in order to reveal patterns in price movements. An important theory about the true value of security prices is the efficient market hypothesis (Bodie et al. 2002; Brealey et al. 1999). In the first part of this chapter I give a short description of random walk theory and efficient market hypothesis. The second part is devoted to technical analysis and two popular trading rules.

2.1 Efficient Market Hypothesis and Random Walk Theory

2.1.1 Random Walk and *Théorie de la Spéculation*

The Random Walk Theory of stock market prices has existed for over 100 years. This theory states that security prices change randomly, with no predictable trends or patterns (Bodie et al. 2002; Brealey et al. 1999). Therefore, the historical prices give no useful information about future price movements. Brealey et al. (1999) say, *"economists express the same idea more concisely when they say that ..."the market has no memory"*. This expression comes from Fama's (1965a) article on random walk. This assumption plays a crucial role in fundamental analysis.

The theory on share price movements can be traced to French mathematician Louis Bachelier who wrote a Ph.D. thesis titled "Théorie de la Spéculation" in 1900. His work was published in *Annales Scientifiques de l'École Normale Supérieure,* one of the leading French scientific journals of the time. Courtault et al. (2000) wrote a paper about life and work of Bachelier. They regard his work as probably *"the first attempt to use advanced mathematics in finance"*. Bachelier analysed the stock and option products at the French stock market. Based on his results several valuable ideas in both finance and probability were initiated: *"the theory of Brownian motion, Markov processes, diffusion processes, and even weak convergence in functional spaces"*. These theories were used for *"the mathematical*

modelling of price movements". Bachelier assumed, *"the expectation of the speculator is zero"*. In other words, the conditional expectation given the past information is zero and *"the market evaluates assets using a martingale measure"* (Courtault et al. 2000).

Bachelier's research results did not attract attention until the mid-1950s. At that time investors believed that markets were inefficient, and traders used both fundamental and technical analysis to outperform the market. In 1953 Maurice Kendall, a well-known statistician, studied the behaviour of stock and commodity prices in the United Kingdom stock market, looking for price patterns (Bodie et al. 2002; Brealey et al. 1999). However, he found the following, *"the pattern of events in the price series was much less systematic than is generally believed...The data behaved almost like wandering series"*. Kendall suggested in his paper that changes in the UK stock market prices were random. Many others, including Paul Samuelson and Eugene Fama, have later expanded on Bachelier's and Kendall's work.

In 1965 Paul Samuelson published "Proof That Properly Anticipated Prices Fluctuate Randomly". In this paper he proposed a *"theorem of fair-game futures pricing"*. His main idea was that in competitive markets price changes must follow a random walk if they are properly anticipated. By giving logical examples and questioning general assumptions, Samuelson discussed that market participants are taking advantage of all available information in order to maximise their profits. In this way all information is already included in prices, giving no opportunities for superior returns. His theorem supports this idea. However, Samuelson emphasised that his theorem is not absolute, and *"it does not prove that actual competitive markets work well"*. He separated the logical problem from *"the applicability of the model to economic reality"*, which he left for further research.

His article shifted the focus of price studies from statistical properties of price movements to the martingale processes. Researchers got an inspiration to investigating market efficiency and information variables that cause price movements.

2.1.2 The Efficient Market Hypothesis

The efficient market hypothesis is related to the theory of a "random walk" (Bodie et al. 2002; Brealey et al. 1999; Fama 1965a). Professor Eugene F. Fama at the University of Chicago Graduate School of Business developed the efficient market hypothesis as a theory in his Ph.D. dissertation. In the article "Random Walks in Stock Market Prices" (1965a),

Fama built up on the theory of random walk and gave the following definition of an efficient market:

> *"An 'efficient' market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value"* *(Fama 1965a).*

As we can see above, Fama based his definition of the EMH on several assumptions: the rationality of the participants, profit-maximizing approach to trade, and the almost free availability of the important information. He realised the limitations of these statements in the real and uncertain world. However, Fama argued that there is a difference between individual investor's judgement and a market *"on the average"*. He wrote, *"the actions of many competing participants should cause the actual price of a security to wander randomly about its intrinsic value"*, and if the difference between them is systematic, then *"traders attempt to take advantage of this knowledge, however, they will tend to neutralize such systematic behaviour in price series"*. It means that even all market participants are not rational and do not pursue profit-maximization, market as a whole will be rational, and prices are fair. Fama also suggested that due to the active trading all *new information on intrinsic value* will *be reflected "instantaneously" in actual prices*.

Further in his article Fama discussed challenges posed by the random walk and the efficient market concept to technical and fundamental analysts. He looked at the superior versus average analysis. The superior analysis can give better profits than the random selection some time, but can an analyst prove that he can *consistently* do better? Frequent trade and complex analysis imply higher costs. Considering extra costs it is not obvious that the use of analysis is better than the random selection approach.

2.1.3 Levels of Market Efficiency

The efficient market hypothesis has set off a lot of empirical studies. In the article of 1970, Fama developed his idea further and, based on the empirical research and literature of available at that time, presented three forms of the efficient market hypothesis: the weak, semi-strong, and strong. Each of the forms had a different description of the available information and reflected tests done on the adjustment of prices to this information.

The EMH and its versions are essential to understanding of the markets and are included in all study books, such as Bodie et al. (2002) and Brealey et al. (1999).

The weak-form hypothesis (the random walk theory) considers only historical prices and states that prices are already adjusted to all prior information (Fama 1965a and 1970). As previously written, this form of efficiency implies no possibility for superior returns. This presents a challenge for technical traders, because if the weak hypothesis holds, then the technical analysis has no value. However, fundamental analysis may be used to generate excess profits, *"as long as he* (analyst) *can more quickly identify situations where there are non-negligible discrepancies between actual prices and intrinsic values than other analysts and investors"* (Fama 1965a). Studying financial statements, macroeconomic variables, or other information about business and economic prospects can help to find over – or undervalued securities (Brealey et al. 1999). There are several ways to test this form of efficiency, such as fair game models, serial correlation, runs tests, reversals, distributional tests, and filter tests. All of them are concerned with *"return predictability"* (Fama 1965a, 1970 and 1991).

The semi-strong-form hypothesis is more restrictive than the weak-form and, in addition to the history of past prices, it includes *"all obviously publicly available information"* (Fama 1970). Such information can be internal announcements, stock splits or other macroeconomic news. The hypothesis implies that one cannot make superior returns from publicly available information, because prices adjust almost instantly. Nevertheless, if prices do not change after the announcement of the news, then it can be concluded that there was no relevant information in them. If this holds, then fundamental analysis and technical analysis have no practical value (Brealey et al. 1999; Fama 1970). The tests of this version of EMH are based on the event studies and look at how quickly prices adjust to new information (Fama 1970 and 1991).

The strong-form hypothesis elevates the level of all available information to the point where *"no individual has higher expected trading profits than others because he has monopolistic access to some information"* (Fama 1970). In such a market, prices would always be fair, and no investor could earn superior profits. As the semi-strong-form EMH, this hypothesis also concludes that neither technical nor fundamental analyses are valuable (Brealey et al. 1999; Fama 1970). Empirical evidence includes tests on private information, which is mostly accessible to corporate insiders, and pension fund and mutual fund managers (Fama 1970 and 1991).

Later, due to empirical evidence against market hypothesis, discussed in chapter 3, the basic theoretical model of the EMH was reviewed. The weakness in the definition of the EMH is a disregard of information and transaction costs. Jensen (1978) gave more general description: *"A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t"*. Talking about economic profit, he meant *"the risk adjusted returns net of all costs"*. Fama (1991) rephrased it like **"prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs"**.

In 1980, Grossman and Stiglitz found a logical inconsistency in the hypothesis, commonly known as the paradox of efficient markets. They proposed an equilibrium model in which *"prices reflect the information of informed individuals (arbitrageurs) but only partially, so that those who expend resources to obtain information do receive compensation"*. By giving proof to their theorems, they showed, *"when the efficient market hypothesis is true and information is costly, competitive markets break down"*. Grossman and Stiglitz argued that if investors get no value from information, they stop buying it, and prices do not *"reflect all available information"* (Fama 1970). On the other hand, they claim that since *"information is costly, the price cannot perfectly reflect the information, which is available"*. This was summed up like *"fundamental conflict between the efficiency with which markets spread information and the incentives to acquire information"*.

However, Grossman and Stiglitz idea did not totally contradict Fama, as he regarded the EMH's statement that prices *"at any point in time "fully reflect" all available information"*, as *"an extreme null hypothesis"* (Fama 1970). Therefore, it does not reflect the reality. By introducing the weak, semi-strong and strong forms, he intended to identify *"the level of information at which the hypothesis breaks down"*.

The debate about market efficiency plays a crucial role in the decision between active and passive investing (Bodie et al. 2002; Sharpe 1991). Based on the logical assumption, Sharpe wrote, *"the average actively managed dollar must underperform the average passively managed dollar, net of costs"*. However, he accepted that some active managers may outperform the market even after costs, but they are in the minority. In his opinion the challenge was to find a comparable passive management benchmark, so active managers can compare their results. Nevertheless, on average, active management cannot be better than passive one, because active managers can only outperform when some other active managers underperform.

2.2 Technical Analysis

The concept of "technical analysis" is *"essentially the search for recurrent and predictable patterns in stock prices"* (Bodie et al. 2002). The other way to call technical analysts is "chartists" (Bodie et al. 2002; Fama 1965a). There are a lot of trading techniques. The essential assumption behind them is a repeating history in price behaviour (Bodie et al. 2002; Brock et al. 1992; Fama 1965a). In contrast to EMH and random walk, technical analysts believe that *"successive price changes in individual securities are dependent"* (Fama 1965a). By applying various techniques to examination of past prices, they attempt to predict future price movements and identify possibilities for superior profits.

Brock et al. (1992) pointed out that technical analysis is dating back to 19th century. Therefore, it was used way before the fundamental analysis and the initiation of the EMH and the random walk theories. Many consider it to be *"the original form of investment analysis"*. Many of the modern technical trading techniques have been used for over 80 years. Despite that, most academics did not support this approach. As we can see from the paper of Park and Irwin (2007), until 1990th the research on technical trading techniques was limited. This attitude is also present in business school books, where a negligible space is devoted to the concept of technical analysis, compared to the EMH and fundamental analysis (Bodie et al. 2002; Brealey et al. 1999).

There have been developed various techniques that range from simple to quite complex. William Eng (1988) has distinguished between following trading techniques.

- Price-sensitive: moving averages, relative strength, percentage R, oscillators, stochastics, point-and-figure, basic charting, and swing charting.

- Volume-sensitive: market profile / liquidity date bank, tic volume, and on-balance volume.

- Time-sensitive: astronomical cycles.

- Composite methods: Elliott wave and Gann analysis.

In the description of the behaviour of technical indicators in market cycles, Eng (1988) pointed out that the first two sets of techniques are based on the micro analysis of the securities, while the last two require macro analysis. These techniques provide traders with the indicators of overbought or oversold markets. Eng explained that the markets can be trading, trending (bull or bear), or changing between trading and trending. He also described how each technique will behave in different markets. Given different applicability of trading methods, it is logical that traders should use several indicators, in addition to some basic fundamental analysis, when deciding their actions. Wilder (1978) emphasized that *"a successful trader utilizes several different kinds of input into his decisions"*. In a real life all traders employ some fundamental evaluation (Brozynski et al. 2003; Fama 1965a; Taylor and Allen 1992).

> *"In all the years I have spent developing and analyzing technical trading methods, I have yet to see any one system that is **consistently** profitable **in all markets"** (Wilder 1978).*

In practice, price-sensitive techniques seem to be most popular, like moving averages, relative strength indices, channels and momentum oscillators (Park and Irwin 2007). Basic charts and geometrical patterns in price movements are also used.

There are various studies on applicability and profitability of technical analysis. Most of them are published after 1995 (Park and Irwin 2007). The early research showed mainly negative results; however, Park and Irwin (2007) found that studies of foreign exchange markets and futures markets supported technical analysis, e.g. Sweeney (1986). In more recent studies they discovered positive results in all markets, but valid only until mid-1980s – early 1990s.

Research shows that technical analysis indeed widely used in practice. Brozynski et al. (2003) conducted a survey of fund managers, which showed empirical evidence that investors rely on technical analysis and trading rules to some degree. Taylor and Allen (1992) questioned foreign exchange dealers in London and found that *"at least 90 per cent of survey respondents reported placing some weight on technical advice when forming their exchange rate expectations over one or more of the forecast horizons considered"*. However, technical analysis, in combination with fundamental analysis, was mainly used on short-term horizons. With the increasing forecast horizon, traders relied more and more on fundamental advice.

Over time technical trading has advanced either by combining different existing rules or developing new rules using other techniques. The development of electronic equipment, new programs, cheaper computing power, and more price databases can be the explanation (Park and Irwin 2007). For instance, Dueker and Neely (2005) applied *"Markov switching models to the problem of choosing ex ante trading rules in the foreign exchange market"*. Lo, Mamaysky and Wang (2000) used nonparametric kernel regression for technical pattern recognition. Brock et al. (1992) applied bootstrap method to find the optimal trading rule.

In the following, I briefly describe a couple of most popular standard trading rules used by analysts.

2.2.1 Moving Average

Moving average is one of the simplest technical trading rules used by traders. Eng (1988) gave some historical background for it; moving averages were first developed during World War II in an attempt to predict the probable destination of military planes. However, by the late 1950s it became *"one of the leading and, for that time, most advanced methods of analyzing market trends"*.

According to Eng (1988), the main idea behind moving average technique is that *"a market tends to trend in the same direction as it has been going"*. The moving average techniques are used to smooth out daily price fluctuations and reveal an underlying trend (Brock et al. 1992; Eng 1988; Gençay 1996). The moving averages represent the average price of closing prices of a chosen number of days. They are usually *"plotted against daily closing prices in order to detect crossovers of the moving average by price lines"* (Eng 1988).

Technical analysis uses three main types of moving average: simple, weighted and exponential. Based on Hull (2000), Kwon and Kish (2002), Gençay (1996) and Eng (1988), I present moving averages in the following.

An *N*-period *Simple Moving Average* is given by:

$$\overline{P}_t = \frac{1}{N} \sum_{i=0}^{N-1} P_{t-i}$$

P_t, with $t = 1, 2, ..., T$, are daily (normally closing) prices. $\overline{P}_t$ is *"the time t value of a moving average rule of length N"* (Gençay 1996); the last *N* observations in a sequence of prices P_t are summed up, and the result is divided by the number of observations *N*. In the next period, a new observation, P_{t+1}, is added to the sum and the oldest observation, P_{t-N-1}, is dropped, and so on (Gençay 1996). Number of observations should be close to a cycle length of the market (Eng 1988).

A *Weighted Moving Average* gives greater weight to more recent observations:

$$\overline{P}_t^W = \frac{1}{N} \sum_{i=0}^{N-1} \lambda_i P_{t-i}$$

The variable λ_i is the amount of weight given to the observation *i* days ago (Hull 2000). The restriction on the weight λ_i is that $\lambda_0 > \lambda_1 > \lambda_2 > ... > \lambda_{N-1} > 0$, although in most cases the weights are chosen in such a way that they sum to unity.

The *Exponentially Smoothed Moving Average (ESMA)* gives *diminishing weight to days further and further into the past, where the weighting factor is an exponentially decreasing fraction* Eng (1988).

$$\overline{P}_t^E = \frac{1}{N} \sum_{i=0}^{N-1} \frac{1-\lambda}{1-\lambda^{N-1}} \lambda^i P_{t-i}, where\ 0 < \lambda < 1$$

Eng (1988) described different behaviour of the price and moving averages that can be summarized in following. Changes in the trend of the security price are indicated by a crossover between the moving average and the price itself. A change from a rising to a declining market occurs when the price moves below its moving average and vice versa for a change from a declining to a rising market. Gençay (1996) said, *"this rule indicates a buy*

signal whenever the price climbs above its moving average and a sell signal when it drops below".

One can also use shorter moving averages and longer moving averages. The beginning of a falling market is indicated when the shorter moving average moves below the longer moving average and vice versa (Brock et al. 1992; Eng 1988). *"A buy signal is generated when the short moving average rises above the long moving average and a sell signal is generated otherwise"*, Gençay (1996). Kwon and Kish (2002) gave the following presentation of the trading rule for the moving average: *the shorter moving average, L_1, and the longer average, L_2.*

$$\text{If } \frac{1}{L_1}\sum_{i=0}^{L_1-1}P_{t-i} > \frac{1}{L_2}\sum_{j=0}^{L_2-1}P_{t-j} \text{ then Buy}$$

$$\text{If } \frac{1}{L_1}\sum_{i=0}^{L_1-1}P_{t-i} < \frac{1}{L_2}\sum_{j=0}^{L_2-1}P_{t-j} \text{ then Sell}$$

Where P_{t-i} and P_{t-j} are prices at time *t-i* and *t-j*, and $L_1 < L_2$.

The length of average can be all from 1 day to, for example, 50, 100, 150, or 200 days (Brock et al. 1992; Kwon and Kish 2002). One of the popular trading rule is (1, 200) rule, *"where the short period is one day and the long period is 200 days"* (Gençay 1996). The rule can be applied with or without a percentage band, which is used to reduce trading and the trading costs (Gençay 1996; Kwon and Kish 2002). A band eliminates *"whiplash" signals when the short and long moving averages are close"* (Gençay 1996). The trading rule is symbolized then like MA (1, 200, 1) which means that the short period is 1 day, the long period is 200 days, and the band is 1 % (Kwon and Kish 2002).

Eng (1988) pointed that, since moving averages work better in volatile or trending markets, it is advisable to use them in combination with other techniques. Moving averages are frequently used with trading volume to confirm buy or sell signal, or with momentum indicators, which are believed *"to capture the duration or the turning point of a trend"* (Kwon and Kish 2002).

2.2.2 Wilder's Relative Strength Index (RSI)

>*"RSI is an overbought / oversold indicator that tries to predict price reversal points and also attempts to provide an index for comparing any market investment with any other, no matter what the market. It therefore ties in well with broad-based position management strategies"* (Eng 1988).

The Relative Strength Index was first introduced by J. Welles Wilder in his book "New Concepts in Technical Trading Systems" in 1978. It is based on the momentum oscillator concept. The RSI measures *"how much "strength" or likelihood of continuity is left in a trend"* and can *"predict rather than simply confirm important price breakouts"* (Eng 1988). William Eng mentioned two explanations for the name of this index: first, it evaluates the relative strength of recent gains to recent losses, and second, which is the main advantage of this index, it gives the possibility to compare *"any two markets or commodities, or the same market or commodity at two very different times"*.

The RSI is calculated using the following equation (Wilder 1978):

$$RSI = 100 - \left[\frac{100}{1 + RS} \right], \text{ where } RS = \frac{\text{Average of N day's closes UP}}{\text{Average of N day's closes DOWN}}$$

The previous *N* day's close prices are needed for the first calculation of the RSI. Afterwards, it is only necessary to have the previous day's data. Wilder (1978) and Eng (1988) gave a following procedure for the calculation of the RSI:

1) The average UP close – sum the UP closes for the previous N days and divide the sum by N.

2) The average DOWN close – sum the DOWN closes for the previous N days and divide the sum by N.

3) Divide the average UP close by the average DOWN close. This is the market's Relative Strength (RS).

4) Calculate the first RSI using the given formula.

5) To get the next average UP close, multiply the previous UP close by N-1, add to this amount today's UP (if any) and divide the total by N. The same procedure applies to the next DOWN close.

6) Calculate the next RS and RSI.

Wilder (1978) used a period of 14 days in his calculations, but in traders' practice an average period depends on the volatility of the markets and the length of their cycles (Eng 1988).

The index always ranges from 0 to 100; therefore, the momentum of any securities can be measured on the same scale. This, as previously mentioned, can be used to compare them to each other and to previous tops and bottoms within the same security. According to Wilder (1978), tops and bottoms *"are indicated when the index goes above 70 or below 30"*. A security is considered to be overbought once the RSI approaches the 70 % level and oversold when the RSI approaches 30 %.

The rapid price movement either up or down is an indicator of a forthcoming reaction or reversal. As the oscillator measures the rate of change of price movement, it is one step ahead of the price by predicting its breakouts (Wilder 1978). Eng (1988) described trading rules with the RSI like this. The reversal is *"probable when the Index peaks above 70, falls, recovers, and then fails to rise to its former level before heading downward"*. Then, when the RSI again crosses the upper limit from above reaching the previous recovery point, the sell signal occurs. Equally, the reversal around 30 % level happens when *"the Index bottoms below this point, rises, and then returns down again, but not as far as before"*. The buy signal takes place when the Index crosses the lower limit from below reaching the first downturn point. Eng (1988) mentioned that *"better confirmations of overbought / oversold conditions are the occurrence of multiple tops and bottoms"*.

Divergence between price movement and the RSI is also a strong indicator of a market turning point. It takes place when the RSI and price move in different directions. It is also *"the single most indicative characteristics of the Relative Strength Index"* (Wilder 1978).

Eng (1988) wrote that the RSI is a reliable indicator in stable or trading markets. In trending markets traders must use it with caution as it can give false buy and sell signals. He advised also to use other indicators confirming the RSI.

There are many other interesting and complex technical trading techniques nowadays; however, I do not describe them here as it is outside the main purpose of this thesis. This chapter gave a short historical and theoretical overview over EMH and technical trading. That is essential in understanding the background for the research conducted on the financial markets which I describe in the next chapter.

3 Reseach Review

In this chapter I summarise some research carried out by proponents and opponents of the efficient market hypothesis and technical trading rules and discuss the results. Research took two different approaches. The first one focused on proving that the EMH holds and if so, technical trading has no value per definition. The second one focused directly on various technical trading rules and investigated if they could generate returns above simple buy-and-hold strategy (Fama 1965a). Evidence of the profitability of the technical trading rules implies that the EMH does not reflect the market reality.

Early research mostly examined the EMH; however, since 1990s there are more empirical and theoretical studies of the technical trading rules. Park and Irwin (2007) meant that it can be partly due to the publication of several papers empirically supporting technical trading, e.g. Brock et al. (1992) and Sweeney (1986) and partly due to *"the availability of cheaper computing power and the development of electronic databases of prices"*. The other reason can be the development of econometric and other programs since *"academic research on technical analysis generally is limited to techniques that can be expressed in mathematical form, namely technical trading systems, although some recent studies attempt to test visual chart patterns using pattern recognition algorithms"* (Park and Irwin 2007).

The first two parts of this chapter look at the research on the EMH and technical trading, while the third one considers behavioural finance.

3.1 Tests with a Focus on the Efficient Market Hypothesis

The amount of research on the random walk and the EMH is enormous. Since the main focus of this thesis is technical analysis, I give a brief and general overview over the EMH studies and concentrate on the research that can have some practical value for technical traders.

In terms of the weak-form EMH, empirical research of the random walk tests the null hypothesis that *"successive price changes are independent"* (Fama 1965a). There are two different ways to test this: (1) variation of serial correlation and (2) runs analysis (Fama 1965a, 1970 and 1991). Most of the studies found support for the random walk, e.g. Kendall (1953) and Fama (1965b). However, Lo and MacKinlay (1988) conducted a research on the weekly returns on shares at the NYSE and found some positive correlation over short

periods. In the article they argued that the random walk does not exist. Fama gave a good overview of the weak-form EMH research in his article from 1991.

In terms of the semi-strong-form EMH, numerous negative results, so called anomalies, appeared in the early 1980s for different securities (Bodie et al. 2002; Fama 1991; Malkiel 2003). These technical anomalies seemed to contradict the efficient market hypothesis, giving some hope for technical analysts. However, many anomalies are considered to be small and unable to generate risk adjusted returns and cover transaction costs (Malkiel 2003).

One group of anomalies is called the *calendar effects or seasonal effects*. They offer significant excess returns based on specific times of the day, days of the week, or months of the year. The five most persistent calendar effects are the *January effect*, the *turn-of-the-month effect*, the *Monday* (or *weekend*) *effect*, the *day-end effect* and the *holiday effect* (Bodie et al. 2002; Fama 1991; Malkiel 2003).

Rozeff and Kinney (1976) and Keim (1983) documented that the mean returns in January were higher compared to other months of the year. The returns were particularly higher during the first week of January and especially the first trading day. Many attribute this January effect to the end of the tax period (Bodie et al 2002).

French (1980) and Gibbons and Hess (1981) tested the calendar time hypothesis and found that the average return was significantly negative on Mondays, but positive for the other days of the week.

Ariel (1987) showed that returns during the first half of the month were much higher than the returns during the rest of the month. Lakonishok and Smidt (1988) found that for US shares the turn-of-the-month effect was concentrated in the last day and first three trading days of the month. In the same article, they also documented the turn-of-the-week, the turn-of-the-year, and the holiday effect. In the paper of 1990, Ariel provided evidence that returns on the two trading days before national holidays in the US were between 9 and 14 times higher than the average daily returns for the rest of the year.

All these calendar effects seem to be inconsistent with the semi-strong-form EMH. They are empirical regularities and could be exploited by a simple trading rule in order to generate excess returns.

Another set of anomalies is related to the characteristics of the firms. Some researchers discovered that it is possible to generate excess returns by using the public information about a firm size, its market-to-book ratio and its earning yield (earning-price ratio) (Bodie et al. 2002; Fama 1991; Malkiel 2003).

Banz (1981) identified the *small firm effect (size effect).* This irregularity has following implications: investing in small companies with low stock market capitalizations gives investors possibility to achieve positive excess returns. The results suggest that the capital asset pricing model is misspecified. There also appears to be a correlation between the small firm effect and the January effect (Keim 1983).

Fama and French (1992 and 1995) examined the relationship between the return on securities and market-to-book ratios, earning-price ratios and firm size over the period 1963-1990. The first finding of Fama and French was a strong negative relationship between returns and market-to-book ratios. Firms with the lowest market-to-book ratios had higher average returns than firms with the highest market-to-book ratios. Their result suggested that value shares tend to outperform growth shares. Then, they also found a strong positive relationship between returns and earnings-price ratios. Firms with the largest earnings-price ratios had higher average returns than firms with the lowest earnings-price ratios. Since value shares tend to have higher earnings-price ratios than growth shares, this result supported the conclusion that value shares outperform growth shares. Finally, Fama and French documented a strong negative relationship between returns and firm size. The shares of smaller firms tended to have higher average returns than the shares of the larger firms. All these results contradict the semi-strong-form EMH, which says that already known characteristics of firms cannot be used to earn excess returns in an efficient market.

Further evidence against the semi-strong-form EMH is the volatility tests. The first two studies applying these tests were by Shiller (1979 and 1981) and LeRoy and Porter (1981). They found that there was an excess volatility in share prices compared to the volatility of fundamental variables that determined share prices. Similar evidence against the semi-strong-form EMH was also found for bonds (Shiller 1979), exchange rates (Frenkel 1981), futures market (Elton et al. 1984 and Cavanaugh 1987), and options market (Tucker 1987 and Beckers 1981). The question is to find the source of volatility.

There are a lot of studies on different anomalies that I will not present here. Fama (1991) and Malkiel (2003) give a quite informative overview of the research on the semi-strong-form market efficiency with their explanations of causes of inefficiency. The main conclusion is that *"the new work says that returns are predictable from past returns, dividends, yields, and various term-structure variables"* (Fama 1991). This is the most important evidence that can be used by technical analysts in order to improve their trading approach.

When it comes to the strong-form EMH, the results are conflicting. The main concern is that insider trading is illegal in a number of countries. However, Jensen (1968) studied the performance of unit trusts, which spent a lot of resources on research about companies. Thus, this information was private information, but it was not illegal inside information. Jensen (1968) found that unit trusts did not obtain returns, adjusted for risk and costs, superior to the returns from the buy-and-hold strategy. On the other hand, some studies provided proof that insiders achieved profit from trading on private information (Seyhun 1986 and Jaffe 1974). However, the strong-form hypothesis does not hold in the financial world per definition, due to the legal barriers (Bodie et al. 2002).

These evidences questioning the financial market efficiency were criticised by supporters of the EMH (Fama 1991; Malkiel 2003). One of the determined proponents of the EMH is Burton G. Malkiel. In his article from 2003, he summarized the critics of the EMH and presented his version of the explanation. *"As long as stock markets exist, the collective judgment of investors will sometimes make mistakes. Undoubtedly, some market participants are demonstrably less than rational"*, he wrote in the conclusion. Despite all discovered anomalies and critics of the EMH, Malkiel still supported it and found that the predictability of technical trading is nothing more than a short phase due to some temporarily inefficiencies in the market, which soon will be corrected.

3.2 Tests with a Focus on Technical Trading Techniques

Research on the predictive power of technical analysis is quite controversial. Park and Irwin (2007) reviewed the evidence on the profitability of technical analysis. In their paper they looked at 137 technical trading studies published between 1960 and August 2004. Based on the characteristics of testing procedures – *"the number of technical trading systems considered, treatment of transaction costs, risk, data snooping problems, parameter optimization, out-of-sample verification, and statistical tests adopted"* – they categorized

studies into two groups: *"early" and "modern"* studies. The majority of early studies were conducted during a period from 1960 to 1987, whereas the first modern study was considered to be from 1988. There has been a significant increase in the amount of research on technical trading after mid-1990s. In Park and Irwin's paper *"about half of all empirical studies conducted after 1960 were published during 1995-2004"*. This is due to several papers published around 1990 supporting technical trading and technological development allowing more advanced data analysis.

In the following I present some empirical and theoretical studies on different technical trading rules.

One of the fundamental early tests of the profitability of technical trading rules is the test called the *filter rule* developed by Sidney Alexander (1961). It was an attempt to use a more sophisticated mechanical trading rule in finding dependencies in stock prices, compared to common serial correlation and run tests (Fama and Blume 1966). An x % filter rule operates as follows: buy a security if its price moves up by x % above a previous low, hold it until the price falls by x % from the next high, then sell and go short at the same time; hold the short position until the price rises x % from the next low, then cover the short position and go long; ignore movements less than x % (Fama and Blume 1966). Given systematic patterns in security prices, an Alexander's filter rule should capture excess returns over a buy-and-hold strategy. The crucial question is in determining the optimal size of x %. Small x % implies frequent trading and, therefore, high transaction costs. On the other hand, if x % is too large, several turning points will be missed.

Alexander (1961) applied the filter rule for prices from the Dow-Jones Industrial from 1897 to 1929 and Standard and Poor's Industrial from 1929 to 1959. The results showed an overwhelming support for the filter rule profits compared to buy-and-hold strategy. However, there was an essential bias of discontinuities in the price series, and Alexander reworked his study in 1964 (Fama and Blume 1966). In the second paper he did not find the profitability of the filter rule, especially when accounted for transaction costs.

Fama and Blume (1966) meant that the results found by Alexander (1961 and 1964), *"tends to overstate the actual profitability of the filter technique relative to buy-and-hold"* due to several computational biases. They applied the Alexander's filter rule to price series from the Dow-Jones Industrial Average (DJIA) for the period from 1956 to 1962. Fama and Blume

(1966) chose 24 different filter sizes from 0.5 % to 50 %. The study was quite voluminous and included computations of with and without dividend adjustments, gross and net brokerage fees, and other parameters, which were missing in Alexander's work (1961 and 1964). Fama and Blume (1966) found some dependencies of the returns on the filter size. However, after adjusting for transaction costs, filter rule did not produce returns over buy-and-hold. They concluded that *"the random-walk model is an adequate description of price behaviour"*.

In 1988, Richard J. Sweeney re-examined the "surviving" fourteen stocks from Fama and Blume's article (1966). He looked at the stocks in the period 1970-1982 and found that *"it appears that significant profits can be made by investors with low but feasible transaction costs"*. Sweeney assumed constant risk premia and transaction costs that included all opportunity costs. The important note was that only floor traders, without specialist costs, may earn these filter rule profits, and to some degree institutional money managers. Previously, in 1986, Sweeney examined the filter rule in the foreign exchange markets. He analysed the role of risk using the Sharpe-Lintner CAPM and concluded that filter rule's profits *"cannot be explained by risk if risk premia are constant over time"*. These results support filter rule profitability and are in contrast to Fama and Blume (1966).

Robert Levy (1967) tested a technical trading rule the "relative strength" or "portfolio upgrading" (Jensen and Benington 1970). By ranking NYSE stocks, he compared historically strongly and weakly performing stocks. Levy pointed out, *"Although it appears that superior profits can be achieved by investing in securities which historically have been relatively strong in price movement, the random walk hypothesis is not thereby refuted"*. This is due to the fact that his study was limited, missing statistical tests to support his findings. Jensen and Benington (1970) re-examined his study by replicating two of Levy's trading rules and allowing for transactions costs and risk-adjustment. They used data from the NYSE from 1926 to 1966. The study did not support Levy's results. After adjustment for risk and transaction costs, the two trading rules earned less than the buy-and-hold strategy.

A lot of empirical research focused on momentum patterns, which are popular strategies among technical analysts. In a survey, Brozynski et al. (2003) showed that managers, at least partly, do rely on momentum and contrarian as well as on buy-and-hold strategies. They questioned 117 managers of mutual and pension funds in Germany in 2002. All respondents applied momentum and contrarian as a valuable addition in the decision making process.

Momentum strategy is based on trend continuation and reversal; it can be roughly divided into three categories according to the trading strategy horizon: short-run (under 3 months), medium-run (from 3 to 12 months), and long-run. The long-run momentum has a holding period from 13 to 60 months. Long-run profits suppose to demonstrate the various theories on the sources of momentum profits; however, the empirical evidence on this subject is unclear (Stivers and Sun 2004).

Ilmanen and Byrne (2003) looked at pronounced momentum patterns ahead of major events. Their main finding was that *"trend continuation is unusually likely in the run-up to major events and less likely just after them"*. They tested the effect of the US non-farm payroll report on the ten-year Treasuries. This report is a regular event for the bond market, published on the first Friday of the month and has a significant influence on investor expectations and *"instantaneous market impact"*. Researchers proposed that *"traders could exploit this pattern by putting on trend-following strategies at the start of the payroll week, with above-average prospects of success"*. In order to avoid surprises in the report, traders may close the positions just before the announcement and in that way *"capture the pure pre-event momentum"*. In addition, Ilmanen and Bryne (2003) suggested that *"traders may also try to position for post-event reversals for the following week"*. Both strategies can be profitable; however, they found that *"the pre-event continuation is a more important regularity than the post-event reversal"*. Positive, but weaker results appeared to be for other assets and other events. This study showed a quite robust empirical regularity.

Stivers and Sun (2004) studied momentum profits in stock returns with a two-state regime-shifting process. Regime-shifting models are practical in illustrating random structural breaks in time series data, especially for stock returns. They used the monthly stock returns of NYSE and AMEX firms from CRSP. The sample period was from 1962 to 2002. In order to categorize months into two regimes, Stivers and Sun (2004) used expansions and recessions from the National Bureau of Economic Research. In the study they focused on two sources of momentum profits: (1) *"the cross-sectional variance of regime mean dispersions"* and (2) *"the regime transition probabilities"*. The momentum profits were measured by two approaches: (1) the WRSS (weighted relative strength strategy), where weight of the individual stock investment corresponds to the proportion between the stock return and the market return over the ranking period; (2) the decile-based strategy over the ranking period. Analytically, Stivers and Sun (2004) showed that *"(1) medium-run momentum profits with regime-shifting are likely to be substantially larger than the case*

where mean returns are constant", and *"(2) longer-run momentum profits with regime-shifting are likely to be lower than one would expect in a world with constant mean returns"*. Researchers' empirical evidence corresponded to their analytical propositions. They found that, around economic crises and recessions, medium-run momentum profits can become negative due to the uninformative nature of the past returns; and that, after control for regime-mean adjusted returns, profits for the most part disappear. However, Stivers and Sun (2004) could not determine whether the explanation for momentum profits was rational or behavioural. Their general conclusion was that *"regime shifts in stock returns may have an important role in understanding momentum profits"* and that *"any theoretical model that generates regime-shifting may also be capable of explaining prominent features of momentum profits, regardless of whether the underlying economics behind the regime-shifting is rational or behavioral"*.

Osler (2003) studied currency orders and exchange rate dynamics with a focus on two predictions of technical analysis. The study looked at stop-loss and take-profit orders, which were placed National Westminster Bank. Osler used in total 9,655 orders of three currency pairs: dollar-yen (43 %), dollar-U.K. pound (24 %), and euro-dollar (33 %) for the period from 1st of August 1999 to 11th of April 2000. She explained the dynamics of the orders: *"a stop-loss (take-profit) buy order instructs the dealer to purchase currency once the market rate rises (falls) to a certain level; sell orders are defined accordingly"*. The main difference from limit orders is an obligation to execute the transaction. After examining clustering in currency stop-loss and take-profit orders, she provided an explanation for two commonly used predictions of technical analysis: *"(1) downtrends (uptrends) tend to reverse course at pre-identifiable support (resistance) levels, which are often round numbers; (2) trends tend to be relatively rapid after rates cross support and resistance levels"*. She found that *"executed take-profit orders cluster more strongly at round numbers ending in 00 than do stop-loss orders"*, which confirms the first prediction. For the second prediction, the explanation comes from the observation that *"stop-loss buy orders cluster at rates just above round numbers; stop-loss sell orders cluster just below round numbers; there are no similar asymmetries for take-profit orders"*. This supports the practical knowledge of technical analysts and shows that *"technical analysis is useful for predicting short-run exchange rate dynamics"*.

LeBaron (1996) looked at foreign exchange market and examined the possible source of the predictability of the moving average trading rule. As he wrote, *"The fact that simple trading*

rules produce unusually large profits in foreign exchange series presents a serious challenge to the efficient market hypothesis". He chose to consider the interventions from the Federal Reserve as a possible explanation for positive results of the technical trading. In the research LeBaron used weekly and daily foreign exchange series from National Westminster Bank over the period from 2nd of January 1979 until 31st of December 1992. The exchange rates were German Mark and Japanese Yen. One week eurorates were used as the interest rates. This study LeBaron built on the *"statistical evidence on the forecasting properties of a simple technical trading rule"* from his earlier paper from 1991. The standard t-test provided significant support to the forecast ability of the simple moving average rule, so did the test of the statistical significance of the results by bootstrapped random walk. Neither interest rates nor changing from daily to weekly frequency modified the results. The returns were also high enough to cover the transaction costs. Then, LeBaron removed the intervention periods and the results fell dramatically. He concluded that *"These results are strong in suggesting that something different is going on when the Federal Reserve is active in terms of foreign exchange predictability"*. However, he could not prove the causality. There was an attempt to find a common driving process behind the predictability and interventions; volatility was suggested, but there was no certain evidence for that. LeBaron thought that *"it looks unlikely that a common factor will be easy to find"*.

A very influential paper on moving averages was written by Brock et al. (1992). They proposed a combination of the bootstrap methodology and the technical trading rules in evaluation of the null models. Their method can be used on different null models and *"when models are rejected by such a statistical test, information is provided on how to modify the model to achieve a better description of the series"*. Brock et al. (1992) tested two simple and most popular trading rules – moving average-oscillator and trading-rage break (resistance and support levels). They used 90 years of daily data from the Dow Jones Industrial Average, beginning from the 1st January 1897 and through 1986. In addition to the full sample, they tested four sub-samples: (1) 1 January 1897 to 30 July 1914, considering closure during WWI; (2) 1 January 1915 to 31 December 1938, including the 20ths and Great Depression; (3) 1 January 1939 to 30 June 1962, including WWII; and (4) 1 July 1962 to 31 December 1986, a period widely used for research. The standard t-statistics supported the predictability of the trading rules. Brock et al. mentioned the reasons for this predictability: *"(1) changes in expected returns that result from an equilibrium model, or (2) market inefficiency"*. In their sample they found no difference in results between sub-

periods. Then they applied bootstrap method with the following null models: *a random walk with drift, autoregressive process of order 1(AR(1)), GARCH-M, and exponential GARCH*. Those models did not replicate the actual price series, thus giving support to the predictability of technical analysis. In addition, Brock et al. (1992) found that *"returns during buy periods are larger than returns during sell periods"* and that *"returns during buy periods are less volatile than returns during sell periods"*. Their paper gave support for the non-linear nature of prices and returns. Although they showed the profitability of technical trading rules, they failed to account for transaction costs.

Gençay (1996) examined the linear and non-linear predictability of stock market returns using the moving average rules. Gençay (1996) used the daily observations from the Dow Jones Industrial Average Index over the period from 2nd of January 1963 until 30th of June 1988. He also analyzed 6 sub-samples of 4 years each to see if there are some variations. The estimation was done for the moving average rule with *"a small band that eliminates whiplash effects from the data"*. As linear conditional mean estimators, he used AR and GARCH-M(1,1). Among the nonparametric regression techniques Gençay (1996) chose single-layer feedforward networks. The measurement of the out-of-sample performance was done by the mean square prediction error (MSPE). Gençay's (1996) results showed that *"the introduction of the band around a moving average rule improves forecast accuracy"*. The other important result was the significant forecasts improvement with the use of feedforward networks (non-linear) that *"consistently achieve the 10 % forecast gain over the benchmark model for all data periods"*. This indicates *"strong non-linear predictability"* of the stock returns. However, Gençay (1996) did not consider transaction costs and brokerage fees, which seemed to be high due to the high frequency of transactions.

Another important research on moving averages was conducted by Kwon and Kish (2002). They examined three popular technical trading rules: the simple price moving average, moving average with momentum, and moving average with trading volume. The objective was to test *"whether the returns of any moving average trading rules on the basis of the information are greater than a buy-and-hold strategy in terms of a 'fair game' efficient model"*. The study was based on the NYSE value-weighted index over the period from 1st of July 1962 to 31st December 1996. In order to see if the profitability of trading rules varies over time, Kwon and Kish used three sub-periods: from the 1st of July 1962 until the end of 1972, 1973 – 1984, and 1985 –1996. The examination of the profitability of technical trading rules using the traditional *t*-test showed significantly higher results compared to buy-and-

hold strategy for two first sub-periods; though, the sub-period of 1985 – 1996 was an exception. The sub-period findings are similar that of Brock et al. (1992), who also did not find differences between sub-periods until 1986. However, we cannot compare the third period as Brock et al. only examined data before 1986. On that basis, Kwon and Kish suggested that the trading rules profitability could depend on the sample period and that moving averages could be more robust in capturing profits over small stocks than over large stocks. The other interesting finding of the volume use was a significant increase in profitability, especially, taking into consideration that the number of buy-sell signals was less in this model. They concluded that *"the trading volume may reveal additional information over the sequence of prices"*. Nevertheless, the assumptions of the t-test do not correspond to the revealed summary statistics of the data. Therefore, Kwon and Kish also used the bootstrap method to analyze the significance of the technical trading rules. In order to do that, they applied following null models: a random walk model, the GARCH-M, and the GARCH-M with instrument variables. The results showed that the random walk model could not explain the returns of the moving average and moving average/momentum technical trading rules, but there was evidence of the information value of the trading volume. The conditional means obtained from both the GARCH-M model and GARCH-M with instrument variables model by bootstrapping seemed to replicate the returns of technical trading rules; however, these models could not match the conditional standard deviations. On the other hand, in a trading rule with volume, the models succeeded in the replication. This gave a support to the technical trading rules, and the main conclusion of Kwon and Kish was that "*the return series itself under various models does not fully reveal the information about the market. The technical trading rules may capture non-linear dependencies in the returns or relations between returns and trading volume"*. The other notable finding was the weaker returns in the third sub-period, *"indicating a dissipation of the value of trading rules over time"*; this might be due to the technological improvements and better information in the market.

While some research focuses on the existing technical trading rules, other investigates the possibility of theoretical development of trading models. For instance, Blume et al. (1994) studied the informational role of volume for technical analysis. Their goal was *"to determine how the statistical properties of volume relate to the underlying value of the asset and to the behavior of market prices"* and to explore how traders can use it in practice. Blume et al. (1994) developed a model of *"an alternative equilibrium approach"* for security markets,

where they showed that *"volume provides information about the quality of traders' information that cannot be deduced from the price statistics"*. They showed the positive correlation between volume and price changes and argued that a combination of price and volume help traders to achieve a superior decision making process.

Duecker and Neely (2005) made an attempt to develop *"economically useful trading rules"* by combining non-linear Markov switching models with high-frequency technical trading rules. The goal is to find criteria for choosing the ex-ante trading rules. Based on a switching model they developed a trading rule with filters and accounted for transactions costs. Then it was applied on the daily exchange rate data for German mark, Japanese yen, British pound and Swiss franc. For a comparison the moving average trading rules are used. Duecker and Neely (2005) found that *"Markov models generate statistically and economically significant out-of-sample returns that are 0.85 percentage points larger, on average, than those of conventional technical trading rules, and these returns appear to be fairly stable over time"*. The discovered advantages of the Markov trading rule over moving average trading rule are in (1) equally weighted portfolio of them gives an improved risk-return trade off, and (2) *"the Markov rules are strongly superior to the MA rules on the most recent data, in which the MA rules' profitability appears to disappeared"*. The same trend was detected by Kwon and Kish (2002). Duecker and Neely (2005) pointed out two advantages of the econometric methodology. The first one is the possibility *"to generate the entire multi-period distribution of exchange rate returns, enabling the risk-averse investor to better assess the risk-adjusted expected returns"*. The second one is *"the stability of the model structure – rather than the return moments – can be assessed in real time, enabling traders to change their trading rules with the structure of the data generating process"*.

Many studies investigated moving averages and momentum trading rules; nevertheless, in practice traders use a lot of charts and geometrical patterns, which apparently did not get the same attention in the empirical research. Charting is one of the main technical trading approaches that can be used in all markets (Eng 1988). Because charting is the visual, geometrical presentation of price analysis, it is challenging to replicate it by computational algorithm. The development in computer technology gave an advantage to *"quantitative finance* [which] *is primarily algebraic and numerical"* (Lo et al. 2000).

Lo, Mamaysky and Wang (2000) conducted an essential study by using nonparametric kernel regression, a smoothing technique, as an approach to technical pattern recognition.

They evaluated daily stock returns in U.S. for NYSE/AMEX and Nasdaq from 1962 to 1996. The objective was to *"evaluate the effectiveness to technical analysis"*. They compared *"the unconditional empirical distribution of daily stock returns to the conditional distribution"*. In the paper Lo et al. (2000) focused on five pairs of technical patterns used by technical analysts: head-and-shoulders and inverse head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, rectangle tops and bottoms, and double tops and bottoms. Their approach integrated *"the essence of technical analysis: to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data"*. Smoothing estimators, like kernel regression, estimate nonlinear relations by averaging out the noise. The results were mixed. Lo et al. (2000) pointed the difference in the informative value of technical indicators for NYSE/AMEX and Nasdaq stocks, which might be due to the difference of sample sizes. In brief, they found that some of the patterns, especially for Nasdaq sample, may have some predictive value, if they are applied to many stocks over long time. In the conclusion they wrote that *"while this does not necessarily imply that technical analysis can be used to generate "excess" trading profits, it does raise the possibility that technical analysis can add value to the investment process"*. An idea of "optimal patterns" was launched in the paper. It suggested that there might be different optimal patterns for specific objectives such as detecting statistical anomalies or maximizing trading profits. The main shortcoming of Lo et al.'s (2000) research is that they focused on informative content of patterns, but did not look at the profitability of technical analysis.

3.3 Efficiency of Financial Markets and Behavioural Finance

More recent research took a new approach and adopted a psychological perspective to explain the the anomalies. Evidence in the psychology literature showed that individuals have limited capabilities in analysing the information, are making mistakes, and tend to follow others (Barberis and Thaler 2003; Malkiel 2003). This contradicts the main assumption of the EMH – the rationality of the participants (Fama 1965a).

*"Behavioral finance is a new approach to financial markets that has emerged, at least in part, in response to the difficulties faced by the traditional paradigm. In broad terms, it argues that some financial phenomena can be better understood using models in which some agents are **not** fully rational"* (Barberis and Thaler 2003). Behavioural finance explains that

investors predominantly do not consider whether prices are cheap or expensive but whether they expect them to rise or fall. However, market imperfections exist due to overconfidence, optimism and wishful thinking, representative bias, conservatism, information bias, and other human errors (Barberis and Thaler 2003). Following explanation of the content of behavioural finance has been given:

> *"The field has two building blocks: <u>limits to arbitrage</u>, which argues that it can be difficult for rational traders to undo the dislocations caused by less rational traders; and <u>psychology</u>, which catalogues the kinds of deviations from full rationality we might expect to see" (Barberis and Thaler 2003).*

Barberis and Thaler (2003) explained that there are two types of investors in the market: rational speculators or arbitrageurs and noise traders or irrational traders who trade on the basis of imperfect information. *"An arbitrage is an investment strategy that offers riskless profits at no cost"*. While the actions of noise traders cannot affect the fundamental prices of securities, they can increase the risk present in the market. This implies several large potential pricing anomalies. Fundamental values respond to information, but securities prices respond to both information and noise. The difference between the actual price and the fundamental value of a share creates a mispricing, which provides an investment opportunity. Arbitrageurs, therefore, face greater potential profits but also greater risks. However, correction of the mispricing can be *"both risky and costly, thereby allowing the mispricing to survive"* (Barberis and Thaler 2003). They indicate following possible correction challenges: fundamental risk, noise trader risk, and implementation cost. Under these circumstances, rational traders can be powerless.

Behavioural finance approach is developing in several directions that can facilitate the trading and understanding of market theories. Among its fields of study are investor behaviour, understanding bounded rationality, limits to arbitrage and empirical investigation of anomalous effects (Barberis and Thaler 2003).

Nevertheless, rational expectations are clearly not enough to prevent bubbles and crashes. For example, there was a stock market crash of October 1987 or Black Monday. On this day most stock exchanges crashed at the same time and that cannot be explained by theories of stock pricing (Malkiel 2003; Shiller 1991). The explanation can be either in the mechanics of the exchanges or the irregularities of human nature. Shiller's (1991) survey results indicated

that most investors traded because of price changes rather than news about fundamentals. Therefore, excessive volatility in the market can be caused by a general trend which may have no rational or logical explanation. Then there are the technology bubbles in 2000-2002, the fall of equity markets 2007-2009. Behavioural supporters believe that the mistake was in neglecting the role of human nature.

Behavioural finance can also be used to outperform the market. In 1993, Thaler has founded *Fuller & Thaler Asset Management, Inc*. It is an institutional investment firm with an investment approach that uses insights from behavioural finance. Their goal is following:

> *"Investors make mental mistakes that can cause stocks to be mispriced. Fuller & Thaler's objective is to use our understanding of human decision making to find these mispriced stocks and earn superior returns" (Fuller & Thaler Asset Management, Inc. Website 2010).*

Explaining the global financial crisis of 2008 in their Quarterly Update (Fuller & Thaler, 3Q2008), they pointed out two fundamental insights from behavioural finance. The first one was the *complexity* of the real world compared to economic models. The second one was *the role of social trend following, i.e., "herding"*.

Major contribution of behavioural finance is giving more realistic psychological assumptions to market theories and increasing their explanatory power. Thus, behavioural psychology approaches might be among some of the most promising alternatives to the EMH. However, many of the current theories about rationality and behaviour are incorrect and better theories are expected to emerge (Barberis and Thaler 2003).

In the next chapter I present some estimation methods and econometric models used in the discussed research.

4 Estimation Methods and Econometric Models

In this chapter I show some of the estimations models used in the articles presented in chapter 3.

The value of technical trading rules was often examined using the traditional *t*-test. But since the traditional *t*-test statistics does not consider the dependencies between returns and assumes the normality of return distributions, the significance of technical trading rules can be tested using the residual bootstrap distribution of test statistics. There are several models developed to account for the non-linear properties of prices. Among them are an AutoRegressive Conditional Heteroskedasticity model (ARCH(m)), a Generalized AutoRegressive Conditional Heteroskedasticity in Mean (GARCH-M), an exponential GARCH-M, and a multivariate GARCH-M, all of which can be tested using a bootstrapping methodology. It is also important to understand the volatility estimation. Most of the estimation equations come from Hull (2000), Wooldridge (2003) and articles of Kwon and Kish (2002) and Brock et al. (1992).

4.1 Test Statistics

The popular method to test the statistical significance of the technical rules is the t-statistic. Kwon and Kish (2002) present the estimation of t-statistics of a trading rule can be presented like this [Brock et al. (1992) and Wooldridge (2003) present with other letters and in different form]. The *h* day holding period return at time *t* is defined as $R_t^h = \log(P_{t+h}) - \log(P_t)$. Based on price information up to and including day *t*, the trading outcomes each day in the sample are either a buy (*b*), sell (*s*), or neutral (*n*) signal. The mean return and variance conditional on a buy/sell signal over *N* periods can be written as:

$$\overline{X}_{b(s)} = E\left(R_t^h \mid b_t \ or \ s_t\right) = \frac{1}{N_{b(s)}} \sum_{t=0}^{N-1} R_{t+1} I_t^{b(s)}$$

$$\hat{\sigma}_{b(s)}^2 = E\left[\left(R_t^h - \overline{X}_{b(s)}\right)^2 \mid b_t \ or \ s_t\right] = \frac{1}{N_{b(s)}} \sum_{t=0}^{N-1} \left(R_{t+1} - \overline{X}_{b(s)}\right)^2 I_t^{b(s)}$$

Where $N_{b(s)}$ is the number of total buy (sell) days, R_{t+1} is daily return at time $t+1$, and $I_t^{b(s)}$ is one for a buy (sell) signal observed at time t and zero otherwise.

The analysis tests whether the returns of the trading rule on the basis of the information are greater than a buy-and-hold strategy in terms of a fair game efficient model. The null and alternative hypotheses are expressed as:

$$H(1)_0 : \overline{X}_r - \overline{X} = 0$$

$$H(1)_A : \overline{X}_r - \overline{X} > 0$$

where $\overline{X}_r$ and $\overline{X}$ are the mean return from the buy or sell signals and the unconditional buy-and-hold mean return for each sample period tested.

The t-statistic for returns of the buy (sell) trading rule over the buy-and-hold strategy is:

$$t = \frac{\overline{X}_r - \overline{X}}{\sqrt{\hat{\sigma}_r^2 / N_r + \hat{\sigma}^2 / N}}$$

where $\overline{X}_r$, $\hat{\sigma}_r^2$, and N_r are the mean return, variance, and number of the buy or sell signals, and $\overline{X}$, $\hat{\sigma}^2$, and N are the unconditional mean, variance, and number of returns for the entire sample period. For the buy-sell or the buy-sell spread, the t-statistic is:

$$t = \frac{\overline{X}_b - \overline{X}_s}{\sqrt{\hat{\sigma}_b^2 / N_b + \hat{\sigma}_s^2 / N_s}}$$

Where $\overline{X}_b$, $\hat{\sigma}_b^2$, and N_b are the mean return, variance, and number of the buy signals, and $\overline{X}_s$, $\hat{\sigma}_s^2$, and N_s are the mean return, variance, and number of the sell signals.

4.2 The ARCH Model

Volatility measures the uncertainty of the returns provided by the security. The volatility of a security can be defined as the standard deviation of the return provided by the security in one year when the return is expressed using continuous compounding (Hull 2000).

There are two most important causes of volatility claimed by analysts: the random arrival of new information about the future returns and the trading itself. The results from empirical tests suggest that volatility is largely caused by trading itself (Fama 1965, French 1980). ARCH and GARCH are non-linear and they recognise that volatilities and correlations are constant.

Hull (2000) gave following model description. An unbiased estimate of the variance rate per day, σ_n^2, using the most recent m observations on the u_i is $\sigma_n^2 = \dfrac{1}{m-1}\sum_{i=1}^{m}(u_{n-i} - \bar{u})^2$. For the purposes of calculation, the formula is usually changed in a number of ways:

- u_i is defined as the proportional change in the market variable between the end of the day $i-1$ and the end of the day i so that $u_i = \dfrac{S_i - S_{i-1}}{S_{i-1}}$.

- $\bar{u}$ is assumed to be zero.

- $m-1$ is replaced by m, a maximum likelihood estimate.

These three changes make very little difference to the variance estimates that are calculated. The formula for variance becomes $\sigma_n^2 = \dfrac{1}{m}\sum_{i=1}^{m}u_{n-i}^2$. This equation gives equal weight to all u_i^2's. Given that the objective is to monitor the current level of volatility, it is appropriate to give more weight, α_i, to recent data. The variable α_i is the amount of weight given to the observation i days ago. The α's are positive, and $\alpha_i < \alpha_j$ when $i > j$, because we wish to give less weight to older observations. We furthermore assume that there is a long-run average volatility (V) and that this should be given some weight (γ). This leads to a following model: $\sigma_n^2 = \gamma V + \sum_{i=1}^{m}\alpha_i u_{n-i}^2$. The weights must sum to unity, $\gamma + \sum_{i=1}^{m}\alpha_i = 1$. This is known as an ARCH(m) model, Autoregressive Conditional Heteroscedasticity, first suggested by Engle (1982). The estimate of the variance is based on a long-run average variance and m observations. The older an observation, the less weight it is given. This is a model of dynamic heteroscedasticity where the variance of the error term, given past information, depends linearly on the past squared errors.

4.3 The GARCH Model

The GARCH (1,1) model was proposed by Bollerslev in 1986. The equation for GARCH (1,1) is (Hull 2000):

$$\sigma_n^2 = \gamma V + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

The weights sum to one, $\gamma + \alpha + \beta = 1$. The "(1,1)" indicates that σ_n^2 is based on the most recent observation of u^2 and the most recent estimate of the variance rate. The more general GARCH (p,q) model calculates σ_n^2 from the most recent p observations on u^2 and the most recent q estimates of the variance rate. Setting $\omega = \gamma V$, the GARCH (1,1) model can be written as

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

This is the form of the model that is usually used for the purposes of estimating the parameters. Once ω, α, and β have been estimated, we can calculate γ as $1 - \alpha - \beta$. The long-term variance V can then be calculated as ω / γ. For a stable GARCH (1,1) process we require $\alpha + \beta < 1$, otherwise the weight applied to the long-term variance is negative. The weight applied to u_{n-i}^2 is $\alpha \beta^{i-1}$, and the weights decline exponentially at rate β. The parameter β can be interpreted as a "decay rate".

In practice, a variance rate exhibits what is known as mean reversion. Although it moves around randomly, over time it tends to get pulled back toward some long-run average level. The GARCH (1,1) model incorporates mean reversion (Brock et al. 1992; Engle 1982; Kwon and Kish 2002).

4.4 Maximum Likelihood Methods

To estimate parameters in the models one uses maximum likelihood method, which selects values for the parameters that maximize the chance (or likelihood) of data occurring. Once the parameters are determined, the model can be judged by how well it removes autocorrelation from the u_i^2 (Hull 2000). Assuming that the probability distribution of u_i

conditional on variance is normal. Searching for the parameters in the model that maximize the following expression:

$$\prod_{i=1}^{m} \left[\frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(\frac{-u_i^2}{2\sigma_i^2} \right) \right]$$

Taking logarithms we see that this is equivalent to maximizing:

$$\sum_{i=1}^{m} \left[-\ln\left(\sigma_i^2\right) - \frac{u_i^2}{\sigma_i^2} \right]$$

GARCH volatility changes with time. During some periods volatility is relatively high, during other periods it is relatively low. In other words, when u_i^2 is high there is a tendency for $u_{i+1}^2, u_{i+2}^2, \ldots$ to be high, and when u_i^2 is low there is a tendency for $u_{i+1}^2, u_{i+2}^2, \ldots$ to be low. This can be tested by studying the autocorrelation structure of the u_i^2.

Assume there is autocorrelation in u_i^2. If a GARCH model is working well it should remove the autocorrelation. We can test whether it has done this by considering the autocorrelation structure for the variables u_i^2 / σ_i^2. If these show very little autocorrelation, our model for σ_i has succeeded in explaining autocorrelations in the u_i^2. We can use the Ljung-Box statistics with m observations: $m \sum_{k=1}^{K} w_k \eta_k^2$, where η_k is the autocorrelation for a lag of k and $w_k = \frac{m-2}{m-k}$.

The GARCH model can be used to forecast future volatility. Letting $\gamma = 1 - \alpha - \beta$, the variance rate estimated for day n is:

$$\sigma_n^2 = (1 - \alpha - \beta)V + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

so that

$$\sigma_n^2 - V = \alpha(u_{n-1}^2 - V) + \beta(\sigma_{n-1}^2 - V)$$

On day $n + k$ in the future we have

$$\sigma_{n+k}^2 - V = \alpha(u_{n+k-1}^2 - V) + \beta(\sigma_{n+k-1}^2 - V)$$

The expected value of u_{n+k-1}^2 is σ_{n+k-1}^2. Therefore, the expected value is:

$$E\left[\sigma_{n+k}^2 - V\right] = (\alpha + \beta)E\left[\sigma_{n+k-1}^2 - V\right]$$

Using this equation repeatedly gives:

$$E\left[\sigma_{n+k}^2\right] = V + (\alpha + \beta)^k (\sigma_n^2 - V)$$

When $\alpha + \beta < 1$, the final term in the equation becomes progressively smaller as k increases. The variance rate shows mean reversion with a reversion level of V and a reversion rate of $1 - \alpha - \beta$. The forecast of the future variance rate tends towards V as we look further and further ahead. If $\alpha + \beta > 1$, the GARCH process is unstable and it should be rejected in favour of the other moving average models (Engle 1982; Hull 2000).

4.5 Bootstrap Analysis

Brock et al. 1992 and Kwon and Kish 2002 wrote about the reason behind the bootstrapping method. The *t*-test methodology used in the analysis assumes normality, stationarity, and independent distributions. Therefore, the interpretation of the results may be incorrect and misleading since the summary statistics may reveal that the return distributions are leptokurtic, auto-correlated, and conditionally heteroskedastic. Furthermore, the mean returns of buy and sell signals might not be independent of the unconditional buy-and-hold returns. To get more correct information about the profitability of the technical trading rule, its significance is analysed using a bootstrap methodology (Brock et al. 1992; Kwon and Kish 2002). *"There are several advantages of using a bootstrap methodology. First, the bootstrap procedure is relatively robust in terms of accounting for non-normality, autocorrelation, and conditional heteroskedasticity. Second, unlike the traditional statistical methods, the bootstrap method allows (this study) to avoid the difficulty of deriving a test statistic for the significance of trading rule. Third, it permits the estimation of standard deviations and confidence intervals for the estimators. Finally, the bootstrap method allows (this study) to simulate distributions of the trading rule returns by any specified model"* (Kwon and Kish 2002).

To employ the bootstrap methodology, returns from an artificial price series are generated and trading rules are applied to the series. *"The residuals are randomly chosen with replacement to generate the bootstrap return series based on the log difference of the prices"* (Kwon and Kish 2002). Then, using the bootstrap method, conditional distributions for mean buy and sell returns are estimated. Prices and returns are forecasted under the linear and non-linear models, for instance, random walk, ARCH, generalized autoregressive conditional heteroskedasticity in mean (GARCH-M), and GARCH-M with instrument variables.

5 Research Results from Trader's Perspective

In this chapter I look at the research results from the trader's perspective. I consider what might be useful for trading analysts and if technical analysis is reliable in the process of decision making.

Research on the predictive power of technical analysis is a matter of controversy. In the chapter 3 of this thesis, I presented some research done by proponents and opponents of EMH and technical trading. The results are mixed; however, it seems to be many problems with the validity of the EMH and choosing right technical trading model.

If we compare two major investors' approaches, we will see that they have different investment horizon. Fundamental analysis looks at the market at much longer horizon compared to technical analysis. While technical analysis analyses weeks, days or even minutes, fundamental analysis often considers several of years. The goals of a purchase and sale are also different for each approach. Technical analysis is mainly used by traders who look for some profitable buy-sell possibilities. Fundamental analysis, on the other hand, is used for an investment in assets that can increase in value over time. However, the research of Taylor and Allen (1992), Brock et al. (1992), and Brozynski et al. (2003) showed that technical analysis is an essential tool used in practice. Although it is normally used in besides the fundamental analysis and there different rules applied to different markets.

The research on technical analysis has various objectives, and it is obvious that the paradigm changed over the years. Early studies, Alexander (1961 and 1964), Fama and Blume (1966), Levy (1967), and Jensen and Benington (1970) used less advanced statistics and focused primarily on the profitability of technical trading rules over the buy-and-hold strategy. They also used linear models for testing. Modern studies, as Park and Irwin (2007) called them, took other approach. In addition to analysing momentum patterns (Ilmanen and Byrne 2003; Stivers and Sun 2004) and statistically advanced tests of moving average rules (Brock et al. 1992; Gençay 1996; LeBaron 1991 and 1996; Kwon and Kish 2002), modern studies made an attempt to theoretically develop trading rules and find an optimal rule (Blume et al. 1994; Duecker and Neely 2005). Finally, Lo et al. (2000) looked at a potential method for technical pattern recognition that allows examining technical charts. There has been a significant progress in technical studies after 1990s. Now I describe more in detail how various studies can be useful to technical analysts.

In 2007 Park and Irwin reviewed the evidence on the profitability of technical analysis. In their paper they looked at 137 technical trading studies published between 1960 and August 2004. Park and Irwin found that *"early studies indicate that technical trading strategies are profitable in foreign exchange markets and futures markets, but not in stock markets"*. They also looked at research done after 1988, and *"among a total of 95 modern studies, 56 studies find positive results regarding technical trading strategies, 20 studies obtain negative results, and 19 studies indicate mixed results"*. Based on their findings they concluded that *modern studies indicate that technical trading strategies consistently generate economic profits in a variety of speculative markets at least until the early 1990s"*.

This review seems to give a positive empirical support to technical strategies. However, they found that *"most empirical studies are subject to various problems in their testing procedures, e.g. data snooping, ex post selection of trading rules or search technologies, and difficulties in estimation of risk and transaction costs"*.

I find most fascinating a paper published by Lo, Mamaysky and Wang in 2000 in which they proposed a new approach to evaluating the efficacy of technical analysis − *"systematic and automatic approach to technical pattern recognition using nonparametric kernel regression"*. In their study they looked at 10 chart patterns. In order to gain information from technical patterns, the unconditional empirical distribution of returns was compared with the corresponding conditional empirical distribution, conditioned on the occurrence of technical pattern. The objective was to *"identify regularities in the time series of prices by extracting nonlinear patterns from noisy data"*. Even they had mixed results and could not prove that technical analysis generate profits over buy-and-hold strategy, they have showed that using an automated algorithm can improve technical techniques. It was a significant attempt to determine "optimal patterns". They also proposed the idea of different optimal patterns for different objectives. Lo et al. (2000) summarized the main value of their study like this: *"from a practical perspective, there may be significant benefits to developing an algorithmic approach to technical analysis because of the leverage that technology can provide. As with many other successful technologies, the automation of technical pattern recognition may not replace the skills of a technical analyst, but can amplify them considerably"*.

Others also attempted to find an optimal trading rule. One of the most influential studies on technical trading is "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns" by Brock et al. (1992). They have explored two of the simplest and popular rules:

moving average-oscillator and trading-range break, by evaluating their ability to forecast future price changes. In their paper they have for the first time applied the bootstrap method to overcome the weaknesses of conventional t-tests, and evaluation of model specifications by the use of technical analysis. The combination of these techniques is the major contribution of this study. *"This procedure allows testing a wide range of null models. When models are rejected by such a statistical test, information is provided on how to modify the model to achieve a better description of the series"*. Brock et al. have also addressed the problem of data-snooping biases by using technical trading rules that were popular over a long period of time. The conclusion of this paper gives valuable information to the traders: technical rules have predictive power and stocks follow the non-linear model. The useful finding for trader might be that buy periods give larger returns than sell periods and that in the buy period returns are less volatile.

Ilmanen and Byrne (2003) proposed an investment strategy around major events. Traders may position themselves to pre-event trend and post-event trend. Researchers examined the US non-farm payroll report. I wonder if it is possible to apply their findings to the EMH anomalies. All calendar effects can be considered as regular events and the relationship between technical rules and seasonal can be exploited. I find all the EMH anomalies, both calendar, firm related and others, to be a significant, additional tool in decision making strategies.

Stivers and Sun (2004) found that, around economic crises and recessions, medium-run momentum profits can become negative due to the uninformative nature of the past returns; and that, after control for regime-mean adjusted returns, profits for the most part disappear. However, they could not determine whether the explanation for momentum profits was rational or behavioural. The conclusion here is that regime-shifts carry valuable information and traders can exploit it.

Osler (2003) found that *"executed take-profit orders cluster more strongly at round numbers ending in 00 than do stop-loss orders"* and that *"stop-loss buy orders cluster at rates just above round numbers; stop-loss sell orders cluster just below round numbers; there are no similar asymmetries for take-profit orders"*. These findings have practical application for technical analysts of currency exchange market and shows that *"technical analysis is useful for predicting short-run exchange rate dynamics"*.

LeBaron (1991 and 1996) as well studied currency exchange market and discovered an effect of Federal Reserve interventions on predictability of the simple moving average rules. He could not prove the causality but thought that there might be a common driving process behind the predictability and interventions, but *"it looks unlikely that a common factor will be easy to find"*.

Gençay's (1996) showed that *"the introduction of the band around a moving average rule improves forecast accuracy"* and that there is a significant forecasts improvement with the use of feedforward networks (non-linear) that *"consistently achieve the 10 % forecast gain over the benchmark model for all data periods"*. This can be applied by traders who use the moving average rules.

Kwon and Kish (2002) and Blume et al. (1994) showed the positive correlation between volume and price changes and argued that a combination of price and volume help traders to achieve a superior decision making process. Kwon and Kish (2002) provided evidence that the technical trading rules may capture non-linear dependencies in the returns.

Duecker and Neely (2005) discovered the advantages of the Markov trading rule over moving average trading rule: (1) equally weighted portfolio of them gives an improved risk-return trade off, and (2) *"the Markov rules are strongly superior to the MA rules on the most recent data, in which the MA rules' profitability appears to disappeared"*. Duecker and Neely (2005) pointed out two advantages of the econometric methodology: better assessment of risk-adjusted returns and possibility to change trading rules with the structure of data process.

In addition, behavioural studies give the EMH and the random walk theory more realistic psychological assumptions. Barberis and Thaler (2003) and Shiller (1991) show how price fluctuations can be predicted by knowing traders' psychology. Understanding the behaviour of the participants increases the explanatory power of the market theories.

However, there is one question that puzzles me. Why several studies found that profitability of the technical trading rules disappears after 1990s? Park and Irwin (2007) mentioned it; Kwon and Kish (2002) and Duecker and Neely (2005) found the same tendency. Do trading rules stop generating profits because of the advanced technology and more efficient information exchange? Maybe it is time for "old" trading rules to give place to the new ones, like the new Markov trading rule of Duecker and Neely (2005)?

Among most innovative proposals I consider the Lo et al.'s (2000) automation of technical pattern recognition and the Duecker and Neely's (2005) Markov rule as a substitute for moving averages.

As the research results show, technical analysis alone can be unreliable in the process of decision making. Old technical analysis strategies seem to provide incomplete background for modern trading and new trading rules emerge. By integrating technical, fundamental, and psychological analysis into an investment or trading approach, one can handle increasingly complex contemporary markets. Even some empirical studies give unclear results, they provide traders with new ideas, methods, and techniques.

6 Limitations and Futher Research

This thesis has covered just a small part of the research conducted on market efficiency. The number of articles is enormous, and it is not possible to analyse all of them in the scope of this thesis.

Nowadays, due to technological development and new ways of information exchange, trading in financial markets has become very complex. To get more concrete image of the applicability of the research results in trading, it is advisable to study the research on each class of security separately, e.g. shares, bonds, futures, foreign exchange and options. Different types of securities behave in different ways, and there are techniques that are more suitable for a trade in one security than in the other. Alternatively, one can focus the research around one particular trading rule.

In this thesis, I did not separate either among security classes or trading rules. Therefore, there are only few articles on each topic, and I could not give the same detailed attention to all of them. It is a general rather than in depth study.

Some empirical articles and computational theories were at an advanced level, demanding broad knowledge of both previous empirical studies and statistical methodology. However, I am only at the master programme. Therefore, I felt that I would have profited from some more advanced courses in statistics, mathematics and finance.

I am interested in the cultural and international issues. I think that it could be exciting to investigate the evidence on technical trading rules and their profitability across countries and cultures. Are there any differences or are trading rules universally applicable? If there are any variations, the next question would be to look for the causality effect.

7 Conclusions

Financial theories are subjective. Thus, the point of this thesis is not that EMH is wrong and that technical analysis is right, but rather to explore the theory by looking at it from a user's perspective.

"In an uncertain world, however, no amount of empirical testing is sufficient to establish the validity of a hypothesis beyond any shadow of doubt" (Fama 1965a).

The research on the EMH plays an important role in understanding of the securities market. Nevertheless, contemporary literature shows that criticism of EMH has become more overwhelming. It is now clear that information is not the only variable affecting security valuation. Researchers have provided empirical evidence that security prices could deviate from their equilibrium values due to psychological factors, fads, and noise trading (Barberis and Thaler 2003).

"By the start of the twenty-first century, the intellectual dominance of the efficient market hypothesis had become far less universal", admitted Malkiel in his article in 2003.

Brock et al. (1992) wrote that *"all major brokerage firms publish technical commentary on the market and individual securities, and many of the newsletters published by various 'experts' are based on technical analysis"*.

The main focus in research on technical trading rules is to find the profitability and predictability of future price movements. An understanding of the benefits and limitations of technical analysis can be a powerful tool in decision making for both traders and investors.

I found several useful results from the research articles. Brock et al. (1992) indicated a difference between buy and sell period returns and volatility. Results provided by Ilmanen and Byrne (2003) give a pre- and post-event positioning strategy, which I assume can be exploited in connection to the EMH calendar effect anomalies. Lo et al. (2000) proposed development of automation of technical pattern recognition, which can substantially ease the work of the traders. Stivers and Sun (2004) found that regime-shifts carry valuable information and traders can exploit it. Osler (2003) found a system in take-profit and stop-loss order clustering. LeBaron (1991 and 1996) discovered an effect of Federal Reserve interventions on predictability of the simple moving average rules and tried to find a

common driving process behind the predictability and interventions. Gençay's (1996) showed how to improve the accuracy of forecasts applying the band around a moving average rule and that non-linear statistical models provide better results. Kwon and Kish (2002) and Blume et al. (1994) showed the positive correlation between volume and price changes and argued that a combination of price and volume help traders to achieve a superior decision making process. Duecker and Neely (2005) discovered the advantages of the Markov trading rule over moving average trading rule and pointed out two advantages of the econometric methodology. Their results give new idea of the future development of trading rules and use of modern computational programs.

However, many studies are limited as they either did not use suitable statistical tests, allow for transaction costs, risk adjustment, or did not take into consideration data-snooping and other estimation problems (Park and Irwin 2007).

Among most innovative proposals I consider the Lo et al.'s (2000) automation of technical pattern recognition and the Duecker and Neely's (2005) Markov rule as a substitute for moving averages. There are also other potentially useful and applicable strategies for a trader.

There is one question that puzzles me. Why several studies found that profitability of the technical trading rules disappears after 1990s? Park and Irwin (2007) mentioned it; Kwon and Kish (2002) and Duecker and Neely (2005) found the same tendency. Do trading rules stop generating profits because of the advanced technology and more efficient information exchange? Maybe it is time for "old" trading rules to give place to the new ones, like the new Markov trading rule of Duecker and Neely (2005)?

I think that an individual trader is not especially preoccupied with the market as a whole, but rather focuses on his/her individual achievements. If he/she can earn profits over buy-and-hold strategy, then all efficient markets theories have no value for him/her at that moment. The most important idea is that he/she can both win and lose, so it is crucial to stay alert, be flexible in decision making and accept that trading environment is in a constant change.

Since 1990s, the behavioural finance proposed that cognitive biases cause market inefficiencies (Barberis and Thaler 2003). As the research results show, technical analysis alone can be unreliable in the process of decision making. In order to understand the nature

of price movement, one should consider an approach combining traditional technical tools with fundamental analysis and behavioural finance.

The pursuit of innovation is essential in finance industry, and new theories and approaches will emerge in the future. However, the goal remains the same – to outperform the market and obtain superior investment performance.

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