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**USING TECHNICAL ANALYSIS TO PREDICT FUTURE PERFORMANCE OF
INTEREST RATE FUTURES**

Relative Strength Index, its modifications and Moving Average as trading rules

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ABSTRACT

During the recent years financial markets have been going through one of the most challenging periods in history as first USA and now Europe is struggling with a damaging credit crisis. As crisis is not calming the market is very volatile and technical analysis has gained more ground. This study analyses the performance of technical trading rules in the short term interest rate futures market. The purpose of this study is to examine if these trading rules can generate excess returns in relation to Buy-and-hold rule and if efficient market hypothesis can be criticized due to market inefficiencies.

The weak-form of the efficient market hypothesis states that all historical trading data is reflected in the asset prices. This is challenged by Relative Strength Index, its new modifications and Moving Average rules as they use historical trading data to try to yield higher returns than what is attained by buying and holding. As Relative Strength Index in this study is based on the original rule of 14-day periods a new modification of it, DRSI, applies two different length indices with influences from Moving Average rule. There are three versions of DRSI rule used in this study with some differences in an optimization process. In this study 1-50 method of Moving Average rule is used.

Data of this study consists of 132 short term interest rate futures denominated in seven currencies: USD, EUR, GBP, JPY, CHF, NZD and MYR. The futures data gathered from January 1st 2000 to July 31st 2009 contains total amount of 149,212 observations after filtration process. As previous studies have shown there is a difference in profitability between developed and developing market while technical trading rules are used and therefore also in this study data is divided into two periods, illiquid and liquid.

The findings of this study show that trading rules often generate higher risk adjusted returns but they cannot consistently generate excess returns versus Buy-and-hold method. However, it is shown that the MYR denominated market is not efficient and Moving Average and DRSI common optimization rules yield significant excess returns. In addition it was found that optimization has a huge impact on returns of trading rules.

KEYWORDS: technical analysis, interest rate futures, relative strength index, moving average, efficient market hypothesis

1. INTRODUCTION

Technical analysis has been used to predict future performance of financial instruments for over a hundred years. It is widely argued for and against by finance professionals in the academic field and by market professionals as well. Still there is no simple or perfect answer to the question whether it is worth of using or not. However, the use of technical analysis has increased faster than use of other methods in the recent decades and it is the most important trading method nowadays for 30–40% of the professional traders (Schulmeister 2006:1).

Technical analysis can be divided into several different methods but the main purpose combining all of them is to utilize historical data of an instrument to predict its future performance. Because it is in interests of all investors to get the best revenues as possible it is self-evident that new trading rules are invented and then measured time after time.

Fairly often technical analysis is associated with the stocks though it can be used with all financial instruments. Since derivatives have begun to be familiar for all of the investors interests in using technical analysis with them is also increasing. Previous academic research of derivatives and technical analysis mostly concentrates on using commodity or currency futures as data. This is well-grounded as commodity futures are important hedging tools for corporates when planning the purchases of the raw material. On the other hand, the corporates are growing and their business is getting more and more global. This means growing demand for hedging foreign exchange risks as well. Equally, large firms have huge deposits and liabilities that need hedging against interest rate risk, uncertainty in the future interest rates. This problem can be relieved by interest rate futures. In general, there is a future for almost every purpose. This together with the fact that there are low trading costs in futures market makes them popular and thus also very liquid instruments.

The history of futures as an exchange-traded instrument started few years after the Chicago Board of Trade was found in 1848. At first the purpose of the futures was in standardizing the quantities and qualities of grains but quickly futures contracts began to be in popularity of other investors as well. Later, in 1919 another futures exchange, Chicago Mercantile Exchange, was established. However, the last 30 years have been extremely important for the development of all derivatives and for the trading activity of them. Nowadays, new derivative products are invented nearly round the clock and they

are traded at least to some extent in exchanges all around the world. This is one of the reasons why derivatives are more and more in the focus of academic research. (Hull 2006: 1–9.)

The current credit crisis, however, can be a threat for the deregulated derivative markets on some level at least. Based on the information we have today, there might be restrictions that somehow regulate the free-floating use and invention of derivatives. This hopefully does not involve all of the derivatives securing the liquidity of the market but those structures that are used to hide parts of the risk behind a dissimulated structure. Nevertheless, the public opinion is that speculators, investment bankers and credit rating agencies are responsible for the worst crisis of the history. Politically it is a very explosive situation and obviously somebody needs to be made a scapegoat as traditional political parties are losing their hold of power all over the Europe. Indeed, politicians have recently got their part of the criticism as well.

1.1. Problem statement, hypotheses and research methodology

This study concentrates on both of the previously covered themes: technical analysis and derivatives referring only to interest rate futures in this paper. Even though technical analysis is widely covered in the previous studies these themes make this study very timely given that methods of technical analysis are more popularly used than ever as investors seek new methods to utilize volatile market sentiment. Current market volatility also highlights the importance of interest rate futures as an asset as market participants want to hedge their intensely fluctuating interest rate portfolios. While speculators might be most interested in the studies using technical analysis on futures market it can be useful information also for hedgers, such as an investor holding a bond portfolio or a CFO of a company as these trading methods could be used as a tool for well-timed purchases and sales of protection against interest rate risk too.

The purpose of this study is to examine if using technical trading rules have an effect on returns versus using Buy-and-hold method and if the efficient market hypothesis is therefore questioned. In this study, the technical trading methods are based on two separate trading rules: Relative Strength Index and momentum-based Moving Average. Relative Strength Index is a barometer that measures past average returns separately for the days of positive and negative returns. The purpose of the Relative Strength Index is to indicate when an instrument should be bought and when it should be sold. There is a

scale in Relative Strength Index ranging from 0 to 100, where a trend going towards zero indicates a bear market and a trend towards 100 is an indicator of bull market. However, levels of buy and sell signals according to the original trading rule by Wilder (1978) are 30 and 70, respectively, meaning that an instrument should be bought when the indicator rises above 30 and again it should be sold when indicator drops under 70. In addition, there are three other Relative Strength Index based trading rules used in this study to refine the performance of the original rule. These new modifications use two different length RSI indices with some influences from Moving Average trading rule. The difference between these trading rules is in the parameters' optimization process that is slightly customized in each of the rules. Relative Strength Index and these modified rules are specified more carefully in the section 4.2.

Another method, Moving Average, is narrowed in this study to consider only Moving Average crossover rule. According to this rule there are two moving average indicators needed, one short and another longer. In this study the short indicator is closing price of a single day and the longer indicator is an average of closing prices of 50 days referring to the 1-50 method. A buy signal is created when the shorter indicator of average prices rises above the longer indicator indicating a rising momentum of an asset price. Sell signal on the other hand is created when the shorter indicator drops under the longer one indicating a downturn. Also Moving Average rule is more thoroughly covered later in the section 4.3.

Data of this study, interest rate futures, consists of a set of 164 short-term interest rate futures quoted in seven currencies and traded in seven exchanges around the world. The underlying security of a short-term interest rate future is a three-month deposit or loan. Data period begins on January 1st 2000 and ends July 31st 2009 making the total amount of observations to 149,212 per trading rule after filtering out some of the futures time series with a small amount of observations. The data set is challenging as results generation and especially optimization process should be conducted with such large amount of data. There are 3500 alternative combinations as a result of optimization for each of the futures in every half year optimization period. In this study these processes were partly automated using Visual Basic add-in of Microsoft Excel reducing some manual procedures but obviously increasing the time used for encoding the procedures. However, the data set is further specified in the section 4.1.

According to the theories underlying the efficient market hypothesis, e.g. the random walk model, the trading rules should not be able to consistently generate greater profits

than Buy-and-hold strategy. This is why profits earned by technical trading rules used in this study are compared to the profits earned by Buy-and-hold strategy on the same time period. The weak form of the efficient market hypothesis is tested in this study as there is only historical trading data, such as asset prices and trading volumes, used to predict future performance.

Rather many of the previous studies, covered in the following subchapters, imply that returns on the futures markets are greater when investing using technical trading rules versus what is achieved by Buy-and-hold strategy. Therefore there are the following three hypotheses tested:

- H1: Interest rate futures markets are not efficient in terms of weak-form of the efficient market hypothesis and abnormal returns are consistently generated using Relative Strength Index trading method
- H2: Interest rate futures markets are not efficient in terms of weak-form of the efficient market hypothesis and abnormal returns are consistently generated using Relative Strength Index based trading methods
- H3: Interest rate futures markets are not efficient in terms of weak-form of the efficient market hypothesis and abnormal returns are consistently generated using Moving Average trading method.

According to Fama (1970) where and when efficient markets are observed, no trading rule can yield substantially and constantly better returns compared to the Buy-and-hold strategy. However, as the trading rules are compared in this study the risk of a particular security must be considered as well because of different risk aversions among the investors. It cannot be assumed that a U.S. treasury bill and a particular stock would constantly generate equal returns. This is not inconsistent with the efficient market hypothesis as both of the securities have different risk premiums.

In this study, assets are not compared between each others but the trading methods are in the spotlight. Thus, measuring the risk of an asset is not that necessary but it will be done for another reason. According to the Buy-and-hold strategy, the asset is supposed to be bought in the beginning and sold in the end of the period. When trading rules are used there can be several buy and sell signals during the same period, which obviously differentiates the holding period between the methods. Because the holding period of an

asset is not the same, the risk cannot be assumed to be the same either. Accordingly, the risk is important to be measured and the method used in this study is Sharpe's measure. Furthermore, statistical significance also needs to be covered to tell whether the results really are what they look like. To measure the significance Mann-Whitney U-test and Student's t-test are used in this study.

It needs to be mentioned that shorting is not applied in this study as only long positions are used. In addition the transaction costs are excluded out of the study because they are so small using short-term interest rate futures that they are not relevant and would make the study only more complex. However, in the section 4 there are more detailed descriptions of the trading rules and data presented. Also further delimitations to the processes of the study are presented in more details over there.

1.2. Previous studies

Relative Strength Index and short-term interest rate futures are both very commonly used by market participants but not very well covered by the previous studies. This makes it harder to review relevant academic material for the study while a study using same data and trading rules could not be found. The previous studies are therefore reviewed from many different point of views to get the most accurate image of the current status of the subject in terms of academic research. There are loads of studies about technical analysis in general, technical analysis using futures and Moving Average trading rule. In these cases the most referred studies published in the highly valued academic publications are used. However, studies about Relative Strength Index and short-term interest rate futures are so rare that a case-specific qualification process is used depending on the importance of the study.

In the 30's Working (1934) observed randomness in wheat prices. As a conclusion he suggested stock prices to act random way too. However, in the early 50's Kendall (1953) was the first to show that stock prices really act in a random way after realizing that he was not able to predict the future prices of stocks with the information he had. These results were later verified by Roberts (1959) and Fama (1970) who carried on the research and built up the suggestions of weak-, semi strong- and strong-form of the markets which are later known as efficient market hypothesis.

Levy (1967) presents interesting findings in his study which partly try to disprove the efficient market hypothesis and theory of random walk, a theory of random stock market reactions. He finds trading rules that can significantly beat the returns made by Buy-and-hold strategy. However, according to the studies of Jensen (1967) and Jensen and Benington (1970) the findings of Levy are not on a solid ground. Conversely, the findings by them follow the random walk and return profits that are slightly smaller for trading rules than what is achieved by Buy-and-hold strategy. This is considered as the beginning of the eternal polemic between the partisans of technical analysis and random walk.

Often, the technical analysis is said to be possible because of irrational human behaviour. De Bondt and Thaler (1985) study the psychological effects of human behaviour related to the market returns in their study. They wanted to find out if many investors tend to overreact to unexpected news. Their findings indicate that so called past losers, i.e. portfolio of stocks with poor past performance, actually progress 25 % better in three years period than so called past winners.

The field of studies concerning technical analysis and trading rules is discovered more in the following subchapters. These studies are handling technical analysis as a phenomenon but more important is to find out how trading rules have developed and do they work in the futures markets.

1.2.1. How technical analysis performs in general?

There is a lot of evidence showing randomness in stock prices but as a contrast there are also many studies giving profitable returns using technical trading rules. These rules have been used in the market much longer than the methods of *fundamental analysis* which utilizes financial information such as financial statements and macroeconomic news to prospect discounted future cash flows and to further represent an insight into the valuation of an asset (Bodie, Kane and Marcus 2005: 377). This might make technical analysis hard to replace especially by theories that do not fully explain the behaviour of the market. (Brock, Lakonishok & LeBaron 1992: 1731–1732)

In a study by Alexander (1961), he filter rules to test if some sort of trends can be found from the stock prices or do they follow the random walk. As data he used the Dow Jones industrial average and the Standard & Poor's industrial average indices from 1897 to 1959. Alexander finds in his study that indices act according to the random walk

hypothesis but he noted also that a current move is likely to go on for some time; when market has moved in one direction by x percent it tends to move to the same direction by x percent at least before moving to opposite direction by x percent.

Fama and Blume (1966) show that only few positive returns can be earned by using these filter rules used by Alexander (1961) if trading commissions are included. Excluding the commissions, the situation is clearly better for trading rules but still not as good as simple Buy-and-hold strategy. In their study, Fama and Blume use the daily closing prices of all the stocks included in the Dow-Jones Industrial Average index from January 1956 to April 1958, approximately.

Levy (1967) finds that stocks that have done well in the short-term past gain better return than average. Stocks that managed poorly in the short-term past are doing badly in the near future as well. If the stock has high volatility and it has done well in the short-term past superior profits would be gained compared to the randomly selected stocks. According to his results also long-term loser stocks in the past, meaning stocks that have done worse than average, tend to perform way better than average in future and long-term winners again to manage worse than average. His interesting findings partly contradict the random walk hypothesis, however, the results do not show that the returns would be better when also risk is considered. Levy uses weekly data of 200 stocks listed on the New York Stock Exchange from October 1960 to October 1965 i.e. 260-week period, in his study.

In a paper by Sweeney (1986) USD-DEM exchange rates of 1,289 trading days from 1975 to 1980 are used as data to study the profitability of the filter rule trading strategies. He uses Capital Asset Pricing Model (CAPM) to take risk into account. Sweeney's results indicate that filter rules gain better returns compared to the Buy-and-hold strategy as only one exception is observed. Nevertheless, all of the excess returns of filter rules cannot be considered as only 30% of the results are significant. The excess returns observed by Sweeney cannot be explained by CAPM in most of the cases of his study.

Brock et al. (1992) test the usefulness of technical analysis with data of Dow Jones Industrial Average index of 90 years period. They present results supporting technical trading rules, Moving Average and trading-range-brakes, tested in their study. On a 10-day period they present rough 0.8 % return with these strategies compared to the normal market return of 10 days being 0.14 %.

Based on his study Gençay (1998) encourages for more research on technical trading strategies. His results indicate that Moving Average trading rule is performing better compared to simple Buy-and-hold strategy in general. However, the results are not only united but some discrepancies are observed as well. When trading rule performs well in the strongly fluctuating market, where both up- or down-going trends can be discovered, Buy-and-hold strategy outperforms the trading rule in the market where no erratic trends are found. Gençay uses a long data of 90 years from the beginning of 1897 till the end of June 1988. Data is gathered of daily quotes of Dow Jones Industrial Average Index.

1.2.2. Does technical analysis work with futures markets?

Stevenson and Bear (1970) were among the first to study the performance of trading rules on the futures markets. In their paper, daily closing prices of two important commodity futures, soybean and corn futures traded on the Chicago Board of Trade from 1957 to 1968 are used as data. Stevenson and Bear argue that the random walk hypothesis cannot explain the price movement of those futures. During a long-term period the random walk is more correct than during a short-term period. However, the trading rules used in the study are more profitable in every case than the Buy-and-hold strategy on the commodity futures markets according to them.

Neftci and Policano (1984) study the futures markets as well but with a different and slightly larger selection of futures where daily prices of soybean, gold, copper and T-bill futures are used. They are using two technical trading rules, slope method and Moving Average in their study. The results indicate that the slope method cannot be used to predict any future prices of futures. However, the Moving Average trading rule generates dissimilar results as it is successful to predict the futures prices. In addition Neftci and Policano suggest it to be useful to predict the credit spreads as well.

Efficiency of the futures markets has also got support. Murphy (1986) shows that in terms of statistical significance no excess returns compared to Buy-and-hold strategy can be earned when technical trading strategies are used. However, he argues that technical trading strategies are at least as effective as the passive alternatives meaning that no less than trading costs can be earned. According to his study, Murphy observes significant abnormal returns by trading rules if transaction costs are excluded. In addition he discovers the futures funds used in the study to be less profitable than the stock market or the T-bill market over the sample period. In the Murphy's data there are

60 monthly observations of technical futures funds from May 1980 through April 1985. In comparison, 30 US futures contracts are used for Buy-and-hold strategy and S&P 500 is used as a stock market indicator.

Taylor's (1994) paper discovers the markets of the currency futures and channel rule trading rule a bit further than others had done before on the same topic. The data of him consists of the daily closing quotes of GBP, DEM, CHF and JPY futures in terms of US dollars. The prices are gathered from December 1981 through November 1987. Taylor shows that the future prices cannot be predicted by the channel rule. Conversely, the direction of the movement can be provided and therefore net trading profits can still be earned. This is slightly surprising as the maximum correlation between the returns on different days is said to be under 0.02.

Kho (1996) again continues studying the issue of trading rules on the foreign exchange markets. Not a completely new opinion but a different one was brought by him: even though the performance of the trading rules is statistically measured the results have to be compared after observing the risk of the strategy. He finds at least as good profits or even better than earlier had been shown by others regarding to Moving Average trading rule used in the foreign exchange markets. However, Kho reveals that the returns earned by the Moving Average strategy are not abnormal after the risk is considered. If anything, the trading rule profits are construed as outgrowths of the time-varying risk premia and high volatility, in other words the returns are higher during the high risk periods and vice versa. Kho uses weekly returns data of the of GBP, DEM, JPY and CHF futures traded on the Chicago Mercantile Exchange from January 1980 through December 1991 in his study.

Pukthuanthong-Le and Thomas (2008) examine further the foreign exchange markets as they use JPY, DEM, GBP, CHF, CAD and AUD denominated currency futures but also few less liquid currencies for a period from 1975 through 2006 as data of their study. They discover that momentum trend and Moving Average trading rules used to be profitable in the past also for the liquid main currencies but they are not that anymore. Even though these profits on the developed markets have vanished Pukthuanthong-Le and Thomas show that trading rules can be profitable using futures on the illiquid currencies. In contrast, they expect these abnormal returns to decrease and finally to disappear over time. Finally, they suggest that the decreasing returns observed are an outcome of evanescent inefficiencies explaining the results of them.

Considering the previously covered research the returns earned by the trading rules are higher when the futures markets are more undeveloped, say more inefficient. The situation is the same on developing markets as it was on developed markets some decades ago. According to this some excess profits would be available still but they will reduce while the emerging markets develop. This is discovered also by Kidd and Brorsen (2004) claiming that the returns have decreased already after year 1990 on the commodities futures markets. As data they have daily futures prices of commodities from January 1975 to December 2001 in their study.

1.2.3. Moving Average

A paper by Van Horne and Parker (1967) handles the issue that clearly was the day's topic among researchers of finance in late 60's, theory of random walk versus technical trading rules. They test in their study if the past stock prices can be used to predict future stock prices by using three different Moving Average trading rules. Daily closing prices from January 1960 to June 1966 of thirty randomly selected stocks on the New York Stock Exchange are used as data in their study. Van Horne and Parker present results that support the theory of random walk without a doubt. Moving Average yielded better returns than Buy-and-hold strategy only in 8.7 to 15.3 % of the cases. They argue that the biggest reason for the trading rule failure is the wrong timing when selling the stocks. In many cases the sell signal is given just before a significant increase in the price of the stock. Only one year later Van Horne and Parker (1968) extended their paper by using weighted Moving Average where more weight is given for the recent stock prices compared to the earlier ones. In the study, they have the same data as in their earlier paper. However, the results are not very different compared to earlier ones; Buy-and-hold strategy clearly beats the weighted Moving Average trading rule.

Brock et al. (1992) wanted to use two popular but simple trading rules, and they use Moving Average and trading-range break rules in their widely noticed paper. They have several Moving Average methods chosen by the popularity of use: 1-50, 1-150, 5-150, 1-200, 2-200, where the first value is meaning the short period and the last value means the longer period in days. They use a daily data of 90 years from 1897 to 1986 on Dow Jones Industrial Average index. Their results indicate that these trading rules do help and gain economically and statistically significant returns when historical data is used to predict the future performance of an asset. However, they note that it is truly important to measure the magnitude of the transaction costs when investing using technical

trading rules. Because on their research only simple trading rules are studied they argue that even better returns might be obtained if more complicated trading rules are used.

Lee and Mathur (1996 a) study the profitability of foreign exchange market by using two different trading rules: Moving Average and channel rule. In their study, daily closing prices of ten cross-rates of major currencies denominated in USD are used for time period ranging from May 1988 to December 1993. In the results of Lee and Mathur, only two cross-rates DEM-JPY and CHF-JYP yield positive returns where Moving Average and channel rules are used, but only when convenient circumstances are observed. Their findings show that even when trying to find a profitable trading rule one can be almost sure to suffer losses on the foreign exchange market when cross-rates are used.

Foreign exchange market was again studied by Szakmary and Mathur (1997) to find out whether Moving Average can gain positive returns or not and if the central bank interventions have some effects on the profitability. Only one of the five currencies, CAD generates negative returns while other four, DEM, JPY, GBP and CHF give transaction cost-adjusted excess returns from 5.4 to 9.8 % when Moving Average trading rule is used. Szakmary and Mathur present a strong link between Moving Average trading rule and central bank interventions for DEM, JPY and GBP. In addition a strong day-of-the-week effect is observed. Mondays and Fridays are having significant positive mean daily returns while other days remain with negative returns or statistically insignificant results. As the data they have daily closing prices of foreign currency futures and spot rates for the five currencies from June 1977 to June 1991.

Okunev and White (2003) examine if Moving Average trading rule can generate positive excess returns on foreign exchange market. Their results indicate that Moving Average rule can be a key to significant returns even when risk and transaction costs are included in the analysis. A slightly different view compared to the previous research is that no frequent trading is needed to gain such profits according to their study. Nonetheless, the use of end-of-month exchange rates surely affects to the need of trading frequency, being a possible reason for this finding. However, they argue that there are two reasons for the inefficiencies of the foreign exchange market: noise trading and central bank interventions. As the data Okunev and White use end-of-month spot exchange rate of eight main currencies from January 1975 to June 2000.

Olson (2004) studies if the profits using Moving Average are smaller with the recent data than they are if the earlier data is used. As data he uses daily exchange rates of 18 currencies from 1971 until the end of the year 2000. Olson finds that excess returns by Moving Average trading rule have been statistically significant in the 70's, in 80's already insignificant and in 90's there was no excess returns anymore. Because the currency market profits have declined over time, he argues that interim inefficiencies have existed earlier but nowadays the market performs better. However, Olson emphasizes that more developed trading rules must be used in future if one wants to have excess returns in sight.

Another interesting aspect regarding to inefficient markets is studied by Lee, Gleason and Mathur (2001). They cover 13 Latin American currencies from January 1992 to August 1999 and test if trading rules can be used as an advantage for the investors trading there. Their findings indicate that most of the tested Moving Average and channel rule trading rules provide no additional profits where only a third of the foreign exchange markets is found to be profitable. With and without the influence of transaction costs, similar results are found by Ratner and Leal (1999) who used data of ten Latin American equity indices from 1982 to April 1995. However, they discover also that over 80 % of the cases provide correct information of the next direction on the market.

Fifield, Power and Sinclair (2005) examine the same aspects as Lee et al. (2001) and Ratner and Leal (1999) but the data consists of 11 European stock market indices from 1991 to 2000. Their results show that in the emerging markets of Europe the excess returns of filter rule and Moving Average trading rules can be moderately profitable. Nevertheless, the developed markets are found to produce no excess returns when trading rules are used. This can be explained by stating that informational function of emerging markets' is inefficient and more developed markets function better, as they should while regarding them as efficient markets. From market to another they find disparities in profitability of the trading rules: while Moving Average gives the best returns somewhere, filter rules might be better in another country.

Fong and Yong (2005) study the engrossing phenomenon of internet stocks in the time of millennium; could the traders have exploited the rise and fall by using Moving Average trading rule for their investments? Their results show that no significant returns are found when trading rules were used. Thus the most of the stocks perform according to random walks as only one of the trading rules is found to be profitable in only certain

circumstances. Fong and Yong have data of daily closing prices of 30 internet stocks from September 1998 to January 2002 in their study.

Finally, the latest point of view is examined by Metghalchi, Chang and Marcucci (2008). Their study considers the efficiency of Swedish stock market by testing three different Moving Average rules on 30 most actively traded stocks on the Stockholm stock exchange. Data includes daily closing prices of the time period that begins from January 1986 and ends to September 2004. However, the results of Metghalchi et al. (2008) show that the Moving Average trading rules generate statistically highly significant positive returns. In addition the trading rules outperform clearly the Buy-and-hold strategy even after including the transaction costs, which is normally weakening the results of the trading rules related to the Buy-and-hold strategy because of larger number of buys and sells. The results are not too surprising where researchers examined the thinly traded or emerging markets have provided same sort of results according to the studies discussed earlier.

1.2.4. Relative Strength Index

Relative Strength Index was originally presented by Wilder (1978). His attention was on few problems of earlier invented momentum oscillators. First worry was erratic movement of the oscillator during the extreme points. These values of extreme points should be smoothed somehow. Secondly, problems considered also the scale used to measure high and low values of the oscillator. When oscillator is going down which level can be measured as low and vice versa while going upwards? The scale changes might be complicated also when the asset is changed to another making it even harder to interpret. The last and the least concern was played by handling and storing enormous data sets. As a solution these problems Wilder introduced the Relative Strength Index trading rule. (Wilder 1978: 63–70.)

Even though there is only little of academic research about Relative Strength Index, thirty years later, Relative Strength Index is often covered on Futures magazine. For example Thachuk (2000: 37–38) says Relative Strength Index is perhaps the best known oscillator as it is calculated by popular charting companies and numerous computer programs. However, when using Relative Strength Index he places emphasis on choosing the correct number of days for the time period of calculation. He also argues that traders should be aware of too long trends going to the same direction in the market

while using this trading rule. It takes then longer for oscillator to give a buy or sell signal.

Ruggiero (1998) tries to develop new trading methods when using Relative Strength Index as a trading rule. He uses different number of days to find the optimal parameters. He argues that the longer average periods work better with Relative Strength Index. He also finds that buy and sell signals are statistically too biased for the use as a stand-alone trading rule. Also Meissner (2001) finds that Relative Strength Index with long term averages works better by giving more correct signals for traders. He proves that if the signals are given by extreme values it results better success rate for Relative Strength Index trading rule. In addition he criticizes the problem of mistakenly timed buy and sell signals.

Hales and Hayenga (1995) examine if the three trading rules Relative Strength Index, Dual Moving Average and Directional Movement Indicator can be profitably used on the live hog futures market at Chicago Mercantile Exchange from 1987 to 1992. Relative Strength Index is the only of the three trading rules that could make profit consistently. On the other hand, the two other trading rules are not performing very successfully.

A slightly different way to use Relative Strength Index is introduced by Seiler (2001) who emphasizes the meaning of optimization of input values in his study. By this he wants to achieve a better performance for trading rules when own input values for each of the stocks are optimized. As data he uses daily stock prices from January 1992 to September 1999 of one randomly selected stock, Corning Inc. Seiler finds that optimizing the input values of Relative Strength Index trading rule can lead to highly profitable results while method of using the standard input values is left with no profit but a little loss. In addition he observes that the number of trades is highly reduced when optimized values are used. This leads to a conclusion of having less inefficient buys and sells.

Moving Average and Relative Strength Index are used as trading rules in a study by Wong, Manzur and Chew (2003). They have data of Singapore Stock Exchange's Singapore Straits Times Industrial Index (STII) from 1974 to 1994. With Moving Average they use four different variations: Single 5-day; Dual 3-day and 5-day; Triple 4-day, 9-day and 18-day; and t-value Moving Average. With Relative Strength Index the crossover was simply 50. The findings of the paper are that the methods of technical

analysis give significantly positive results and Single 5-day Moving Average gains the best results which are followed by Dual 3-day and 5-day Moving Average and Relative Strength Index. In addition Wong, Manzur and Chew suggest that technical analysis can give some useful information when timing buys and sells of the assets.

Shik and Chong (2007) compare the two trading methods, Relative Strength Index and Moving Average. The rules are tested by comparing the profitability of the trading methods on currencies: AUD, CHF, DM, JPY, GBP and Euro. The data consists of US dollar quotes for these currencies. Shik and Chong show that only the results of the Deutsche Mark and the Japanese Yen are valid by significance and the Sharpe measures of these two currencies indicate that Relative Strength Index and Moving Average can gain positive risk-adjusted returns. To be exact, Relative Strength Index is more profitable for Deutsche Mark when Moving Average again performs better with Japanese Yen, when US dollar quotes are used. In addition, they note that central banks' interventions have a clear effect on the profitability of the trading methods, the more interventions the better image of profitability. Therefore, they suggest observing the effect of central bank interventions of data.

2. EFFICIENT MARKETS

In the markets, there is a lot of different sort of information. It does not make it any easier to piece together that by using this market information investors try to attain better returns than average in several ways such as using technical analysis and trading rules or fundamental analysis. Besides these methods of investing should be waste of time, they should be waste of money as well if the efficient markets are supposed to prevail. Accordingly, any new information concerning an individual asset or the markets as a whole should be fully reflected immediately in the securities' prices but in a correct way as well. This condition where assets fully reveal all available information is referred to as *efficient market hypothesis* (EMH). Latham (1985: 2) proposes a new definition of market efficiency that both prices and portfolios are unchanged as information is revealed to the market. (Rubinstein 1975: 812; Fama 1991: 1575; Copeland, Weston & Shastri 2005: 354–355.)

Fama (1970: 387) defines efficiency by three conditions that are adequate to create market efficiency:

- I No transaction costs exist when securities are traded
- II All information is available free of charges to everyone in the markets
- III The influence of currently available information for the current price and distributions of futures prices of each asset is approved by all of the market participants.

Grossman and Stiglitz (1980) define in their paper that all the costs for trading and for the information concerning an asset must always be zero that the conditions of the efficient markets could be met. However, Jensen (1978: 96) sees it a bit differently as: “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 . In other words, all available information is reflected in the asset prices to the point where the profits of using it do not exceed the costs of using it.

As every investor knows, these conditions are not fully prevailing nowadays even though almost forty years have gone after defining them. It is providential that the three conditions are not necessary for the efficiency of the markets while they can be partly true to form the efficient markets. For example, the information available is accessed only by a certain amount of investors or the divergence in the implications of the

information regarding to the asset pricing can still let the efficient markets exist but only as long as no investor is capable to constantly evaluate the prices better than the market and thus generate *excess returns*. (Fama 1970: 387–388; Copeland et al. 2005: 354–355.)

There are lots of studies evaluating different ways to attain better returns by trading rules than what is gained just by holding an equal portfolio. Alternatively, if the markets are efficient excess returns should not be possible. The market efficiency is verified by as many studies as the excess returns generated by the trading rules. Now, in the efficient markets, one can earn at least as large profits when investing by Buy-and-hold strategy as others by investing according to technical analysis or fundamental analysis. In this sense, it should not matter either if a private investor selects randomly a portfolio of securities or if a professional investor uses several pricing and forecasting methods to select an ‘invincible’ portfolio of securities, over time same returns should be observed by them. (Malkiel 2003: 59–60.)

The critiques against EMH often trust on the errors of valuation in the markets. However, it is important to note that mispricing may still be consistent with EMH. During the Internet bubble, for instance, around the millennium most of the prices were certainly irrational but this does not mean automatically that the markets were inefficient. (Malkiel 2003: 60.)

2.1. The three forms of the efficient market hypothesis

Fama’s paper (1970) is often associated with EMH, even though it is more like a compilation or a review of the previous literature as he designates it. For example Roberts (1959) suggests two forms of information level, where the first one considers only historical asset prices and the other contains all of the information in the markets that is relevant for the asset pricing. However, Fama constructed EMH into the form we know it today and divided it in three categories according to the different steps of information level, as Bodie et al. (2005: 373) forms it: “...what is meant by the term ‘all available information’.”

Nevertheless, Fama (1970: 388) reminds that the circumstances of the EMH where the asset prices fully reflect *all available information* are considered as an extreme null hypothesis that is not expected to be entirely true or at least not in every case. The

categorization of the hypothesis into the weak form, semi-strong form and strong form makes it a lot easier to identify the information level where the hypothesis breaks.

2.1.1. Weak form

According to the weak form of the EMH securities prices reflect the information set θ_t that contains only the historical prices in the markets at time t (Fama 1970: 383, 388; Jensen 1978: 97). Later, the weak form condition was extended to contain also trading volume, volatility, dividend yield, interest rates and other announcements that are relevant for the asset pricing in the securities markets. This sort of data is available to the public and there are no fees of using it. Only asset prices are sometimes chargeable if real time bids and offers are wanted. The weak form hypothesis entails that no trend analysis or any trading rule can consistently produce any additional profits to an investor. In fact, no one is ready to pay for the historical asset prices. The value of such information set is zero because there is no new information there. Even if analysis or data could produce an indication of the future prices of securities all investors would have already learned to use it. This would push the price of a security to a proper level and free lunches can be observed no more. (Fama 1991: 1576; Bodie et al. 2005: 373; Copeland et al. 2005: 359.)

The early weak form tests concentrated on testing the serial independence in returns of securities and the profitability of technical trading rules based solely on the historical securities prices. More recent studies, however, examine the subject further by testing the long-term dependencies in security returns by using variance ratio, rescaled-range and tests for chaos for instance. (Boldt & Arbit 1984: 23; Al-Loughani & Chappell 1997: 173.)

Evans (2006) studies the weak form efficiency of the futures markets in the United Kingdom by investigating the randomness of changes in futures prices. In the paper, he uses three financial futures as data: FTSE100 stock index futures, Long Gilt bond futures and Short Sterling interest rate futures. The results of Evans show that British futures markets are weak form informational efficient. Before the electronic trading system was launched the Long Gilts used to be the most efficient of those but after the automation FTSE100 futures became the most efficient futures of the three.

2.1.2. Semi-strong form

The semi-strong form of the efficient market model asserts that information set θ_t reflected in the market prices includes all publicly available information such as announcements of the annual earnings, new security issues, stock splits, product lines, earnings forecasts and accounting practices at time t . Obviously, all of the weak form information is included in this form as well. However, one may ask: how fast and efficiently information set θ_t is reflected in the prices when semi-strong form of the EMH is observed. After investors have the access for this information, it is expected to be reflected in the prices of the securities. As in weak form, in semi-strong form no investor holding this information can use it to constantly earn abnormal returns. (Fama 1970: 383, 388; Jensen 1978: 98; Boldt & Arbit 1984: 24; Fama 1991: 1576–1577; Bodie et al. 2005: 373.)

Typically, the semi-strong form tests have focused on examining how quickly the formation of some information is reflected in the securities prices. The information becomes public usually by announcements, such as earnings or dividends announcements as described previously. However, information that is consistent with the semi-strong form can be a consequence of another information-generating event that has no official announcement. In many cases, this sort of information is not even concerning the capital markets but may have a major effect on them. (Boldt & Arbit 1984: 24–28.)

Pearce and Roley (1985) study the semi-strong form efficiency in the US stock market. To go deeper, they examine the effect of money supply, inflation, economic activity and the discount rate announcements on the stock prices of the Standard & Poor's 500 index. Pearce and Roley show firstly that monetary policy and directly related announcements have a significant effect on the stock prices. Secondly, only limited amount of evidence is supporting the view that surprising announcements of inflation or levels of real economic activity would have an influence on the stock prices. Thirdly, as also the EMH states, their results indicate that anticipated components of the economic announcements do not have a significant effect on daily stock price movements. In addition, Pearce and Roley show that most of the previously described announcements cause the most of the effect immediately on the stock prices but some of the announcements, however, are not fully reflected in the prices until beyond the announcement day.

2.1.3. Strong form

The most intensive one of the three forms is referred to the strong form of the efficient market model. When this form is observed, asset prices reflect the information set θ_t that is taken to be all information that is relevant for the asset and available or known to anyone at time t . According to the previous forms of EMH, even a holder of all information accordant with the strong form of the EMH cannot generate abnormal returns constantly. It is in the interests of the most of the investors that there are no certain investors or groups, such as mutual fund managements, who have exclusive access to the relevant information for price formation. To put it in other way, it is in interests of all investors that all relevant information is public. Later, Fama (1991: 1576–1577) redefined these groups with exclusive access to be the holders of the private or insider information. (Fama 1970: 383, 388; Jensen 1978: 98; Boldt & Arbit 1984: 28; Bodie et al. 2005: 373.)

Using of insider information for trading purposes by anyone is strictly forbidden by the law in the most of the countries. However, there are some anomalies observed on the market that are slightly awkward for the officers trying to root out the insider trading. For example, stock prices tend to rise few days before positive earnings announcements as an indication of the information leakage. Also, the stocks are succeeding better mostly when insiders hold them than during the times when they do not. (Bodie et al. 2005: 98–99.)

Not a large amount of studies supporting this strong form of EMH have been published. However, it is self-evident that the insiders have certain private information about the profitable and unprofitable moments for their companies such as bad earnings of the year or declining sales on the next year. Therefore, the studies examining the strong form efficiency concentrate on testing whether there are investors that are really using some superior private information for their trading purposes and how acting of them is affecting the financial markets. The academic field is also interested in knowing how big profits the insiders may gain compared to the others. (Finnerty 1976: 1141, 1146; Boldt & Arbit 1984: 28–30.)

Givol and Palmon (1985) examine the insider trading in the US stock market with data of American Stock Exchange through 1973–1975. In addition they use the description of insider trading by SEC where all the insiders of the US companies have to report their security trades. The results of Givol and Palmon indicate that the trading by

insiders does not seem to be timed so that an illegal use of insider information would exist. However, the trades of the insiders instead have an influence on market prices so that abnormal returns after insider trading are observed. This is obviously a consequence of other investors believing that insiders have private information as a background of their trades.

2.2. Testing the market efficiency

According to the definition of the EMH, in the efficient markets the prices are fully reflecting all available information. However, what is meant by the expression ‘fully reflecting’ is so general in every means that it makes the market efficiency not possible to measure by the means of empirical methods. Thus, the pricing process must be accurately defined and ‘fully reflecting’ defined to be exact. (Fama 1970: 384.)

The EMH is often associated with the random walk model as it is the most popular way to test the EMH empirically. Though, the random walk is not the only method, to be precise. The two other are the fair game model and the submartingale model. These three models will be covered more in the following subchapters. (Fama 1970: 384–386.)

2.2.1. Fair game

Before the 70’s the most of the empirical work used to be based on an assumption that the market equilibrium could be stated in terms of expected return. Fama (1970: 384), however, suggests that equilibrium of expected return on a certain security is a function of its risk being conditional on applicable information set. If only expected return is considered, it could be expressed according to the equation (1) as

$$(1) \quad E(\tilde{p}_{j,t+1} | \Phi_t) = (1 + E(\tilde{r}_{j,t+1} | \Phi_t))p_{jt}$$

where E is the operator of the expected value, p_{jt} is the security price j at time t , $p_{j,t+1}$ is the price of the same security at time $t+1$, $r_{j,t+1}$ is the one-period percentage return of the security as it is expressed in the equation (2), Φ_t is an information set assumed to be fully reflected in the security price at time t and the tildes above $p_{j,t+1}$ and $r_{j,t+1}$ mean that they are random variables at time t . (Fama 1970: 384.)

$$(2) \quad \frac{(p_{j,t+1} - p_{jt})}{p_{jt}}$$

Because Φ_t is assumed to be fully employed in the equilibrium expected returns it should be fully reflected in the security price, p_{jt} as well. Whole market equilibrium is based on assumption that equilibrium expected returns fully reflect the information set Φ_t . Accordingly, investing only by the information Φ_t it is not possible to earn any excess returns above the equilibrium expected returns. This equilibrium is verified by equations (3) and (4) as

$$(3) \quad x_{j,t+1} = p_{j,t+1} - E(p_{j,t+1} | \Phi_t)$$

$$(4) \quad E(\tilde{x}_{j,t+1} | \Phi_t) = 0$$

where the sequence $\{x_{jt}\}$ represents the *fair game* with respect to the information sequence $\{\Phi_t\}$. In other words, $x_{j,t+1}$ is the difference at time $t+1$ between the observed market price and the expected value of the price that was predicted by the information Φ_t at time t . If the asset price always equals its expected price at a terminal date then the price at every date equals the expected price at any point of time in future before the terminal date. Equivalently, the equations (5) and (6) too are assumed to be true as

$$(5) \quad z_{j,t+1} = r_{j,t+1} - E(\tilde{r}_{j,t+1} | \Phi_t)$$

$$(6) \quad E(\tilde{z}_{j,t+1} | \Phi_t) = 0$$

while sequence $\{z_{jt}\}$ is fair game with respect to Φ_t , the information sequence. (Fama 1970: 384–385; Rubinstein 1975: 821–822.)

It must be taken note of that it might not be enough just to presume this and count on accurate market pricing mechanism, while the distribution of returns could be expressed better as only one possible measure of the distribution, expected value, is considered; market efficiency does not have any special importance in the equation (1). (Fama 1970: 384.)

To go further again, if we presume that equation (7) based on the information set Φ_t is true it tells to the investor the amount of funds that are available at time t to be invested in each of the available n securities as

$$(7) \quad a(\Phi_t) = (a_1(\Phi_t), a_2(\Phi_t), \dots, a_n(\Phi_t)).$$

The excess value that is generated by such a system of equation (7) is summed altogether in equation (8) where

$$(8) \quad V_{t+1} = \sum_{j=1}^n a_j(\Phi_t) (r_{j,t+1} - E(\tilde{r}_{j,t+1} | \Phi_t))$$

and the fair game is again confirmed in the equation (9) as

$$(9) \quad E(\tilde{V}_{t+1} | \Phi_t) = \sum_{j=1}^n a_j(\Phi_t) E(\tilde{z}_{j,t+1} | \Phi_t) = 0$$

by the means of the equations (7) and (8). (Fama 1970: 385.)

However, Malkiel (2003: 60) reminds that return always has to be compared to the risk of the asset before anything can be said about true excess returns. This is important because efficient financial markets do not let investors constantly to gain above-average risk adjusted returns.

2.2.2. Submartingale

Fama (1970: 386) argues in his paper that according to submartingale model the price of a security follows a submartingale with respect to the information sequence $\{\Phi_t\}$. Hence, submartingale model states that the expected value of a security price in the next period is either equal to or greater than the current price of a security where the expected value of a security is predicted by the information Φ_t . The equilibrium of submartingale model is expressed in the equation (10) and equivalently in the equation (11) where we have

$$(10) \quad E(\tilde{p}_{j,t+1} | \Phi_t) \geq p_{jt}$$

$$(11) \quad E(\tilde{r}_{j,t+1} | \Phi_t) \geq 0.$$

If these equations are equal the price sequence is observed to follow a martingale. The equations (10) and (11) include an important assumption considering the EMH. The equations imply that based only on the information Φ_t , mechanical trading rules cannot be used to generate greater expected returns compared to the strategy of Buy-and-hold during the period in future that is in question. (Fama 1970: 386.)

2.2.3. Random walk

When Kendall (1953) observed randomness in the movement of the stock prices it was not fully understood what it was supposed to mean in regards to the financial markets. At first, it was considered as a malfunction of the markets in an irrational way. However, it was soon realized that actually this malfunctioning meant the well-functioning markets, not a failure or an error of them. (Bodie et al. 2005: 369–370.)

As described before, the EMH argues that any information having an effect on the pricing of an asset should already be reflected in the price of the asset. When new information is observed in the markets it has an immediate reflection on the bids and offers of the asset and the price will change to a proper level. Therefore, the price changes of today are reflected only by the news of today and the changes are independent of the news observed yesterday. New information, however, is unpredictable. If the coming information could be divined correctly, then the forecast would be included in the current available information. This means that any information that can be used to predict the price of tomorrow or the price in the next month is already reflected in the prices of the securities markets. Thus, the asset prices in the markets must be unpredictable and random as a response to the unpredictable new information flow. This is commonly known as a theory of *random walk*. (Stevenson & Bear 1970: 65; Malkiel 2003: 59.)

According to the EMH the current price of a security fully reflects all available information. It is supposed to imply that successive one-period returns are mutually stochastically independent and that successive returns are identically distributed. In other words, the conditional and the marginal probability distributions of an independent random variable are identical. This is illustrated in the equation (12) as

$$(12) \quad f(r_{j,t+1} | \Phi_t) = f(r_{j,t+1})$$

that constitutes the equilibrium of the random walk hypothesis. (Fama 1970: 386; Cheng & Deets 1971: 11.)

Cheng and Deets (1971: 11) divide the theory of random walk into two hypotheses. Firstly, an economic assumption reminds that security markets do not let any investor to earn systematically superior returns compared to the market. Secondly, a statistical assumption is to assume that the price changes of a particular security are independent random variables.

Fama (1970: 387) considers the random walk model as an extension of the fair game model, where the random walk model states a better and more detailed expression of the economic environment in the securities markets. He distinguishes between the equation (1) of the general expected returns and the equation (12) of the random walk model. If the equation (1) is restricted so that expected return is assumed to be constant over time for a security j , the equation (13) is observed as

$$(13) \quad E(\tilde{r}_{j,t+1} | \Phi_t) = E(\tilde{r}_{j,t+1})$$

where the mean of the distribution of $r_{j,t+1}$ is to be independent of Φ_t , the available information at time t . Conversely, the random walk model asserts in the equation (12) that the whole distribution is independent of the information set Φ_t . (Fama 1970: 387.)

3. TECHNICAL ANALYSIS

Technical analysis is one of the most popular and the most widely used tools for the investors on the financial markets. There is not only support that it has faced especially from the academic field but lots of criticism as well as previously described. However, investors use the trading rules of technical analysis from day to another and they feel to success with them, but are they wrong? It is a hard task to solve because of diversity of the financial markets. The only field where researchers seem to agree is that technical analysis works better on the emerging, not yet efficient markets. When the main markets in US, Europe or Japan are considered, academic researchers have gathered suggestive results but still the findings are not too similar at all.

Investors using technical analysis for their trading purposes are attempting to find securities that are *undervalued* or *overvalued* by searching patterns in historical prices of the security to predict the future changes. From the other point of view, the investors using technical analysis are searching for the securities that have not incorporated all of the information considering the security on the market yet. In addition to historical prices also other historical data such as trading volume or announcements could be used to predict the future. When considering the trading volume for instance, it may contain some information that is not impounded in the current prices because the methods are not publicly known or worse, the information is not fully available for everyone. If so, the less-informed traders are able to identify the proper market price by comparing the volumes related to the prices whereas the well-informed and usually price-conscious traders are normally investing large sums of money to the market. Thus, technical analysis makes market better-informed, at least in theory. (Antoniou, Ergul, Holmes & Priestley 1997: 361–362.)

In addition to finding mispriced securities the other purpose of technical analysis is considering trends. According to technical analysis market movements create trends which again are constructed by investor's opinions about economical and political universe but psychological issues as well. The simplest idea of *trend spotting* would be to identify the up-going period before it begins and the down-going period before it begins. Actually, it is all that technicians, the users of technical analysis, are striving for. By studying the markets and how they have previously reacted in a similar environment before technical analysts try to create strategies that could be helpful while identifying market turning points. Therefore technical analyst states that markets keep on moving

according to the same behaviour from time to time or in other words markets repeat itself by doing the same mistakes done in the past. (Pring 1980: 2.)

There are maybe millions of investors that are reaching for the same ambition. Because everyone are willing to buy or sell the asset for the correct market price or for the price that is favourable for them, the prices in the markets should be forced on a proper level in relation to the available information, just as EMH states it is. This is the exact problem behind the technical analysis – because the information considering the assets cannot be known before hand, the prices are as likely to go up or down on the next period. (Brealey, Myers & Marcus 2004: 161.)

If an investor believes that EMH is valid or he thinks that fundamental analysis is the way to go it may be hard to argue why one should take a look at technical analysis too. A reason why technical analysis could work is mass psychology – when someone is changing his mind it makes others to think maybe I should do it too. If the price is going up investors tend to jump in and jump out when price goes down. This makes the asset prices to move according to investors' mind. Along with this statement the investors themselves make the technical strategies work as they believe something will happen and act the way the strategy tells to. Because the strategy says that an asset should go up investors start to buy it and it is going up indeed as everyone is just willing to buy the asset. (Black 1971: 18.)

The other argument for technical analysis is that there are very different levels of investors, highly professional traders and pure amateurs and anything in between these two. When professional traders are given a signal by the strategy they are ready to execute it immediately. However, amateurs are not following the markets with that intensive look and they may react even weeks after the signal was given. While the very first trades after the signal are done the market participants may still be disunited whether the signal was acceptable. When time goes on more and more investors have executed their deals and it seems more likely that the signal was confirmed. This makes real-money-investors to put more money in and that feeds even bigger move. In the end, all of the investors are informed of the change in the strategy and the signal gets its final effect. (Black 1971: 18–19.)

3.1. Technical analysis in theorems

The most of criticism towards technical analysis is related to EMH and random walk as they are widely regarded as the theories best describing the movements of financial markets. On the academic field technical analysis is suffering also because it has no supportive theoretical background. Most of the literature regarding technical analysis discusses technical trading rules and how they perform on a specific markets. This is why it is rather well known how the methods of technical analysis work in practice but the theoretical side is not that well covered.

A statement that covers most of the technical trading rules is that short-term movements in the markets are considered as more important relative to long-term trends. The task of a day-trader is to make money by buying an asset at lows of each movement and sell at highs. As simple as it sounds it may not be but obviously one makes more money with such strategy versus a strategy taking benefit of the major trends only, at least in theory. Another thing that brings most of the technicians closer to each others is that fundamental information is published too late to get a maximum profit. As fundamentalist has to wait for the fundamental information to come out while a technician can react to such information immediately as the effect is seen in the prices of an asset. Even though a fundamentalist would predict exactly correct what the future economical conditions will be the markets may disagree and act completely opposite way what was predicted by fundamentalist's projection. So far only technical analysis has tools for analysing the markets in terms of psychological and emotional issues instead of economical and financial. Also if there is some inside information it can only be interpret through analysing the market behaviour. (Levy 1966: 84.)

However, Levy (1966) puts it all into a theorem where technical analysis is recapitulated along these lines:

1. Market values of assets are placed to levels where they are merely by demand and supply
2. The levels of demand and supply are generated by more rational fundamental factors but also by more or less irrational factors as opinions, assumptions, sentiments, speculation and guesses. All of these factors are reviewed by the market participants continually
3. Despite the *noise* i.e. every day variation of the markets, the asset prices tend to move in trends that usually last remarkable period of time

4. The beginning of a new trend period takes place after a change in the relationship of demand and supply. Whatever the reason behind these changes is the market participants can identify them as a transform in a way how market behaves. (Levy 1966: 83.)

Even though technical analysis is widely covered by academic research and lots of different trading rules are invented there are two principles that have been over the others. Dow Theory and Elliott wave theory, originating from the early 20th century, have been essential for the progress of technical analysis.

3.1.1. Dow Theory

Dow Theory is known as the first doctrine of technical analysis. The base ideas of it were initially made up by Charles Henry Dow, the founding editor of Wall Street Journal (WSJ), from 1889 to 1902. Dow's theory of market movements was written down by his follower as a WSJ editor, William Peter Hamilton, who is frequently writing editorials about trends and forecasting them on the stock market in U.S. Even though Dow invented the basic theorems behind the theory Hamilton's input into the Dow Theory is considered as essential. (Levy 1966: 83; Brown, Goetzmann & Kumar 1998: 1311–1313.)

The Dow Theory defines, firstly, three trends for trading rules to identify and secondly, a task to give the correct signal for the user. The trends are called *primary trend*, *secondary trend* and *tertiary trend*. Primary trend is a long-term movement of the security prices as this sort of trend can last from several months to even several years. Primary trends are better known as bull and bear markets. Shorter secondary trends are short-term price deviations compared to the underlying primary trend line. A secondary trend lasts usually from several days to several weeks or even a month until the deviations are corrected and price will be set to a proper level again. Tertiary trends again are considered as fluctuations of an independent trading day with only little extent of importance when the big picture is considered. All these three trends are illustrated in the figure 1. where there is a time series of a USD denominated Eurodollar short term interest rate future with a delivery on September 2009. (Brown, Goetzmann & Kumar 1998: 1313–1314; Bodie et al. 2005: 373–374.)

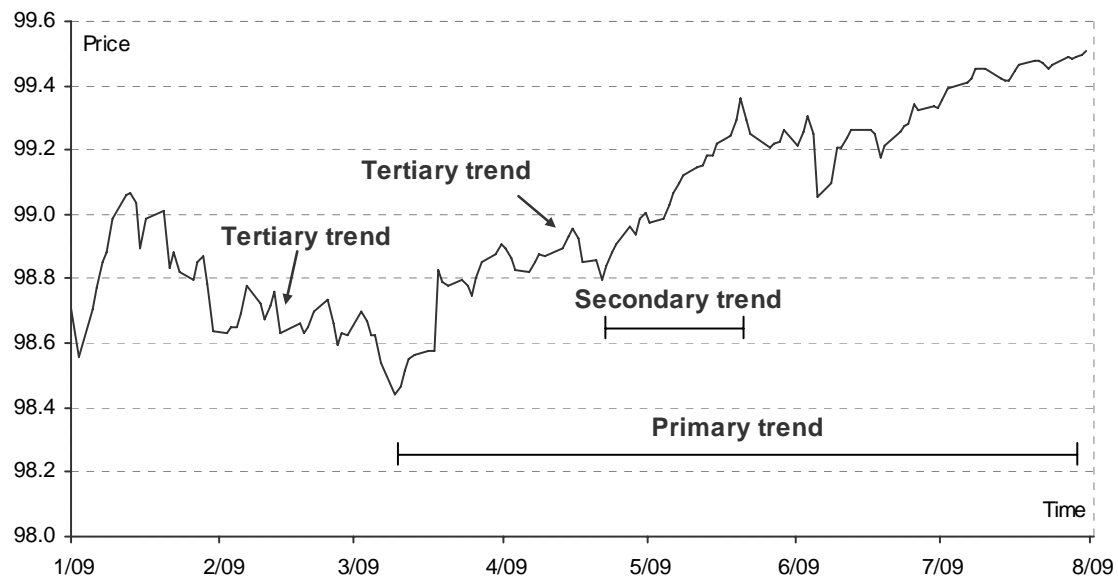


Figure 1. Trends on the financial markets.

The primary trend is not too complicated to identify where the lowest point of the indicator or as commonly known the lowest price paid for the security on the time period is the beginning and the highest point of the indicator or the highest price paid for the security on the same period is considered to be the end of a primary trend. The secondary trend could be expressed according to the same manner but instead of the long-term time period a shorter time period is observed. (Bodie et al. 2005: 374.)

When the price of an asset hits its peak and goes down it has created a *resistance area*. The resistance area is tested when asset price goes up again and hits the same peak level. If the price goes through the previous peak it is likely to keep on rising for a while and continue the rising trend it had. However, if the price cannot get through but bounces back to a lower level the price is likely to go down for some time and it is a signal that the trend might be turning. In practice the resistance areas might be tested for several times before one can conclude what the ongoing trend would be. Declining trends are observed with the similar manner but the other way down. (Black (1971: 17.)

The issue of confirming the signal or testing the resistance works just as well for all of the three trends defined by the Dow Theory. Asset prices fluctuate the same way in the big picture as intraday and therefore the resistance areas are created similarly in primary, secondary and tertiary trends. The resistance tests are caused by shorter trends as they define where the longer trend is going. If we assume that there is an up-going primary

trend observed by the markets and also a secondary trend is going up after a little slump. At some point it will test the resistance level that has been the previous highs of the primary trend.

3.1.2. Elliott wave theory

Wave theory by Ralph Nelson Elliott is another theorem of technical analysis that is trying to obtain certain patterns of market movements. The Elliott Wave theory, that was initially created in 1930's, concentrates on identifying the sets of wave patterns in the prices of a security. *Waves* are similar way to observe the markets as Dow Theory suggests tertiary, secondary and primary trends. However, Elliott's theory does not limit the number of waves or trends to three. A wave can last anything from a short intraday pattern to a wave lasting for centuries. By counting and classifying the waves one can interpret the situation where the market is going. (Gehm 1983: 51–52.)

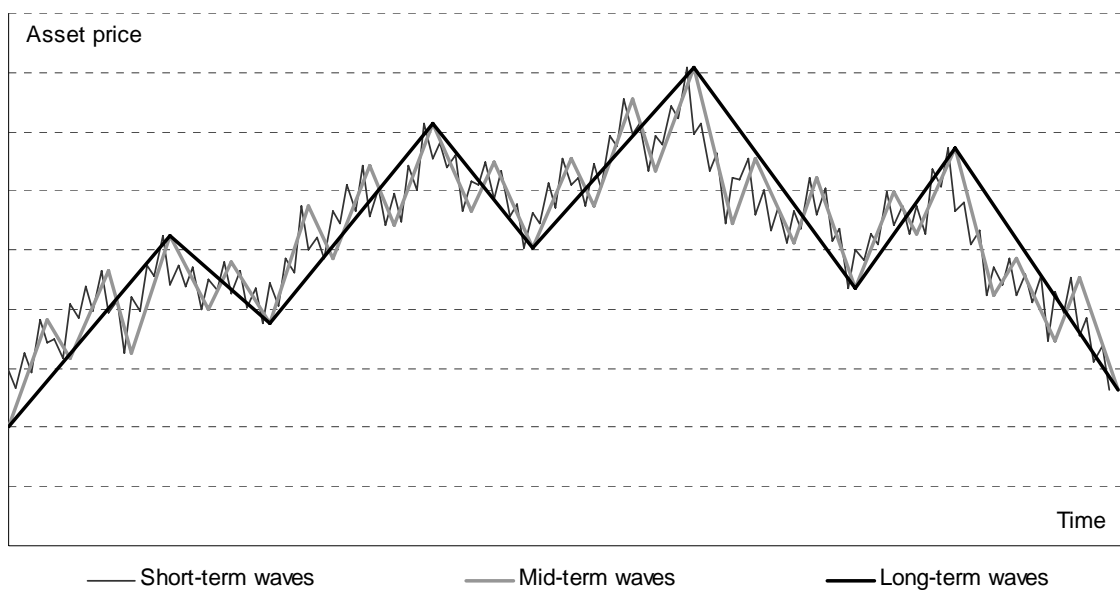


Figure 2. Trends of Elliot wave theory. (Gehm 1983: 52–56.)

According to the theory financial securities are following the series of Fibonacci numbers: 0, 1, 1, 3, 5, 8, 13, 21, 34, 55, 89, 144 etc., where each of the following numbers is a sum of the previous two numbers. Because Elliott saw a connection between Fibonacci numbers and financial assets he divided each wave into eight shorter periods of waves where five first construct a wave going to a same direction with the

on-going main trend and the following three short waves create another wave going to opposite direction. As shown in the figure 2. waves 1, 3, 5, A and C are going to the same direction with the main trend. Each of them consists of five shorter waves. On the other hand waves 2, 4, and B are going to the opposite direction with the main trend and they are constructed by three smaller waves. (Gehm 1983: 52–53; Prechter 1996: 19, 21.)

When long-term and short-term wave patterns are overlaid the investor is able to interpret the patterns so that predicting broad future movements should be possible. However, the criticism against Elliott's theory has got a lot of pace. A biggest single problem regarding the theory is the wave itself and its definition. Where the wave begins and when it ends are the key questions when investor is using this strategy. If there is not an answer or it is indistinct it is even harder to tell the answer. In reference to his letters in Financial World magazine that Prechter (1996) aggregated, Elliott certainly has an answer how the waves should be understood but for some reason they make it so complex ensemble that it is not easy at all to follow in practice. Even though the waves would be quite straightforward there may still exist more than one interpretation of counting the waves because of the way how markets are moving. This gives more space for criticism around the Elliott wave theory. (Gehm 1983: 53, 57.)

3.2. Trading rules

There are some theoretical principles that most of the technicians are ready to share. However, there is not a single technical trading rule that would belong more among technicians than the other. There are thousands of trading rules created during a hundred years of history of western technical analysis. Despite huge amount of different trading rules the most of them can be categorized into groups with other similar rules.

Alexander (1961) used *filter rule* in his study to test whether market movements consists of such trends that one could profitably use for investment strategies. He assumes that market trends are disrupted with little temporary vibration that must be filtered out to see where the trend behind is going. Fama & Blume (1966) outline the rule of x percent filter as follows: if the price of a security goes up x per cent or more the investor should go long the security and hold it. When the price goes down x per cent or more from the previous highs investor should sell the security and stay short until the price of a security moves up at least x per cent after preceding lows. Price

variations less than x per cent are ignored when using filter rule. (Alexander 1961: 22–23; Fama & Blume 1966: 227–228.)

Idea behind the filter rule is based on momentum of the movement meaning that the winners are expected to stay as winners and the losers perform poorly for some time in future. To make the rule profitable price of an asset has to move to the same direction with the given signal at least with the amount of the filter percentage while the opposite signal for turning the positioning is not given before an opposite move of the filter percentage has happened (Fama & Blume 1966: 228).

There are various modifications of the filter rule used in the markets nowadays. One of the simplest modifications is that definition of highs and lows is different. According to the original rule the highs or lows are the extreme levels of current hold position. However, they could be defined as extreme values of a certain time period for instance. Also used filter percentages can be very different but Alexander (1966) showed that the small filters should generate the best profits. A problem with small filters is that one needs to be updating the position more often than with the large filters. At a very volatile environment this makes the strategy inefficient too and increases the transaction costs. (Alexander 1966: 23; Sullivan, Timmermann & White 1999: 1655–1656.)

In accordance with trend-spotting it is important for an investor to try to estimate the future changes in a trend. *Oscillators* are trading rules that are meant to tell the investor when the trend is reversing. Some of the oscillator rules are momentum oscillators which are measuring the rate of directional movement. A rapid move in the price can cause the asset to be overbought or oversold and prices are expected to reverse shortly. A momentum oscillator rules have an indicator that signals if the asset is overbought or oversold. RSI is such momentum oscillator and its scale is 0–100 where 30 or under means that the asset is oversold and 70 or over indicates the asset to be overbought. RSI trading rule is covered in the section 4, Data and methodology. (Wilder 1978: 63; Wong et al. 2003: 545.

Moving Average trading rule has some properties that makes it an oscillator but it is actually very similar to filter rules too. Short- or long-term averages of prices can be considered to be the filters where the price of a security in relation to these filters is a trigger to buy or sell the security. The idea behind the rule is momentum in the price movement of a security as in filter rules as well. Also, Moving Average strategies are covered in a more detailed way in the chapter 4, Data and methodology.

A rule that has influences of the both Moving Average rule and the Dow Theory is *support and resistance*. To put the rule in a simple format it suggests an investor to buy when the asset price goes over the highest price of the previous n days, the resistance level. Sell signal is given when the price of an asset goes under the lowest price of previous n days, the support level. Kavajecz & Odders-White (2004) use rolling one-week window in their study that is updated every half-hour. However, they see that instead of such window more often technicians use the previous highs and lows in their support and resistance strategies. (Sullivan et al. 1999: 1656–1657. Kavajecz & Odders-White 2004: 1050.)

A very similar to rule support and resistance rule is *channel breakout* or trading range breakout rule. Perhaps they are more just variations of each others than different trading rules. While support and resistance relates more to the previous highs or lows channel breakout rule takes generally a longer-term movement into a consideration. Coutts & Cheung (2000) give a loosest definition of the rule as a buy signal of an asset is produced when the asset price rises over a predefined resistance level and vice versa for the sell signal. So they leave it open to interpretations how the resistance and support levels are defined. (Coutts & Cheung 2000: 581.)

The most similar interpretation of the channel breakout rule to the support and resistance is that buy and sell signals are generated when the asset price rises above or falls below locally characterized maxima and minima, respectively. This is specified in the equations (14) and (15) in the following way:

$$(14) \quad \text{Res}_t(m) = \max(P_{t-1}, \dots, P_{t-m}) \quad \text{thus buy if } P_t > \text{Res}_t(m)$$

$$(15) \quad \text{Sup}_t(m) = \min(P_{t-1}, \dots, P_{t-m}) \quad \text{thus sell if } P_t < \text{Sup}_t(m).$$

Maxima and minima can be defined using a 50, 150 or 200 day periods for instance. It is common to use also an x per cent band around maxima and minima to make sure that the given signal is not market noise. (Brock et al. 1992: 1736; Hudson, Dempsey & Keasey 1996: 1122–1123, 1128; Coutts & Cheung 2000: 581.)

Consequently, Sullivan et al. (1999) define a channel as an area where the high price of the preceding n days is within x per cent of the low price of the same period where the current price is not included. In harmony with the other interpretation the buy signal is produced when the price goes up through the channel and sell signal when price falls

below the channel. After the new signal is given the long or short position is held for a predetermined number of days. (Sullivan et al. 1999: 1657.)

As discussed before, the top desires of technicians are to buy at lows and sell at peaks. When a price is heading to the peak it is facing resistance not to climb above the previous peak because the market participants are selling the asset before the anticipated peak. If the price rises above the previous peak despite the resistance it is an indication that a lot of market players are not expecting the price of an asset to go down or stay at the previous peak level this time. They expect the price to go up. This is the idea behind support and resistance levels in channel breakout rule and support and resistance rule. (Brock et al. 1992: 1736.)

Vast majority of the technical strategies concentrate on price history of an asset. However, there is another important factor that is favourable for technician to observe, trading *volume* of an asset. Volume is rarely used by itself only but together with tools using price history. Thus technical tools using volume are rather secondary tools. Blume, Easley & O'hara (1994) show in their study that large price movements and trading volume are actually deeply related. When a price of an asset makes a massive move also volume of trading picks up significantly. Therefore volume is in a substantial role when investors are trying to find out the quality of the buy or sell signal they were given. To observe the changes in the trading volume investor might need some tools for that. One could use the same tools for volume than for the price such as oscillator strategies or moving averages to observe the changes in a trend of volume. (Blume et al. 1994: 169–171, 177; Sullivan et al. 1999: 1657.)

3.3. Critics towards technical analysis

Technical analysis has been in the focus of academic dispute for a century already, but we are not done yet. Neither is the market. Crowds of investors are using these methods from a day to another when they trade and at least as many of them are not. To be honest, the issue is not that simple at all. It is very hard to measure especially those strategies that are not purely mathematical. Most of the arguments are based on attitudes and opinions of either of the sides and do not have too strong fundamental background.

Even though some of the arguments are not that valid there are arguments that have a solid setting behind. According to EMH and random walk market prices should reflect

all the information existing and the future price changes are independent of the price changes in the past. For this reason there is no guarantee of the future capabilities of technical analysis though it previously used to work. This is the main conflict between technical analysis and efficient markets. (Fama & Blume 1966: 226; Wong, Chew & Sikorski 2001: 60.)

Another concern is that the technical strategies are causing the market movements themselves. This means that when enough investors are using the strategy for their trading purposes it can have an effect on the market prices while all of the investors are executing the same strategy at the same time. Maybe there is no problem with this but when many enough are using the strategy it does not only have the effect on the prices but the price movement happens so fast that most of the investors cannot take advantage of it. This is because every investor wants to take advantage of the potential profit. The reason why this argument might not be that valid is that probably the most profitable strategies are not brought to public because of this exact reason – to keep it working in the future as well. Also there could be too few investors anyway taking advantage of the strategy while majority of the investors do not believe in technical analysis or they are unimpressed of the strategies for other reasons. (Levy 1966: 87.)

An issue that is criticized even among the technicians is the subjectivity that some technical strategies are involved with. Obviously, this does not doom all of the technical rules but those that need a human opinion about the markets and the price movements. However, computers have made it easier for investors to develop strategies that are not depending on human decision. This rules out the possibility of luck. (Levy 1966: 88.)

4. DATA AND METHODOLOGY

Even though the efficient markets hypothesis and methods of technical analysis in general are rather well covered subjects there is still something to study. Two main subjects examined in this study, short-term interest rate futures and Relative Strength Index trading rule, are both quite well-known in the markets, at least among the market professionals but for some reason almost unknown in the academic research.

4.1. Interest rate futures

A futures contract is an agreement either to buy or sell an underlying asset at some point in the future for a specified price. Futures are traded on exchanges according to the contract terms standardized by the exchange. The following few terms are the key elements of every futures contract: underlying asset, delivery month, delivery arrangements, contract size and margins. The *delivery date* of a futures contract is the date when contract will be settled either by cash or by physical underlying settlement according to the *delivery arrangements* specified by exchange in the contract terms. Futures contracts however do not necessarily include an expression of the delivery date, but the *delivery month*. In that case the contract terms have the details such as: the contract goes into delivery on third Wednesday of the delivery month. Nominal value of a Future is called *contract size*. Movements in the underlying asset are settled in terms of price and size of the contract. When trading futures exchanges require *margins* from investors to secure the position of itself and the counterparties of the contract from insolvency of investor in radical market movements. Normally margins are *marked to market* daily to cover the possible losses. If there is not enough money on the margin account to secure the positions of the counterparties the investor is asked to increase the amount on the margin account. (Hull 2006: 21–29.)

This study is using short-term interest rate futures as data to investigate whether there are inefficiencies or technical trading opportunities in that market. The purpose of these interest rate futures is not originally to be just a trading instrument but to be a tool for hedging a loan or investment portfolio against interest rate risk. There are interest rate futures quoted in different currencies such as US Dollars, Euros, British Pounds, Japanese Yen, Swiss Francs etc. A three-month Euribor future for instance is an obligation in a three-month loan or deposit of EUR 1 million depending of the positioning of an investor (Bernoth & von Hagen 2004: 6).

Pricing a short-term interest rate future is a bit different than pricing the most of the other financial assets. Normally market participants are discounting the future cash flows of an asset while short-term interest rate futures are priced in a similar way with the T-bills, the money market instruments issued by the US government. All other factors being equal as the time goes on the price of a T-bill goes up because the face value is all the time nearer to present and therefore it is more valuable for the investor. Also in the short-term interest rate futures the time value is taken into account but it does not have that large effect on pricing as it is only a part of the present value of discount rate or the interest rate on a three-month deposit or loan. Therefore short-term interest rate future is an easy hedging instrument as the time value is not playing such big role as interest rate, given that it is the risk factor why investor is hedging his portfolio.

In the markets every single price is somehow related to another. If price of the other asset changes it is likely that price of another asset changes too because most of the arbitrage opportunities will vanish as fast as they are discovered. This holds also for interest rate curve, the curve that tells spot interest rate levels for each of the maturities. If an investor is eager to make a deposit for 12 months it is priced to equal the price of a six-month deposit from now on together with a six-month deposit commencing in six months. Or a three-month deposit from now on together with a three three-month deposits commencing in three, six and nine months equals as well. This is expressed in the equation (16) as

$$(16) \quad 1 + R_{12 \times 0} = \left(1 + \frac{R_{6 \times 0} * t}{360}\right) * \left(1 + \frac{R_{6 \times 6} * t}{360}\right) = \\ \left(1 + \frac{R_{3 \times 0} * t}{360}\right) * \left(1 + \frac{R_{3 \times 3} * t}{360}\right) * \left(1 + \frac{R_{3 \times 6} * t}{360}\right) * \left(1 + \frac{R_{3 \times 9} * t}{360}\right)$$

where $R_{T \times N}$ is the interest rate of a deposit for T months commencing in N months. t is the number of days on a particular deposit period where basis of 360 days is observed, as usual in money market instruments.

Where R_F is the annual future spot rate of return that is implied from the current price of an short-term interest rate future, the price of the future, shown in the equation (17), is quoted as

$$(17) \quad 100 * (1 - R_F).$$

Assuming that long rate, R_L , is the annual rate of return for lending or borrowing money from present to three months after the maturity of the short-term interest rate future, and the short rate, R_S , is the rate of return for lending or borrowing money from present to the maturity of the short-term interest rate future. Consistent with the previous example of 12-month deposit the return from using the long rate or the short rate and the short-term interest rate future must equal as the following:

$$(18) \quad F = 100 * [2 - (L/S)^{b/n}] \quad \text{where}$$

$$S = (1 + R_S)^{T/b} \quad \text{and}$$

$$L = (1 + R_L)^{(T+b)/365} .$$

Otherwise there would be an arbitrage opportunity on the market. This is formalized in the equation (18) where F stands for non-arbitrage price of the future, T is the number of days to the maturity of the futures contract and n is the length of the underlying deposit i.e. three months while basis of b days is assumed. (Sun & Sutcliffe 2003: 781.)

The most of the short-term interest rate futures are traded either on Chicago Mercantile Exchange (CME) or NYSE Liffe and the most of them are denominated in US Dollars, Euros or British Pounds. To give a view of the liquidity and importance of the interest rate futures used in this study the USD-denominated Eurodollar futures of CME are the world's most actively traded futures contract while the Euribor futures of NYSE Liffe account over 99 % of the EUR-denominated and exchange-traded short-term interest rate futures (CME Group 2012; NYSE Liffe 2012 a). Also the Short Sterling futures of NYSE Liffe are the most liquid GBP-denominated short-term interest rate futures (NYSE Liffe 2012 b).

Eurodollar futures were launched for trading in 1981 by Chicago Mercantile Exchange. When they begun they had no electronic trading environment. However, nowadays electronic platforms allow investors to trade also futures in real-time, when-ever and where-ever they want. When Euribors were launched on the January 1st in 1999 the first short-term Euribor futures were already launched a month before in December 1998 to substitute the short-term interest rate futures of different national currencies in Europe. At first only Eurex of the two European exchanges was able to provide electronic trading platforms which made it easy for investors to start trading with Eurex instead of Liffe. Soon however, also Liffe provided their own electronic trading system and now there are no such major differences between the two providers except on the liquidity

side in favour of NYSE Liffe. (Bernoth & von Hagen 2004: 6; Gwilym, Aguenau & Rhodes 2009: 92; CME Group 2012.)

To compare the interest rate futures market differences to the other markets Evans (2006: 1280–1281) found that the British interest rate futures market in the UK, known as the short sterling market, is not radically different of the two other financial futures markets examined in his study: stock index futures and bond futures markets. However, one of the main findings of his study is that short sterling market got a lot more efficient after launching of the electronic trading system.

In the academic field of finance three month short-term interest rate futures are very thinly studied as data. The other interest rate derivatives are better covered, such as German government bond futures, so-called bund, bobl and schatz futures, perhaps for the reason that they are often used by the fixed income traders to hedge interest rate risk of their fixed rate bond portfolios. Dominance between these short term interest rate futures used in this study and government bond futures changes when going from a country to another. Volume-wise the most liquid short term interest rate futures are traded almost as much as active contracts of German government bond futures but in terms of *open interest* there are clearly larger exposures in short term interest rate futures than in German government bond futures. However, short term interest rate futures are getting more and more important hedging tool for investors and treasurers. For sure it does not go to another direction as long as the interest rates are fluctuating so heavily and the cost of money is sharply rising or decreasing deeply even faster. Before the credit crisis is finally taken care of and the economic growth is on a sustainable road fluctuating interest rates are something that we have to get used to. Therefore, there is a solid background on studying short term interest rate futures market in terms of technical analysis as well.

The short-term interest rate futures covered in this study are denominated in 7 currencies: US dollars, euros, British pounds, Japanese yen, Swiss francs, New Zealand dollar and Malaysian ringgit and they are traded on Chicago Mercantile Exchange, NYSE Liffe, Eurex, Tokyo Financial Exchange, Sydney Futures Exchange, Singapore Exchange and on Bursa Malaysia. The data was gathered from January 1st 2000 to July 31st 2009. The period is very attractive because the so-called IT boom is in the beginning, years lasting period of fast economical growth since a massive decline after IT boom, and the latest sovereign debt crisis and recession due to the biggest credit crisis ever seen.

Data of the study consists of 11 future series and 164 futures used in total. Obviously all of the futures are not available from the beginning of 2000, so they are being used since they are available until the end of the period or until they mature. Only futures having enough trading days are included in this study. To be more exact a future must have at least 352 trading days on the data period of this study to be included. Why 352 days? Because the first 252 days, as one year trading days, are used for optimization of trading rules. The rest 100 days is decided to be the limit of the minimum trading period to get enough data points for valid results. As a result of such filtration 132 futures and 149,212 observations for each of the trading rules are included in the study over the nine-year and seven-month period.

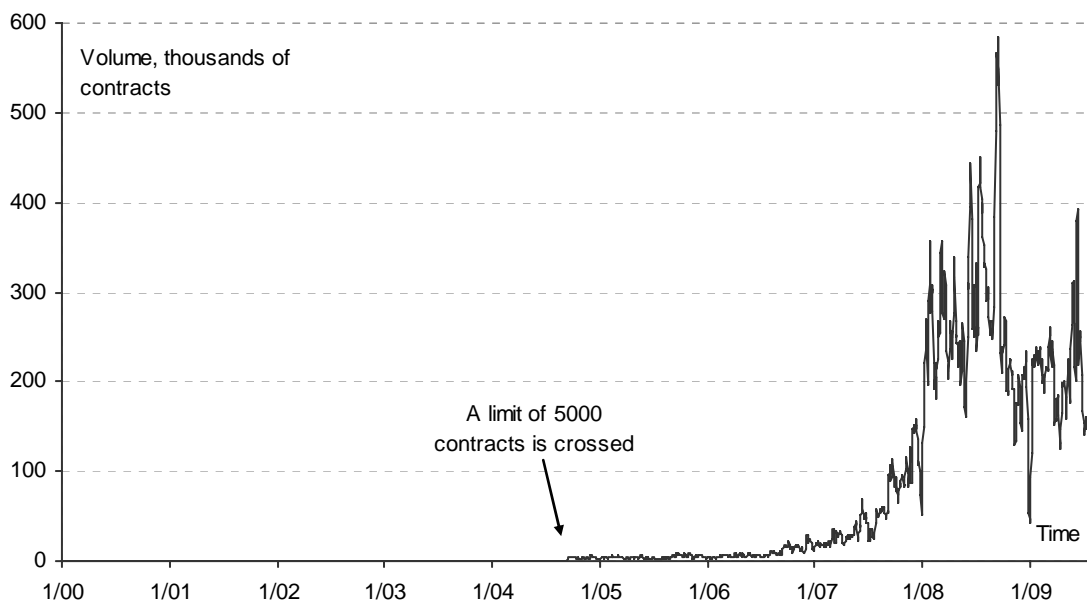


Figure 3. Volumes of a USD denominated Eurodollar short term interest rate future.

The data is tested in two separate sets, illiquid and liquid. The illiquid period covers all of the future data while the liquid period of each future begins when the first daily volume of 5000 contracts or more has been observed. The limit is chosen to be 5000 contracts because it is the point of time after which the volume of a future never drops back to the previous lower levels. The CME's Eurodollar futures, especially, are trading mostly with a one-day accuracy according to the following steps: more than five years before the delivery date the daily liquidity of the contract is rather low, but on the day when there is five years to the last trading date daily trading volume rises above 5000

contracts and stays around that level for two years. When there is three years left to the last trading date the liquidity of the contract goes rapidly up. Eurodollar futures may reach a daily volume of 500,000 contracts a day or more. This is confirmed in the figure 3. presenting volumes of a USD denominated Eurodollar short term interest rate future with a delivery on September 2009.

After the previous filtration and separation, both, illiquid and liquid data sets are further divided into three categories of 58, 39 and 35 futures. The first of the three categories has two futures series in it. These two series consist of the most liquid short-term interest rate futures on earth representing the most liquid futures markets and both of them are USD-denominated Libor based futures series. The second category has three futures series that are very liquid too but not as liquid as the first category. A categorization of this group fits to the developed futures markets. The third category consists of six futures series that are rather illiquid each representing the emerging or illiquid futures markets. After these filtration procedures there is not enough liquid data in the third category futures to examine their liquid period and therefore the third category is analyzed only from the illiquid perspective. Also, some of the futures in other categories do not have enough observations to be included in the study from the liquidity perspective.

Consequently, the futures will be analyzed in five categories:

- A₁: the illiquid period of the most liquid futures (N=58)
- B₁: the illiquid period of the semi liquid futures (N=39)
- C₁: the illiquid futures (N=35)
- A₂: the liquid period of the most liquid futures (N=30)
- B₂: the liquid period of the semi liquid futures (N=16).

The delivery date of the futures used in this study is the third Wednesday of the delivery month and the last trading date is two days prior the delivery date. The specifications of the futures contracts are covered more thoroughly in the appendix 4. There is also a full list of the futures contracts used in the study.

4.2. Relative Strength Index

The Relative Strength Index (RSI) trading rule was invented by Wilder (1978) among some other concepts for technical trading. Nowadays, most of the market professionals around the world commonly use RSI as a part of their trading strategies. It can also be considered as one of the most often offered technical analysis tool used by investment banks and other providers with their clients as a part of their investment analysis services.

Even though RSI is often thought to refer to only one trading method it actually has many modifications. In this study one of them is used as a reference method. However, some influences from the Moving Average trading method are brought in as a new method of using two different RSI rules to get a signal for buying and selling is used. In this study there are presented also two modifications of such rule where optimization processes are slightly modified. Even though some modifications to the RSI trading rule are presented in this study the formula does not change from the original one presented in the following subsection.

4.2.1. Traditional Relative Strength Index methods

RSI is somewhat easy to calculate even though it requires a bit of updating like most of the other trading rules. In the end the amount of work depends of the level of automation of course. The original RSI-method is expressed in the equation (19) as

$$(19) \quad RSI = 100 - \left(\frac{100}{1 + RS} \right)$$

where RS is the average of 14 trading days' up-closes of a security divided by the average of 14 trading days' down-closes of the security. By the averages of up-closes and down-closes the average of security's daily returns to either of the directions is meant. The value of RSI from the equation (19) is something between the zero and one hundred. According to Wilder (1978) the market is reaching its turning point when the value of RSI goes above 70 or goes under 30. Hence, the RSI indicates if the security is getting *oversold* or *overbought*. Wilder (1978: 65.)

Markets have since interpreted the original version of the RSI in many ways whereas here only three of them are covered. 'Touch' method generates a buy signal while the

lower bound is touched and a sell signal while the upper bound is touched by the RSI. ‘Peak’ method creates a buy signal when the value of RSI crosses the lower bound and turns back. The sell signal is given when upper bound is crossed and the RSI turns back. A buy signal by the ‘retracement’ method is created when the RSI has crossed the lower bound and it retraces back to the same level or above the lower bound that is defined in the equation (20) as

$$(20) \quad \text{BUY if } RSI_t \geq 30 \text{ and } RSI_{t-1} < 30 .$$

Conversely, a sell signal is generated while the index crosses the higher bound and comes back to the bound or under. This is characterized in the equation (21) as

$$(21) \quad \text{SELL if } RSI_t \leq 70 \text{ and } RSI_{t-1} > 70 .$$

Because the Retracement method is so widely used among the market professionals it is the reference method used in this study as well. The timing of buy and sell signals by retracement method on the previously used Eurodollar future are illustrated in the figure 4. (Wilder 1978: 65–70; Wong et al. 2003: 545–546.)

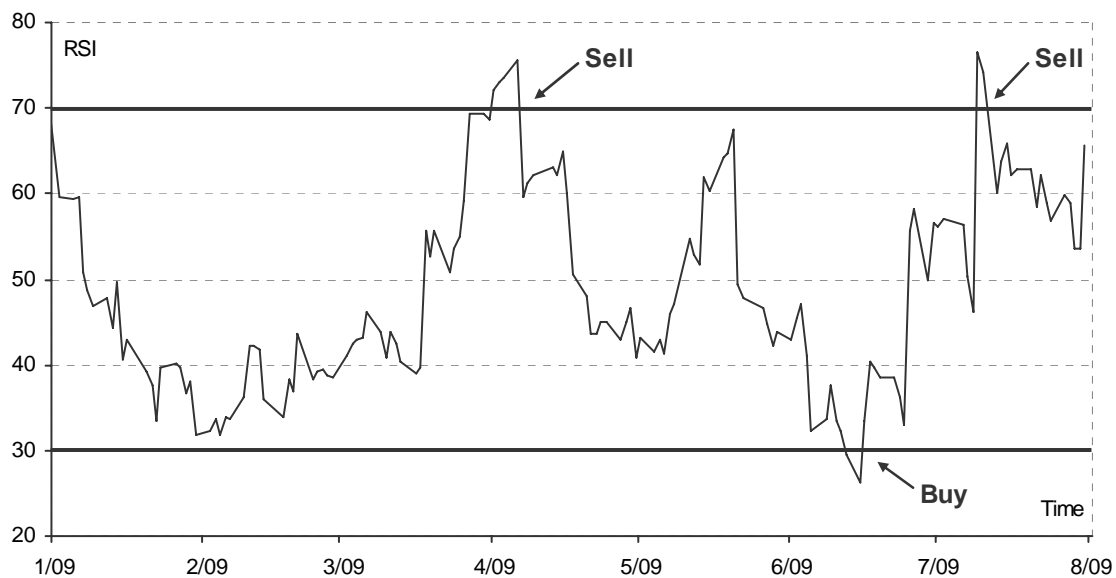


Figure 4. Signals by retracement method of 14-day Relative Strength Index on the Eurodollar future.

4.2.2. A rule of dual RSI – short and long

While the traditional methods of RSI are using an index constructed on the last 14 trading days' market movements in this study the traditional RSI trading method is reformed and used also in a new way. In a rule of dual RSI (DRSI) there are two separate, short and long RSI trading rules used to give a signal for the right moment to buy and sell. Instead of 14 trading days the short rule constructs on a shorter period of averages of up and down-closes while the long rule uses a longer period than the short one.

The advantage of using two RSIs with different lengths is that the shorter RSI should react immediately to the changes in the market prices. This should eliminate or reduce the problem criticized by Thachuk (2000) that if the period of days used to calculate the averages is too long the RSI rule gets too slow for an immediate response to a change in a trend. However, the signals of very short RSI, such as two to five trading days, are often false because of short-term or tertiary trends of one week or so. As Ruggiero (1998) and Meissner (2001) found in their studies an RSI rule using averages of larger number of trading days works better or gives more correct number of signals than with a smaller number of days. To eliminate the false alarms a longer term RSI is used so that the secondary trends of few weeks to few months could be found better. The result should be a trading rule that reacts rapidly when a new trend is about to begin without giving too many false signals.

Because no previous academic experience of using two RSIs can be found *optimization* of the arguments used to calculate RSI is getting very important. The importance of optimization is consistent with the findings by Thachuk (2000) and Seiler (2001). The length of the average period is one of the arguments to optimize. The optimization is constructed so that the number of trading days used by the short RSI can get a value between two and fifteen trading days while in the long RSI the number of days ranges between ten and twenty trading days. Obviously, the long RSI has to be longer than the short one.

The RSI is constructed so that the frequency of buy and sell signals becomes higher due to two reasons: rise in the volatility of the security and shortening in the averages discussed previously. Now that in this study futures are used as data instead of stocks and different lengths of averages are used the optimal values for lower and higher bounds triggering the buy and sell signals must also be optimized. The lower bound is

chosen to vary between 20 and 40 in increments of five index points. The higher bound again can get a value between 60 and 80 in increments of five so that it is maximum 10 increments away from the original bound. Thus, it is assumed that the original bound is approximately at the right area.

The optimization process for the data is done once in every 126 trading day period accompanied with an assumption that every year has 252 trading days. For every coming six months time the last twelve months period is used to analyze which arguments to use. The updating period of six months is chosen because the arguments in use are desired to be most relevant and fresh. On the other hand no shorter period is an option to keep up the number of trades on every period. The twelve months period for analysis is chosen because it is thought to include a fresh sight to how the security behaves but it is important not to choose too long period either to retain the ease of handling the data.

The arguments are optimized for each future differently because the way the futures act is not similar. When having stocks of two different companies they probably and hopefully are having different kind of performance. The stock with high beta may change a lot and a stock with lower beta takes the bullish and bearish times with a bit smaller changes. But when having a totally different instrument the way the security acts can be much more different. The RSI was originally presented as a trading rule for stocks. The variables are obviously then optimized for stocks, but it is important to note that optimization process used in this study would have not been possible in those times because of low capacity of computers. For this reason too the use of only 14 trading days' averages must be questioned today.

A buy signal by DRSI rule in the equation (22) is generated when the longer RSI is at or below the lower bound and the shorter rises to or above the lower bound as expressed here:

$$(22) \quad \text{BUY if } RSI_{S,t} \geq LB \text{ and } RSI_{S,t-1} < LB \text{ and } RSI_{L,t} \leq LB$$

where RSI_L symbolizes the long RSI, RSI_S is a symbol of short RSI, LB means lower bound and HB is the higher bound of the trading rule. The idea of this procedure is to get rid of false signals caused by short-term trends of a day or couple while using only short-term period in RSI. On the other hand if only long-term periods would be in use the most of the profits would already be gone when the trading method gives a signal to

buy or sell too late. A signal by some of the trading methods can take a really long time while long-term periods are used. Hence, when the longer RSI indicates the security or market to be oversold right timing for turning the positioning is achieved by reacting to a change in a trend using the signals given by the shorter RSI.

The equation (23) shows how the sell signal is created by DRSI trading rule as the longer RSI is at the higher bound or above and the shorter RSI slides to the higher bound or under as

$$(23) \quad \text{SELL if } RSI_{S,t} \leq UB \text{ and } RSI_{S,t-1} > UB \text{ and } RSI_{L,t} \geq UB .$$

The figure 5. illustrates the buy and sell signals of the DRSI rule where short RSI is 10 trading days long and the longer is 15 trading days long indices on the same previously used Eurodollar interest rate future.

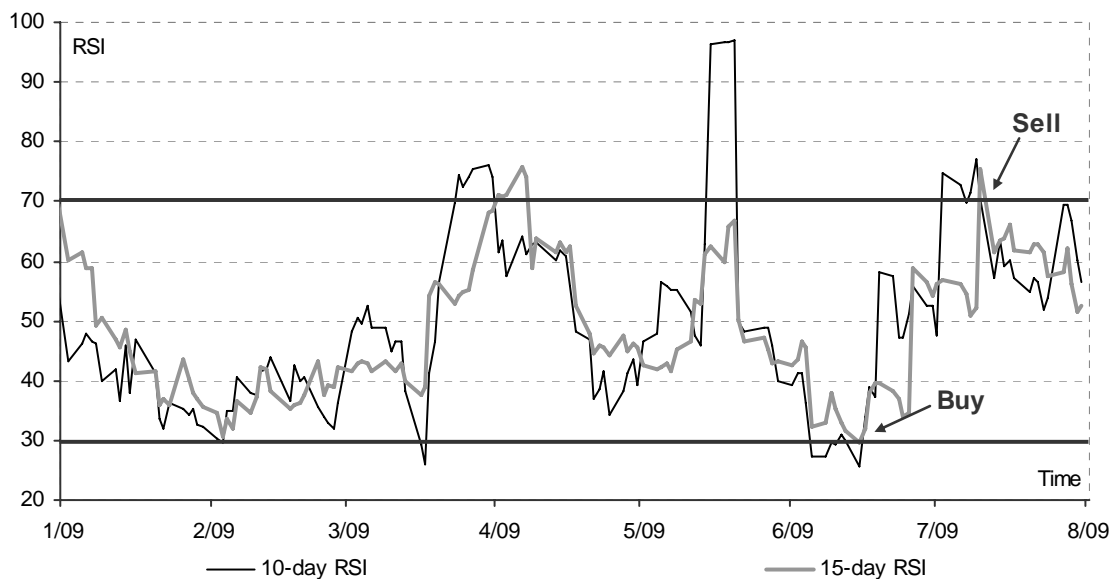


Figure 5. Signals by DRSI trading rule on the Eurodollar future.

4.2.3. Common optimization and frequent parameters rules

With the presented DRSI rule optimization is used separately for every security as it is thought to be most relevant and efficient way to find optimal parameters for that particular security. However, a twelve months period can be too short in some

circumstances to optimize parameters which represent enough different scenarios to prepare for the following six months period. On the other hand it is very time consuming to individually optimize these parameters for such a bunch of securities that are used in this study. For this reason not a much longer historical period could be used for optimization.

As an alternative to the previously presented optimization process there are two more processes or modifications of trading rules covered here: common optimization rule and frequent parameters rule. They both are based on the same calculations and two different length indices as the previously presented base case, DRSI – only the optimization process is different. Instead of individual optimization in the common optimization rule the same parameters are optimized for all of those securities included in each of the five data sets separately over again in one year periods every half year. Thus, the number of days of the averages and the lower and upper bounds are common for all of the securities within each data category. This should get investor closer to the parameters that are optimal for using such data in general, in most of the circumstances. As more observations are used for optimization the performance may weaken in terms of reduced individuality in the parameters.

The frequent parameters rule is used in this study for supportive purposes only as it cannot be considered too scientific method for testing data. In this modification the most frequent parameters of all the periods of all the previous RSI rules are used to examine if there exist parameters that consistently generate better returns than the others. If this trading rule is successful it probably suggests that continuous optimization is not needed. Obviously data of the time period in ‘future’ shouldn’t be used for optimization when back-testing the performance of such trading rule. Because there are such an amount of securities used in this study and the same values for the parameters are used along the whole testing period it should not give too infected results. The large amount of data guarantees that if some values of the parameters are really more popular than others it should be detected. Unfortunately, no longer period of data is achieved to test the performance after the period where the popular parameters are collected from.

4.3. Moving Average

Moving Average trading method is used as a reference model for RSI methods to see whether RSI’s predictive power performs better than one of the most popular methods

of technical analysis, Moving Average. Lee & Mathur (1996 a: 392) describe that reason of using Moving Average trading rule in their study is the popularity of trading method among the market professionals and the fact that there are profits verified on the futures markets achieved by Moving Average trading rule. It does not make the method too unattractive that it is relatively simple to use.

The principle of Moving Average rule is to use short-term and long-term trends to analyse the turning points of the security to generate buy and sell signals. The short-term trend is the average of closing prices observed during desired short-term period. The long-term trend on the other hand works the same way but the period in use is obviously longer than the short one. An upward-trend, bullish trend, of a security begins when the short-term average gets greater or equals the average of the long-term trend and vice versa for the downward trend, bearish trend. Conditions where long position is desirable according to the trading rule are mathematically described in the equation (24) as

$$(24) \quad S^{-1} \left(\sum_{i=1}^S P_{t-i} \right) \geq L^{-1} \left(\sum_{j=1}^L P_{t-j} \right)$$

where S and L mean lengths of the short-term and long-term moving averages, respectively, P_t is the price of a security at the end of the selected time-period. (Lee & Mathur 1996 a: 392–393; Lee & Mathur 1996 b: 952–953; Fong & Yong 2005: 48.)

In this study there is one of the most popular Moving Average rules used, 1-50, where number 1 means that the short index uses only one trading day's closing or spot price and 50 refers to the longer index which consists of the average of 50 trading day's closing prices. The figure 6. illustrates the signalling of 1-50 Moving Average method on the same Eurodollar interest rate future used in the previous examples. As Brock et al. (1992), Fifield et al. (2005) and Metghalchi et al. (2008) describe in their studies that 1-50 is one of the most popular Moving Average rules and more importantly one of the most profitable as well. Among the popular Moving Average rules the 1-50 rule is the nearest to the RSI methods used in the time perspective. As Moving Average rules are needed more or less for reference purposes in this study, only one rule of 1-50 appears to suit the needs of the study.

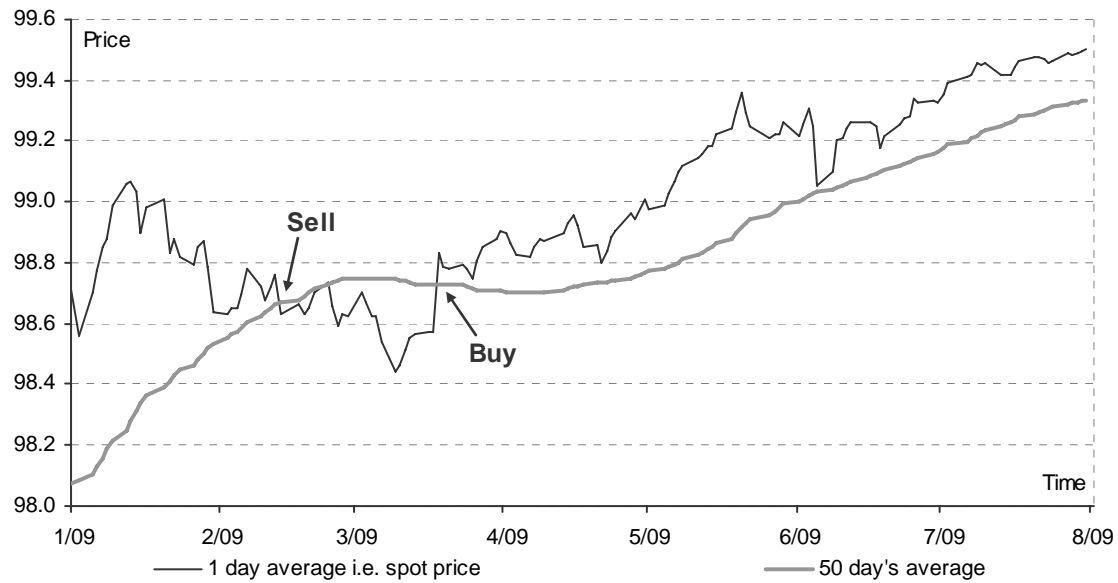


Figure 6. Signals of the 1-50 Moving Average trading rule on the Eurodollar future.

Because there are very different kind of markets and the trends are very dissimilar too there are several modifications made out of this simplest form of Moving Average crossover rule. For example *filters* or *bands* can be used to be sure that a trend is really about to begin and to filter away the false signals. Filter could be, say, 1% meaning that investor would wait for the buy signal until the short moving average goes 1% above the longer one and vice versa when downward trend is observed. (Brock et al. 1992: 1735; Fong & Yong 2005: 48.)

Brock et al. (1992) used fixed length Moving Average in their study where signals are generated in a same manner as in the simple Moving Average. When either a buy or sell signal is given the position is kept for pre-fixed period of time, say 10 trading days. The returns of the strategy are calculated over the fixed time periods after signals are given. However, during the time period when position is taken other signals created by the strategy are ignored. (Brock et al. 1992: 1736.)

Increasing Moving Average works the same way as the simple Moving Average rule. When the longer trend is beaten by the short trend a buy signal should be generated and vice versa for the sell signal. However, a requirement for the buy signal in this rule is that the long-term trend should be going up, being on a positive slope. (Metghalchi et al. 2008: 478.)

Now, that markets are very volatile and no short or long-term trend exist it is popular among market participants to look at especially equity markets from a very different point of view than by having the traditional tools that are more useful when markets are functioning more or less normally. Long-term trends are trying to be found using moving average of a very long time, say 20 years. While having such a long time period there is no sense to look at the indicator on a daily basis as ‘normal’ version of Moving Average does. It is much more valuable to review such long-term trends by having 12 months moving average with a monthly basis.

4.4. Sharpe ratio

When investor chooses an asset or portfolio where to invest it is always admirable either to get more return for the same amount of risk or to get the same return for the smaller amount of risk. Sharpe (1966: 123) redefined this idea to a *reward-to-variability* ratio, R/V . The reward, R , for bearing the risk is described as the rate of return on an asset or a portfolio less the pure risk-free interest rate. Variability, V , determines standard deviation of the annual rate of return. (Sharpe 1966: 123.)

Later the ratio was named after the developer to Sharpe ratio. By using Sharpe ratio investor is able to tell which of the assets, portfolios or strategies produce the best return relative to the risks attached to the return. However, the Sharpe ratio is nowadays described as in the equation (25) as

$$(25) \quad S = \frac{(r_p - r_f)}{\sigma_p}$$

where S stands for the ratio itself, r_p is the return on the portfolio over given time period, r_f is the riskless rate of return over the same period and σ_p is the standard deviation of the portfolio’s rate of return. (Nielsen & Vassalou 2004: 105.)

Shik and Chong (2007) are using Sharpe ratio in their study and find that RSI and Moving Average methods yield positive risk-adjusted returns. Also in this study Sharpe ratio is used for each of the futures and trading rules individually. This is done to get a view of what kind of role the volatility or risk is playing regarding to the return in that particular asset and trading rule. This might gives an answer to why another trading rule is more profitable than the other. Another trading rule could make a remarkably better

return for the asset than the other but it does not tell if the trading rule has made the return because the rule tends to pick up riskier investment periods. On the other hand a trading rule could also tend to pick up the less risky periods and therefore also return could be smaller but the reward for each unit of risk could still be better than with the other trading rule. As all of the trading rules in this study have the same investment period their Sharpe ratios are comparable to each other. Because Sharpe ratios in this study are calculated using average daily returns of the futures and risk-free rates the Sharpe ratios are commensurable between the futures and future series as well.

There has been a long debate over the risk-free rates and which one is the one to use. While Shik and Chong (2007: 371) use 30-year US Treasury Bonds as a risk-free rate in their study Okunev and White (2003: 435) chose another method instead of Sharpe ratio because they could not tell the consensus on the correct risk-free rate. The most often used risk-free rates are US Treasury bills, German government bonds or bills and Euribors. However, all of these have faced problems in terms of risk free rate. United States was downgraded to AA+ in August 2011 by Standard & Poor's followed by negative outlook from each of the three major rating agencies. While Germany is one of the few still holding the untouched AAA rating with stable outlooks there is another problem with government bonds nowadays. Due to the on going credit crisis the volatility in the government bond prices has risen dramatically as investors are jumping in and out. Therefore, intraday trading activities have become more and more common deepening the intraday moves even further and making usage of government bond as a proxy for risk-free rate slightly unattractive.

Euribors are free of such intraday trading activities as they are quoted by a group of European banks once a day. However, also Euribors are problematic nowadays due to the credit crisis as there is a new factor included: risk. At first, Lehman Brothers collapsed in September 2008 making banks all over the world not to trust each others anymore. As the financial system was getting back to its feet again some of the European states were caught of being in worse situation than what was thought before. As banking sector is one of the biggest holder of European government bonds it obviously makes banks not to trust each others again as no one really knows the amount of distressed debt they are really holding and which one of them is the next to collapse. Thus, it is a key thing to exclude the risk factor. EONIA is similarly quoted rate of interest as Euribors are but the EONIA rate is overnight maturity as Euribors are quoted from one week up to one year maturity. As the risk of default increases while maturity lengthens an overnight maturity is considered as very minimal risk versus one month

maturity. In addition EONIA is considered to be combination of current economic conditions, ECB reference rate prospects and macro economic views. Therefore, EONIA has strengthened its position as a market reference of risk free rate in recent years. Based on the previously covered issues the EONIA rate is chosen to be the risk free rate in this study. EONIA is considered to be the reference risk free rate and it is used for futures quoted in other currencies than euro too. Due to simplicity reasons no currency conversions for the EONIA based deposits are made.

4.5. Statistical methods

In this study the data is first analyzed using Kolmogorov-Smirnov test to see whether the price data of the futures is normally distributed. Together with Pearson's chi-squared test the Kolmogorov-Smirnov test is the earliest and probably the most well-known normality test. However, the Kolmogorov-Smirnov test is considered to be more powerful of the two. The test makes a comparison between empirical and theoretical cumulative distribution functions. Usually it is used to tell if the empirical data is significantly different from normal distribution. H_0 hypothesis states that the sample is drawn from a normal distribution. (Lillefors 1967: 399; Breton, Devore & Brown 2008: 624, 629; Castro-Kuriss, Kelmansky, Leiva & Martinez 2010: 1194; Drezner, Turel & Zerom 2010: 693–694.)

The statistics of the Kolmogorov-Smirnov test is calculated as in the equation (26) as

$$(26) \quad \begin{aligned} D^+ &= \max_{1 \leq i \leq n} \left(\frac{i}{n} - z_i \right); \\ D^- &= \max_{1 \leq i \leq n} \left(z_i - \frac{(i-1)}{n} \right); \\ D &= \max(D^+, D^-) \end{aligned}$$

where z_i is the cumulative probability of standard normal distribution, and D_i represents the difference between the observed and expected values. (Stephens 1974: 731; Yaszici & Yolacan 2007: 177.)

The calculated value is compared to the Kolmogorov-Smirnov table of critical values of D . If the value of D exceeds the critical value for the same sample size and desired level of significance the hypothesis H_0 that the observations are from normal population must

be rejected (Lillefors 1967: 399–400). In this study Kolmogorov-Smirnov tests are done using SPSS statistical computer software. In addition of D value also the statistical significance in the form of p -value for the test result is given on the software and therefore represented here in the results to ease the interpretation process.

Each of the trading rule returns are compared to the returns of Buy-and-hold strategy to tell whether the returns of the trading rules are statistically significantly different. This is measured with two separate statistical tests: Student's t-test and Mann-Whitney U-test. Student's t-test is calculated for each of the futures and trading strategies even though it fits only for time series following normal distribution. Consequently t-test is more or less supportive tool in this study. The results of t-test are reviewed only if the time series of a particular security is following normal distribution.

The t-test used in the study is independent two-sample test with an assumption of equal or at least almost equal variances, i.e. $\sigma_1^2 = \sigma_2^2$. The test compares the means of the time series and tells whether the means of the two samples seem to differ from each others. The t-statistics of the test is calculated as expressed in the equation (27) as

$$(27) \quad t = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{S_p^2 \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}}$$

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$$

where X_1 and X_2 are samples of the population, S_1^2 and S_2^2 sample variances and n_1 and n_2 sample sizes respectively. The H_0 hypothesis of t-test states that the samples have the same origin or there is not significant difference between the two time series. (Schechtman & Sherman 2007: 509–510.)

Mann-Whitney test is the primary test of significance in this study to test whether the returns between the technical trading rules are significantly different compared to the Buy-and-hold strategy. While t-test gets the most out of it for the time series of normal distribution Mann-Whitney is a nonparametric test and it does not make such a difference if the samples are normally distributed or not. Let us consider the two random variables of the Mann-Whitney test to be x and y . The continuous cumulative distribution functions of the variables are f and g respectively. To describe the purpose

of the test or the H_0 hypothesis in formal way in the test it is studied if $f = g$. (Mann & Whitney 1947: 50; Edelman 1989: 197)

First, in the Mann-Whitney test procedure all of the quantiles x_1, \dots, x_n and y_1, \dots, y_n are ranked into an ascending order. U is the sum of the number of times that a y precedes an x or, because of two-tailed test, the sum of the number of times that an x precedes a y . Thus, the maximum value of $U = n_x n_y$ and the minimum value of $U = 0$ where n represents the size of the each sample. The critical value tables for Mann-Whitney test can be used to find out the significance in a case of $\max(n_x, n_y) \leq 20$. For larger samples there is the equation (28) where we have

$$(28) \quad z = \frac{(U - \mu_U)}{\sigma_U} \quad \text{where}$$

$$\mu_U = \frac{n_x n_y}{2} \quad \text{and}$$

$$\sigma_U = \frac{n_1 n_2 (n_1 + n_2 + 1)}{12}.$$

The p -value is calculated and expressed as z . (Mann & Whitney 1947: 51; Sijtsma & Emons 2010: 348–349.)

Student's t -test and Mann-Whitney test are also done on the SPSS software where it is relatively easy to retrieve p -values for both of the tests. To stay consistent when presenting the results only p -values are given for all of these three tests. The rationale behind is that it makes it easier to interpret the results.

4.6. Return estimation

In this study it is assumed that a hypothetical investor follows the market rather actively and is able to react to a signal generated on a same day using the closing price of the day as volatility usually decreases towards the end of the trading day. The other relevant alternative would be the mid-price of the day but usually closing price is more often used as it contains more information than the mid-price. At volatile times mid-price may differ radically of the closing price. Therefore, a return of a trading day is observed when the closing price is known i.e. the difference between closing prices of the two successive trading days. In real world investors would obviously be faster to react to a

new set of information and trading would be based on intraday data too. However, in this case intraday data is not used as it would change the nature of the study too much. Even though time series of the futures are divided into periods of 126 trading days it does not have any effect on return calculations or buy and sell signals. They are applied as there was no change in the period. Only the optimization process is updated while the period changes.

The purpose of the study is not to find both, the most profitable future and trading rule together but to compare the trading rules versus Buy-and-hold strategy, the representative of the EMH. The evaluation could be done by comparing the absolute amount of returns but obviously it is more comparable if the returns are made commensurable. Transaction costs can vary between futures and investors. As transaction costs on the futures markets are very small it is not a big issue that they are excluded out of this study.

In addition it is very important to note that *shorting* is not applied in this study. When sell signal is given only the long position is sold, nothing more. The reason behind exclusion of shorting is the pricing mechanism of the short-term interest rate futures where price goes up if time goes by while all the other factors remain the same. In a situation where a sell signal is given for a following half year period for instance and there are no changes in interest rates it would be a serious problem for the profitability of an interest rate future. It would need another study to examine how shorting should be applied while using technical analysis and technical trading rules.

Another, very fundamental issue regarding to the return calculation is the capital or equity that is invested in interest rate futures or which the return on capital is calculated on. For the most of the investors, the particular considered capital invested is the initial margin that is deposited on a margin account of an exchange or a broker. It is not relevant to use the nominal value of the contract as the margin is the only cash flow required from investor when he enters into a contract. In the recent years, however, regulations for the financial institutions have tightened remarkably. The most recent Basel III and Solvency II standards regulate the banks, insurance companies and some other essential investors how they must internally calculate their levels of capital, especially Tier1 capital. For these investors the capital that is committed on an interest rate futures contract is something more than just the margin required by an exchange. It is not essential to cover it thoroughly in this context. However, according to the regulations they estimate the future movements of the price of the contract. Together

with financial supervisors these investors create models, e.g. Value at Risk (VaR), to value the amount of possible losses and thus the committed capital for a particular transaction is defined. Therefore, the percentage return on a capital for regulated investors is different versus a regular investor.

Because the methods used by the regulated investors may vary between the investors, the methods are not publicly reviewed and they would be very time-consuming to apply using margins is preferred in this study. Some exchanges and brokers require a bigger margin from a speculative investor, *speculator*, than from a *hedger*. As traditionally technical trading rules are more used by the speculators than by hedgers it is desirable to use the bigger speculative margins, if available, in this study and simultaneously more moderate returns are observed as an outcome. Thus, the assumptions of investing habits are made from the investor or speculator point of view where the futures are used purely for risk or view taking purposes. Obviously, this does not rule out the usefulness of the study for the hedgers either.

When the returns on futures are determined capital is not the only contrary issue compared to a similar process for stocks or bonds for instance. Behind the definition of return there are several issues that are obvious on stock markets but are not that clear on the futures markets at all. The return itself is easy to calculate: the difference between the closing prices times the tick value of the future, the value of one tick move in applicable currency. Firstly, the return is calculated on the margins, the capital invested, but the value of the contract is based on the nominal value of the contract. Thus, futures are said to leverage an investment as there is only a small amount of committed capital but the return is earned on a much bigger nominal value.

Secondly, the investor would usually reinvest most of the returns earned on an asset but it is a bit more complicated when it comes to futures. Due to mark to market practice the returns are settled daily. If the returns are positive they also need to be reinvested daily but in practice the returns of futures cannot be reinvested as effectively as returns from stocks because the value of the margin is much more than value of a regular stock on the market. If the returns were negative losses should be covered either by closing the existing contracts or by borrowing some money to cover the losses in margins. However, there are several ways to proceed for sure: some cover all of the losses with debt and deposit all of the profits, some may close all or a part of the positions in a case of losses and invest the profits in new futures contracts. It is not too simple from academic point

of view to define the maximum level of losses that can be taken before closing the position.

Thirdly, because the level of leverage is already deep the risks are also remarkably high for the speculators and therefore investors could be cautious about additional level of leverage by reinvesting the returns. It is more likely that investor decides the stage of leverage at the time of investment decision rather than changes the view about the leverage afterwards.

Thus, only one contract per future is used to keep the simplicity and objectivity in the study. All of the profits are deposited while the losses are covered primarily by the earlier profits or alternatively by borrowing money to keep the margin account on the required level. A simplification has been made that investor is thought to deposit the profits and borrow the funds with the same yield of EONIA rate to describe the short funding cost or deposit yield of an institutional client of an investment bank. However, the levels of EONIA rate are updated daily. If the contract is *in-the-money* the investor receives EONIA rate for the profits and cumulative profits on the deposit account and if it is *out-of-the-money* the investor pays EONIA rate for the losses. The interest calculation of *actual/360* is used with the EONIA rate. As the banks settle the interest and principal only on business days also the interests based on EONIA rates are settled for the strategies only on business days together with the returns from the futures. It is assumed that an exchange or broker pays no interest on the margin account.

In a case of losses return on capital is calculated using the initial capital on the margin account added with the amount of debt that is used to tap the margin account as long as future is on loss. Otherwise the new profits of the strategies on loss would look too optimistic as the new profits would be earned on a smaller amount of capital that is truly committed. This is the only condition where the capital refers not to the initial margin.

The generalization, that only one contract per future is used, spotlights the trading strategies to the focus of the study instead of putting too much attention on how to manage the futures portfolio. Therefore, it is seen as essential method to keep the study consistent.

5. EMPIRICAL RESULTS

This study examines whether there are attractive opportunities on the interest rate futures market using technical trading rules. The trading rules used in the study are traditional RSI, DRSI with three different optimization processes, Moving Average and obviously Buy-and-hold rules. First, daily returns for each of the 133 futures and trading rules are calculated according to the methods described in the previous section. To achieve the daily returns of traditional RSI, Moving Average and Buy-and-hold rules the change in a futures price times the tick value is divided by the capital i.e. initial margin in most of the cases.

However, for the modified versions of RSI, where optimization is needed, the process is somewhat more complicated as there are 3500 combinations of parameters for each of the particular future per every half year trading period. Since the optimization is done the returns are calculated in the same manner for the modified versions of RSI rules. Before going into the results of the study some statistical properties of the returns data are covered.

5.1. Statistical properties of the data

Daily returns of the futures are first analysed by some basic statistical procedures. This evaluation is needed to get a view of the distributions and what sorts of procedures are required to get appropriate end results for the study. Individual detailed statistical properties for each of the futures are presented in the appendix 2 where the futures are presented in a liquidity order within each futures series. Interpreted statistical properties of them as a compilation are presented here in the table 1 where A_1 , B_1 , C_1 , A_2 and B_2 are the five categories of data as specified in the chapter 4.1.

The table 1 consists of the total number of tested time series and number of time series that appear not to follow the normal distribution in terms of skewness to right or left, kurtosis i.e. flatness or peakedness, and Kolmogorov-Smirnov test results. In addition there are means, standard deviations, kurtosis and skewness accompanied with their standard errors presented in the appendix 2.

Table 1. Statistical properties of the return time series.

Trading rule	Data category	N of time series	Skewness right*	Skewness left*	Kurtosis flat*	Kurtosis peaked*	Kolmogorov-Smirnov p-value*
Illiquid data set							
Buy-and-hold	A ₁	58	9	23	0	58	58
	B ₁	39	20	9	0	39	34
	C ₁	35	7	22	0	35	35
DRSI	A ₁	58	23	17	0	58	58
	B ₁	39	25	7	0	39	39
	C ₁	35	20	14	0	35	35
DRSI common optimization	A ₁	58	14	26	0	58	58
	B ₁	39	16	22	0	39	39
	C ₁	35	7	23	0	35	35
RSI (14)	A ₁	58	31	22	0	58	58
	B ₁	39	33	3	0	39	39
	C ₁	35	13	22	0	35	35
Moving Average (1-50)	A ₁	58	23	19	0	58	58
	B ₁	39	2	26	0	39	39
	C ₁	35	2	32	0	35	35
DRSI frequent parameters	A ₁	58	12	26	0	58	58
	B ₁	39	24	3	0	39	38
	C ₁	35	11	21	0	35	35
Liquid data set							
Buy-and-hold	A ₂	30	5	1	0	30	25
	B ₂	16	7	3	0	16	11
DRSI	A ₂	30	8	12	0	30	29
	B ₂	16	8	7	0	16	16
DRSI common optimization	A ₂	30	7	9	0	30	30
	B ₂	16	6	8	0	16	16
RSI (14)	A ₂	30	17	10	0	30	30
	B ₂	16	8	7	0	16	16
Moving Average (1-50)	A ₂	30	10	13	0	30	30
	B ₂	16	2	8	0	16	16
DRSI frequent parameters	A ₂	30	6	10	0	29	28
	B ₂	16	6	6	0	16	16

* Number of return time series that appear to diverge from normal distribution

The skewness of the time series describes the shape of the distribution and if the particular distribution is skewed compared to the normal distribution. If skewness gets a

value of zero the distribution is symmetrical. However, a negative skewness indicates that the left tail is longer than the right one and that the mass of the values of the distribution centre to the right side. If skewness is positive the right tail is longer and the values are centred to the left side and therefore there are only few large values.

A distribution with positive excess kurtosis has a sharp peak around the mean and the tails are fatter. If the excess kurtosis is negative the peak is flat and the tails are thinner. When skewness or kurtosis are more than double compared to their standard errors the distribution is considered to be different in relation to normal distribution. The p -value for Kolmogorov-Smirnov test indicates if the distribution varies from the normal distribution on a 95% confidence level.

A quick look to the table 1 reveals that the data is rather equally divided between left-skewed, right-skewed and non-skewed time series. However, in terms of kurtosis the time series are all leptokurtic without an exception as the peaks are sharp and tails are fat. These skewness and kurtosis statistics indicate that the time series do not follow the normal distribution. As there is such doubt the Kolmogorov-Smirnov test is a good tool to find more support for these findings. Also, Kolmogorov-Smirnov test results indicate that with only a few exception the data is else but normally distributed. Thus, the parametric t-test is not a preferred method to measure whether the returns of the time series are significantly different from each others. Consequently, in this study the non-parametric Mann-Whitney test is used for this purpose and t-test is used only as a secondary or supportive tool.

5.2. Returns on Buy-and-hold rule

The amount of results data is so massive that there is a need to present them in summary tables for each of the trading rules. Detailed tables of results are presented in the appendix 1. In the summary tables there are results for all of the five data categories separately. The symbols of the tables are described as follows:

N_{FUT}	number of futures tested per data category
N_O	number of observations
μ_R	an arithmetic mean return per trading day
r	total return on the particular future during the entire test period
n	number of buy signals observed

T	average number of days between buy and sell signals
t	p -value of the t -test
MW	p -value of the <i>Mann-Whitney</i> -test
S	value of the Sharpe ratio

Table 2 presents quantities of those future time series where Buy-and-hold rule is the most profitable trading rule of the ones used in this study. The table is a summary of the detailed tables of results in the appendix 1 where daily returns for each future and trading rule are presented accompanied with other future specific data.

Table 2. Relative profitability of the Buy-and-hold rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A ₁	58	38	12	8
B ₁	39	9	8	4
C ₁	35	11	11	9
Liquid data set				
A ₂	30	11	11	5
B ₂	16	5	4	1

* Number of future time series where Buy-and-hold rule was the most profitable of all trading rules

The daily mean returns on the Buy-and-hold strategy are the highest of all trading rules included in the study in 38 out of 58 or 66 % of A₁ category futures. In the rest of the categories around one third or fourth of the daily futures returns are the highest of all. Also, in terms of daily returns the futures of ‘A’ categories seem to be relatively more profitable than the futures of other categories. This could mean that trading rules do not work as well on the liquid markets as on the illiquid markets giving some support to the views that the developed and liquid markets are not offering as good returns as the illiquid market.

In the end, it is the total return that matters for the investor. However, it is a bit problematic to use total returns as the price fluctuations of futures on a single day on may be very large. In the appendix 2 there are minimum and maximum values of the time series presented where absolute minimum return of the entire data is -146 % and

maximum 343 % on a single day. The problem with the large fluctuations is that the total returns can be remarkably dependent of the holding or trading period. Total return is a good indicator of relative profitability between the trading rules as all of the rules are using the same data. Because of large fluctuations in the data it is not that good estimator of the absolute profitability. For A_1 category the total returns of Buy-and-hold rule over the entire data period are the highest of all trading rules in remarkably lower amount of futures than using daily mean returns. In other words, Buy-and-hold rule appears to be more profitable for this category when daily mean returns are used to measure the performance. However, in cases of other categories there is no big difference between using the daily returns or total returns. A reason behind the strong result by particularly Buy-and-hold rule for the most liquid futures on the illiquid period is that majority of the futures were launched in 2000–2001 when the USD-rates were at the top of the last 20 years and in July 2009 the rates were at the all time lows. In terms of the interest rate futures' pricing, this strong trend of decreasing yields brought the futures prices up so remarkably that Buy-and-hold rule was not easy to beat. To describe the strength of the trend the most profitable future over the entire data period made the investment worth almost 26 times the original investment using Buy-and-hold rule.

Sharpe ratios of the Buy-and-hold rule reveal that returns of the strategy in relation to the risk or standard deviation make other strategies to look more attractive as the Sharpe ratios are the worst part for the Buy-and-hold rule. The result is not that shocking as the technical strategies actually aim to get rid of the negative bear market returns where the risk indicator of the Buy-and-hold rule is normally higher because the data includes all of the days over the period, the days of positive and negative returns.

Table 3. Average returns of the Buy-and-hold rule.

Data set	μR (%)	r (%)	S
Illiquid data set			
A_1	0.310	497	0.0398
B_1	0.345	764	0.0348
C_1	0.543	748	0.0790
Liquid data set			
A_2	0.234	405	0.0305
B_2	0.530	587	0.0661

In the table 3 the averages of categories using the Buy-and-hold rule are measured. A surprise or not, the most illiquid category, C_1 , yields the best average daily mean return, Sharpe ratio and is rather even in terms of absolute return with B_1 category. It is remarkable that B_2 category as a liquid category has a better average return than its illiquid peer B_1 . A reason for this could be that the holding periods in the B_2 are remarkably shorter and therefore only a short market disruption could change the big picture of the category.

According to the tables in the appendix 1 the most profitable future using Buy-and-hold rule has daily mean return as much as 1.45 %. However, there are only 155 trading days in the trading period of the particular future and therefore there is a possibility that the profitable trading period is just a coincidence.

5.3. Returns on DRSI rule

The DRSI rule is based on RSI rule but uses two indices to analyse the correct moment for buy and sell signals. As DRSI rule is new and central regarding to the purpose of the study it is logical to begin the technical trading rule results with that. In the table 4 there are presented the quantities of the future time series where DRSI trading rule is the most profitable trading rule used in this study. The table is a summary of the detailed tables of results in the appendix 1. The results show that DRSI is not the best performer of the trading rules as there are only 6 out of 178 future time series where it generated the best daily mean returns.

Table 4. Relative profitability of the DRSI trading rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A_1	58	1	5	6
B_1	39	1	1	2
C_1	35	1	0	1
Liquid data set				
A_2	30	3	3	2
B_2	16	0	0	1

* Number of future time series where DRSI rule was the most profitable of all trading rules

Regarding to the results of Buy-and-hold rule it is clear that the trading rules should do better than Buy-and-hold in terms of total return and Sharpe ratio. Total return and Sharpe ratio results for DRSI rule, however, give only a slightly better image of the trading rule. As in total return segment DRSI rule is the best performing trading rule only in 9 and in terms of Sharpe ratio only in 12 out of 178 future time series it is apparent that there are better performing trading rules used in the study.

Even though the returns earned by DRSI rule are not winners in the most of the cases in the table 5 it is shown that DRSI manages relatively better if the rule is compared to Buy-and-hold rule only. Still the daily mean returns are better for Buy-and-hold strategy in majority of the futures time series. A_2 is the only data set where DRSI beats the Buy-and-hold in almost one-third of the time series. In general, total returns for DRSI do not perform much better. Categories A_1 and A_2 are the only where also DRSI rule is successful almost in one-third of the cases. However, if returns are reviewed in terms of risk there is a bigger improvement as in 48 out of 178 future time series DRSI rule generate better Sharpe ratios than Buy-and-hold.

Table 5. Profitability of the DRSI trading rule compared to Buy-and-hold rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A_1	58	4	17	15
B_1	39	3	4	12
C_1	35	6	2	6
Liquid data set				
A_2	30	9	8	11
B_2	16	2	2	4

* Number of future time series where DRSI rule was the more profitable than Buy-and-hold rule

There is quite a big margin in favour of Buy-and-hold rule versus DRSI rule. The returns regarding to the statistical significance are observed in the table 6. Even though DRSI rule yielded better total returns than Buy-and-hold in 17 futures time series of A_1 category DRSI rule is left with almost nothing in terms of statistically significant returns. In the C_1 data category there are only three futures where DRSI rule's superiority is statistically significant. In addition there is one future in A_2 data category where DRSI

trading rule performed better than Buy-and-hold. Thus, these results show that there are some occasions when DRSI rule breaks the efficient market hypothesis although it is not common at all. Coincidence or not but these occasions are actually all in the most illiquid categories: C_1 and B_2 .

Table 6. Statistically significant profitability of the DRSI trading rule.

Data set	N_{FUT}	μ_R *	r *
Illiquid data set			
A_1	58	0	0
B_1	39	0	0
C_1	35	3	2
Liquid data set			
A_2	30	0	0
B_2	16	1	1

* Number of future time series where DRSI was more profitable rule than Buy-and-hold rule and statistically significant at 5 % level (MW-test).

Average returns of the DRSI rule, shown in the table 7, are remarkably lower versus Buy-and-hold strategy as they are less than half of the returns generated by Buy-and-hold. A_1 is the most yielding data category in terms of average daily mean returns or average total returns using DRSI rule. It is good to note, however, that the returns between the data categories are rather close to each other indicating some stability in the trading rule returns.

Table 7. Average returns of the DRSI rule.

Data set	μR (%)	r (%)	S
Illiquid data set			
A_1	0.148	283	0.0253
B_1	0.040	260	0.0027
C_1	0.108	118	0.0233
Liquid data set			
A_2	0.135	177	0.0196
B_2	0.141	58	0.0252

Even though the average returns of the DRSI rule are worse than returns by Buy-and-hold rule there are some individual futures time series where DRSI manages to yield a massive return. As shown in the tables of appendix 1 the most profitable future using DRSI trading rule generated a 0.92% daily mean return. However, there is the same problem previously covered in the Buy-and-hold section that trading period of this particular future from A₂ category is not more than 249 trading days being very close to a year. Supposedly, there is a better chance for a large daily mean return while the trading period is short – the longer the period the smaller the chance. In addition, another future from B₁ category gained total returns worth 29 times the original investment, or initial margin, using DRSI rule.

5.4. Returns on DRSI common optimization rule

As DRSI rule is not performing too well on this data it is essential to test whether the problem is in the optimization process. The parameters may have a huge impact on the results and therefore it is crucial to use the optimal optimization process. With DRSI rule the optimization is done separately for each of the futures using data of the previous year updated twice a year. However, with DRSI common optimization rule the optimization is similar but it is based on all future time series in each of the five data categories separately. In other words the same parameters are used for all the futures time series within each data category.

Table 8. Relative profitability of the DRSI common optimization trading rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A ₁	58	14	24	32
B ₁	39	4	2	6
C ₁	35	5	3	1
Liquid data set				
A ₂	30	10	8	10
B ₂	16	0	0	2

* Number of future time series where DRSI common optimization rule was the most profitable of all trading rules

According to the table 8 it can be concluded that the DRSI common optimization rule seems to perform remarkably better versus DRSI rule. The trading rule generates the best daily mean returns of all trading rules in 33 out of 178 futures time series. DRSI common optimization rule seems to work particularly for the both, A_1 and A_2 data categories racking up around one-fourth and one-third respectively of the first places. This trading rule manages to be the most successful trading rule in over 40 % of A_1 category in terms of total returns. These findings indicate that there are other trading rules that have better returns in other, more illiquid, data categories. In terms of Sharpe ratio DRSI common optimization rule performs even better having over a half of the first places in the category A_1 .

If profitability of the DRSI common optimization rule is compared only to the Buy-and-hold rule there are outstanding improvements in the performance compared to the regular DRSI rule as shown in the table 9. When DRSI common optimization was compared to all of the trading rules previously only A_1 and A_2 data categories performed. However, in this case the trading rule performs with a wide range still A_1 category being the best of those. 62 out of 178 futures time series using DRSI common optimization rule gained better daily mean returns than Buy-and-hold. In terms of total returns the trading rule performs better in A_1 data category where as much as 42 out of 58 futures time series were yielding more using DRSI common optimization rule versus Buy-and-hold. The trading rule again has the best performance when Sharpe ratios are reviewed. Over 55 % of the futures time series have better Sharpe ratios using DRSI common optimization rule over Buy-and-hold.

Table 9. Profitability of the DRSI common optimization trading rule compared to Buy-and-hold rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A_1	58	16	42	38
B_1	39	12	8	18
C_1	35	15	7	16
Liquid data set				
A_2	30	14	12	16
B_2	16	5	2	11

* Number of future time series where DRSI common optimization rule was the more profitable than Buy-and-hold rule

Even though DRSI common optimization trading rule shows solid performance versus Buy-and-hold rule in some of the data categories it is shown, in the table 10, that very few of the differences in performance are statistically significant. Also in the previous subsection it is shown that C_1 and B_2 data categories were the only categories to show any statistically significant and superior returns over Buy-and-hold rule. However, in this case in C_1 data category there are 11 futures time series where daily mean returns and 7 futures where total returns by DRSI common optimization rule are better than ones by Buy-and-hold rule. This indicates that there are some inefficiencies in the markets where the futures of C_1 data category belong to. According to the table 27 in the appendix 1 DRSI common optimization rule performs on the MYR denominated interest rate futures market. With DRSI common optimization there is also one successful futures time series in B_2 data category.

Table 10. Statistically significant profitability of the DRSI common optimization trading rule.

Data set	N_{FUT}	μ_R *	r *
Illiquid data set			
A_1	58	0	0
B_1	39	1	1
C_1	35	11	7
Liquid data set			
A_2	30	0	0
B_2	16	1	1

* Number of future time series where DRSI common optimization rule was more profitable than Buy-and-hold rule and statistically significant at 5 % level (MW-test).

In the table 11 there are average returns of the DRSI common optimization rule. After the previous findings it is not a surprise that on average DRSI common optimization rule performs remarkably better than plain DRSI rule. Nevertheless Buy-and-hold has still the highest average daily mean returns, total returns and Sharpe ratios. Only in the A_2 data category the average daily mean returns are higher using DRSI common optimization trading rule than Buy-and-hold rule. Also in the A_1 data category the average total returns are better for this trading rule. In the framework of return versus risk DRSI common optimization rule beats Buy-and-hold in the A_1 and A_2 data categories.

Table 11. Average returns of the DRSI common optimization rule.

Data set	μR (%)	r (%)	S
Illiquid data set			
A ₁	0.282	576	0.0490
B ₁	0.166	427	0.0284
C ₁	0.381	417	0.0614
Liquid data set			
A ₂	0.256	364	0.0355
B ₂	0.289	280	0.0635

It is shown in this section that optimization process have huge impact on the performance of DRSI strategy as DRSI common optimization rule generate better returns in almost every category versus regular DRSI rule. In the tables of the appendix 1 it is shown that the best performing future is from C₁ data category and yields a 1.20 % daily mean return. Also in this case the trading period is not very long with 221 trading days. Another future from B₁ category gained total returns worth as much as over 30 times the initial margin using DRSI common optimization rule.

5.5. Returns on RSI rule

In the previous academic studies RSI never was the most popular trading rule to study. The performance, however, is more or less disunited. Also, for the modified versions of RSI rule, DRSI rule and DRSI common optimization rule, the results show that there are some occasions where these modified versions work and some where they do not work. Therefore, it is interesting to take a closer look at the returns generated by the original RSI rule to see whether there is a place for these modifications or not.

According to the table 12 where quantities of the best performing futures using RSI rule are presented, RSI rule is rather even with DRSI rule. Even though the daily mean returns using RSI rule are the best of all trading rules only in 3 cases RSI rule yields the best total returns in 23 out of 178 futures time series returns. In terms of total returns RSI rule performs clearly the best of its results in the A₁ data category. When risk versus return is took into account the RSI trading rule actually performs worse as 11 out of 178 futures had the best Sharpe ratios of all trading rules.

Table 12. Relative profitability of the RSI trading rule.

Data set	N_{FUT}	μ_R^*	r^*	S^*
Illiquid data set				
A ₁	58	0	14	4
B ₁	39	0	0	1
C ₁	35	1	2	1
Liquid data set				
A ₂	30	0	2	0
B ₂	16	2	5	5

* Number of future time series where RSI rule was the most profitable of all trading rules

Again, in this case RSI rule obviously performs better when it is compared only to the Buy-and-hold rule instead of all the trading rules in the table 13. The improvement concentrates mostly to daily mean returns and Sharpe ratios sections. In the total returns section 28 futures yielded better returns than Buy-and-hold rule. However, as in the previous comparisons the Sharpe ratios are usually weaker for Buy-and-hold rule also in terms of RSI trading rule it performs relatively better as in 38 out of 178 futures time series, or in approximately 21% of the future time series generate better risk compensated returns than Buy-and-hold. According to these results DRSI trading rule is performing slightly better than RSI trading rule.

Table 13. Profitability of the RSI trading rule compared to Buy-and-hold rule.

Data set	N_{FUT}	μ_R^*	r^*	S^*
Illiquid data set				
A ₁	58	7	16	13
B ₁	39	0	0	2
C ₁	35	4	3	11
Liquid data set				
A ₂	30	5	4	6
B ₂	16	4	5	6

* Number of future time series where RSI rule was the more profitable than Buy-and-hold rule

Table 14. Statistically significant profitability of the RSI trading rule.

Data set	N_{FUT}	μ_R *	r *
Illiquid data set			
A ₁	58	0	0
B ₁	39	0	0
C ₁	35	3	2
Liquid data set			
A ₂	30	0	0
B ₂	16	2	2

* Number of future time series where RSI rule was more profitable than Buy-and-hold rule and statistically significant at 5 % level (MW-test).

RSI trading rule apparently works better than Buy-and-hold in some of the cases. However, if these results are reviewed in terms of statistical significance the results in the table 14 are similar to the previous chapters as there is evidence of market inefficiencies only in C₁ and B₂ data categories. DRSI common optimization rule is performing remarkably better compared to RSI rule as there are only 5 futures time series where the daily mean returns are higher and statistically significant versus Buy-and-hold rule. For the total returns the number of futures is not more than 4 futures time series. Therefore, RSI rule's performance sets next to regular DRSI rule.

Table 15. Average returns of the RSI rule.

Data set	μR (%)	r (%)	S
Illiquid data set			
A ₁	0.079	175	0.0110
B ₁	-0.131	-33	-0.0239
C ₁	0.238	216	0.0428
Liquid data set			
A ₂	-0.137	-6	-0.0191
B ₂	0.297	81	0.0500

Looking at the average returns generated by the RSI rule in the table 15, it is interesting that the average daily mean returns, total returns and Sharpe ratios between the five data

categories are rather far away from each others. C_1 and B_2 data categories perform also in terms of average returns over here as the average daily mean returns for these categories are higher than what the corresponding categories generated using regular DRSI rule. However, RSI rule also yields the worst returns so far as in B_1 and A_2 data categories average returns were negative. For C_1 and B_2 data categories the Sharpe ratios show that if the RSI rule works for the data category the risk adapted returns are rather good, but the problem with the RSI rule is that it does not yield consistent returns over the categories at all.

As it is shown earlier in this section RSI rule is rather near to the regular DRSI rule in terms of profitability. However, it is important to remind that volatility in returns is much higher with RSI rule. In the previous section it is observed that optimization matters and therefore it would be interesting to examine whether there would be improvement in the returns using RSI rule if the parameters were optimized using the same procedures. Nevertheless, the best performing future yields 1.00 % on daily average as it is shown in the tables of the appendix 1. It is more than what the best future yielded using DRSI rule but again, the return of this future from B_2 data category is a product of rather short investment period of 145 trading days. Another future from B_2 data category generates the best total return using RSI rule as it generated returns worth almost nine times the investment.

5.6. Returns on Moving Average rule

In the previous sections there are RSI rule and its modifications compared in terms of profitability. It is also observed that trading rules work much better in some of the data categories than in others. Therefore, it is interesting to compare the results with a trading rule that works in a totally different way.

In the table 16 there are the quantities of futures where Moving Average rule is the most profitable trading rule above all others. It is not a surprise that there is not much left in the A_1 data category as Buy-and-hold and DRSI common optimization rule were both performing rather well in this category. However, in the most illiquid categories of B_1 , C_1 and B_2 the game is very different as Moving Average is the most returning trading rule for around half of the futures time series. Especially for B_1 data category Moving Average rule yields relatively the best returns as it generates the highest daily mean returns for 23, highest total returns for 28 and highest Sharpe ratios for 26 out of 39

futures time series. Regarding to the whole data set Moving Average generates the highest daily mean returns for 50 out of 178 futures time series being clearly better than DRSI common optimization rule. Moving Average generates the best total returns for 58 futures time series which is better than any of the other trading rules so far, including Buy-and-hold. In terms of Sharpe ratios Moving Average is even more supreme over the other trading rules as it generates the best Sharpe ratios for 69 out of 178 futures time series.

Table 16. Relative profitability of the Moving Average trading rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A ₁	58	2	2	7
B ₁	39	23	28	26
C ₁	35	16	18	21
Liquid data set				
A ₂	30	2	3	8
B ₂	16	7	7	7

* Number of future time series where Moving Average rule was the most profitable of all trading rules

Table 17. Profitability of the Moving Average trading rule compared to Buy-and-hold rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A ₁	58	3	2	8
B ₁	39	28	30	32
C ₁	35	23	21	24
Liquid data set				
A ₂	30	6	5	9
B ₂	16	8	8	10

* Number of future time series where Moving Average rule was the more profitable than Buy-and-hold rule

While comparing the Moving Average rule only to Buy-and-hold rule it can be seen in the table 17 that in A data categories Buy-and-hold rule is superior. Regarding to the

previous paragraph it is not surprising that in the most illiquid categories of B₁, C₁ and B₂ Moving Average performs better versus Buy-and-hold rule. Moving Average yields the relatively best returns for B₁ category again over the other trading rules. Even though Moving Average performs better in those three illiquid data categories the Buy-and-hold performs so much better in liquid A data categories that it takes the glory in terms of daily mean returns, total returns and even Sharpe ratios while the whole data set is reviewed.

Table 18. Statistically significant profitability of the Moving Average trading rule.

Data set	N_{FUT}	μ_R *	r *
Illiquid data set			
A ₁	58	0	0
B ₁	39	0	0
C ₁	35	13	13
Liquid data set			
A ₂	30	0	0
B ₂	16	1	1

* Number of future time series where Moving Average rule was more profitable than Buy-and-hold rule and statistically significant at 5 % level (MW-test).

Even though Moving Average generates better returns than Buy-and-hold for rather many of the futures time series also in this case as with the previously covered trading rules there are not that many statistically significant returns generated by Moving Average rule. However, the results in the table 18 indicate that in the C₁ data category there are some remarkable inefficiencies on the market as for 36 % or 13 out of 36 futures time series Moving Average generates statistically significantly better daily mean returns and total returns over Buy-and-hold rule. This makes Moving Average slightly better performer versus DRSI common optimization rule.

In the previous section it is observed that averages of daily mean returns, total returns and Sharpe ratios diverge intensely between the data categories. Also in this case of Moving Average rule the averages between the data categories are rather far from each others as shown in table 19. As average daily mean returns for C₁ data category reach as high as 0.605 % for A₂ data category it is -0.026 %. Average daily mean returns and total returns for B₁ and C₁ data categories are higher than by using any other rule

previously covered. In terms of risk versus return Moving Average rule generates the best average Sharpe ratios in addition to B₁ and C₁ also in B₂ data category.

Table 19. Average returns of the Moving Average rule.

Data set	μR (%)	r (%)	S
Illiquid data set			
A ₁	0.004	120	0.0055
B ₁	0.356	997	0.0591
C ₁	0.605	893	0.1005
Liquid data set			
A ₂	-0.026	187	-0.0033
B ₂	0.352	570	0.0773

In this chapter it is shown that the highest returns by Moving Average concentrate to illiquid data categories. This is not surprising as previous literature suggests that there are more inefficiencies on the illiquid developing markets than on the developed markets. However, the best daily mean returns using Moving Average rule are generated by a future from C₁ data category returning 1.15 % daily during 155 trading days. In terms of total returns another future from B₁ data category generated a return of more than 32 times the initial margin through the investment period.

5.7. Returns on DRSI frequent parameters rule

In the previous chapters it is observed that optimization is critical in terms of profitability of the trading rule. Of the RSI based rules examined in this study the DRSI common optimization rule performs clearly better than the rest of them. Furthermore, regular RSI with 14 trading days' average period and signal limits of 30 and 70 suggested by Wilder (1978: 63–65) is not performing any better than DRSI rule with optimization that is separate for each future. It is interesting to see whether such fixed parameters could have been found that generate superior returns for every interest rate future. The most popular parameters of this study and the ones used in with this trading rule are:

- 2 days' average with shorter RSI
- 8 days' average with longer RSI
- lower bound of 40
- higher bound of 80

However, the popularity of the different parameters options is rather equal. This indicates that these 'optimal' parameters may not perform with all of the futures and therefore the results may not satisfy. Also, it is important to remind that the optimization in this case is done with the same data that is used as an investment period. Therefore the results are biased and must be treated with a care. Anyway, it is interesting to see if there could be any potential in the DRSI rule without optimization process that is continuous and updated.

DRSI frequent parameters rule is not very promising according to table 20 where the quantities of futures where the trading rule generated the best returns over all other rules are presented. It seems that DRSI frequent parameters rule is performing best while A data categories and daily mean returns are observed. However, the differences are not remarkable and the overall performance comes across as rather poor. Daily mean returns using DRSI frequent parameters rule are best over other rules in 12 out of 178 futures time series. If considering total returns the amount of futures declines to only 5 and in terms of Sharpe ratios there are 8 futures out of 178 where DRSI frequent parameters rule performs best over other rules.

Table 20. Relative profitability of the DRSI frequent parameters trading rule.

Data set	N_{FUT}	μ_R *	r *	S *
Illiquid data set				
A ₁	58	3	1	1
B ₁	39	2	0	0
C ₁	35	1	1	2
Liquid data set				
A ₂	30	4	3	5
B ₂	16	2	0	0

* Number of future time series where DRSI frequent parameters rule was the most profitable of all trading rules

Comparing the returns of DRSI frequent parameters rule and Buy-and-hold rule in the table 21 the conclusion is rather similar that the rule performs the best in A categories. Daily mean returns are better using DRSI frequent parameters rule versus Buy-and-hold for 33 out of 178 futures time series. When comparing total returns 41 futures time series generate better returns using DRSI frequent parameters rule. In terms of Sharpe ratio the rule performs better than Buy-and-hold in 45 out of 178 futures time series. However, in the A_2 data category for around 30 % of the futures time series DRSI frequent parameters rule performs better than Buy-and-hold rule in terms of daily mean returns, total returns and Sharpe ratios.

Table 21. Profitability of the DRSI frequent parameters trading rule compared to Buy-and-hold rule.

Data set	N_{FUT}	μ_R^*	r^*	S^*
Illiquid data set				
A ₁	58	8	22	12
B ₁	39	2	0	3
C ₁	35	8	4	12
Liquid data set				
A ₂	30	11	10	11
B ₂	16	4	5	7

* Number of future time series where DRSI frequent parameters rule was the more profitable than Buy-and-hold rule

Table 22. Statistically significant profitability of the DRSI frequent parameters trading rule.

Data set	N_{FUT}	μ_R^*	r^*
Illiquid data set			
A ₁	58	0	0
B ₁	39	0	0
C ₁	35	5	2
Liquid data set			
A ₂	30	0	0
B ₂	16	1	1

* Number of future time series where DRSI frequent parameters rule was more profitable than Buy-and-hold rule and statistically significant at 5 % level (MW-test).

In the table 22 there are statistically significant profitability differences compared between DRSI frequent parameters rule and Buy-and-hold rule. Even though the trading rule performs in A_2 data category versus Buy-and-hold rule none of the return differences are statistically significant. The results are very similar to those of regular RSI and DRSI rule as DRSI frequent parameters rule generates statistically significantly better daily mean returns for 6 out of 178 futures time series.

There are averages of the data categories on daily mean returns, total returns and Sharpe ratios generated by the DRSI frequent parameters rule in the table 23. As there is rather large volatility in average returns of RSI rule and Moving Average rule Buy-and-hold and DRSI rules appear to be more stable between the data categories. DRSI frequent parameters rule gives its relative best in the A_1 , A_2 and B_2 data categories. In terms of absolute returns DRSI frequent parameters rule beats regular RSI rule and DRSI rule but comes clearly after Buy-and-hold, DRSI common optimization and Moving Average rules in most of the cases.

Table 23. Average returns of the DRSI frequent parameters rule.

Data set	μR (%)	r (%)	S
Illiquid data set			
A_1	0.236	365	0.0313
B_1	0.060	100	0.0070
C_1	0.235	301	0.0404
Liquid data set			
A_2	0.169	262	0.0219
B_2	0.315	171	0.0371

According to the tables in the appendix 1 the best daily mean return on a single future using DRSI frequent parameters rule is 1.00 % while the best total return observed is over 15 times the initial margin. Because the optimization of parameters is processed during the same period that is used as an investment period should the returns of the DRSI frequent parameters rule be remarkably better to impress with the performance of the trading rule. Therefore, the results on DRSI frequent parameters rule do not support the view that the trading rule with current parameters would be consistently and remarkably better than regular RSI rule or other variations of DRSI rule.

5.8 Other remarkable observations

Whereas the profitability of the trading rules is covered in the previous sections it is observed that technical trading rules can generate significantly better returns versus Buy-and-hold rule mostly in C_1 data category only. Table 27 in the appendix 1 presents that on Malaysian ringgit denominated short term interest rate futures market one can consistently generate excess returns using technical trading rules. Moving Average rule generates statistically significantly better returns versus Buy-and-hold rule in 12 out of 14 futures time series with a 0,167 % difference in average daily mean returns. Meanwhile DRSI common parameters rule is statistically significantly better than Buy-and-hold rule in 8 and DRSI frequent parameters rule in 6 out of 14 futures time series. In terms of yield, Buy-and-hold generates better return versus technical trading rules in 1 futures time series on the Malaysian ringgit denominated short term interest rate futures market.

Another fascinating finding regarding to the profitability of certain interest rate futures series is that DRSI common optimization rule is the best trading rule with no question in A_1 and A_2 categories. For the rest of the data categories B_1 , C_1 and B_2 Moving Average trading rule is clearly the best yielding technical trading rule. A careful examination of the results tables about futures time series in the appendix 1 does not explain why these data categories are divided in such way between DRSI common optimization and Moving Average. It is interesting that using DRSI common optimization rule some of these single future returns and also some average returns of the futures series in the most liquid categories, A_1 and A_2 , are better than what is earned by Buy-and-hold rule while those illiquid B_1 , C_1 and B_2 data categories work best for Moving Average rule. Even though there is evidence of technical trading rules generating better return over Buy-and-hold rule it is important to keep in mind that mostly these results are not statistically significant.

A reason why some of the futures series are more profitable than others may lie in the market trends. In the appendix 3 there are figures presenting the historical interest rates of the relevant period for all of the currencies included in the study. In the figure 7 the US interest rates are reviewed. A trend from the beginning of year 2000 to the end of the time series, 31 July 2009 was very steep. Consistent with the pricing mechanism of interest rate futures if interest rates are coming down the price of the future goes up. Because of so large drop in interest rates it is probable that Buy-and-hold was very hard to beat at that time. However, years 2001 to 2004 there were exceptionally low interest

rates in US meaning high interest rate futures prices at that time. This should convert to lower profits for Buy-and-hold rule. Using table 24 in the appendix 1 and table 31 in the appendix 4 it can be calculated that over 80 % of the futures in the ED-future series whose time series begins in 2001 to 2004 are having lower daily mean returns using Buy-and-hold rule than ED-futures on average. This indicates that Buy-and-hold works the best while there is a steep trend of lowering interest rates while steady or fluctuating interest rates make the rule not-that-profitable.

Other main factors affecting the short-term interest rate futures prices are time and the shape of the interest rate curve. When the time goes by if all other things are equal and the interest rate curve is rising there is a pull to par effect where price of the contract rises when the settlement gets nearer. Also changes in the shape of the interest rate curve affect the prices of the contracts. While the curve steepens prices of short-term interest rate futures go down and when the curve flattens prices go up. This effect is the largest in contracts with the longest time to settlement. The steepness is illustrated in the figures of the appendix 3 as a spread between 3-month and 5-year interest rates. The higher the spread is the steeper the interest rate curve is. If the spread is less than zero the curve is invert. This happens usually only when economic downturn is about to come but central bank actions on interest rates lag versus markets' view of the future interest rates.

One can easily analyse the figures in the appendix 3 and conclude that at least in USD, EUR, GBP, CHF and NZD denominated futures rather likely Buy-and-hold rule is successful only because there is a dramatic decrease in interest rates before the time series end. The interest rate curve steepening reduces the gains achieved by interest rate decrease in these same futures. However, as steepening of the curve has its biggest effect in longer maturities and as in the end of the gathered data period there are 47 out of 164 futures that have more than three years to the settlement the price changes in the short-term interest rate futures are based mostly on changes in level of the whole interest rate curve instead of its shape. Technical trading rules are not able to fully take advantage of price fluctuations or changes in the shape of interest rate curve during the data period as shorting is not applied in this study.

While DRSI rules are compared to regular RSI and Moving Average rules it must be highlighted that returns of DRSI, DRSI common optimization and DRSI frequent parameters rules are very constant from a data category to another and is rather similar to the behaviour of Buy-and-hold rule in that sense. The average returns of each data

category provided by Buy-and-hold rule and the three DRSI modifications are all positive and relatively close to each other while RSI and Moving Average rules generated some negative average returns and there is quite a distinction between some of the data categories meaning higher volatility in returns.

It is also observed that the number of trades and returns of trading rules are not connected to each other. Though, it must be noted that the number of trades is very different between each of the trading rules. For example Moving Average rule has always a bigger number of trades than RSI rule and its modifications. However, it is found that the number of days between buy and sell signal is connected with the profitability of trading rules. While a longer time period generates better return the number of days between buy and sell signal may change from trading rule to another without having an effect to profitability.

In addition, it is found that technical trading rules perform better than buy-and-hold if risk and return are compared, referring to Sharpe ratios. The tables in the appendix 1 reveal that Sharpe ratios of DRSI common optimization rule are better in A1 and A2 data categories than what is generated by Buy-and-hold rule. On the other hand Moving Average rule has the best Sharpe ratios in rest of the three categories, B₁, C₁ and B₂. This finding indicates that DRSI common optimization rule and Moving Average rules can generate better return versus risk than Buy-and-hold. In other words these technical trading rules should reduce the risk profile of an investor without losing any profits. Also in theory this should be the case if trading rules work as they were meant to work: while Buy-and-hold rule is all the time in long position the trading rules are trying to find the most profitable and usually less volatile periods of time to be long in an asset. However, the performance of trading rules is very sensitive as DRSI common optimization and Moving Average rules are the only trading rules in this study which can generate better Sharpe ratios than Buy-and-hold strategy. While these two technical trading rules generate the best Sharpe ratios together for the whole data it must be noted that not a single trading rule can constantly generate higher Sharpe ratios than Buy-and-hold strategy.

6. CONCLUSIONS

The purpose of this study is not to find the most profitable future but to examine if using technical trading methods can challenge the efficient market hypothesis and generate excess returns regarding to Buy-and-hold strategy and compare the trading rules between each others. Thus, the efficient market hypothesis has a role of key theorem in this study as this is another study trying to provide new information about the relationship between the efficient market hypothesis and financial markets.

Theoretical background for the ideas of an efficient market was constructed when Working (1934) and Kendall (1953) suggested that stock prices act in a random way. Alexander (1961) confirmed the randomness in the prices but observed also that there is a momentum effect in the market. Later his findings were questioned by Fama and Blume (1966) as they proved that only few positive returns can be earned by using the same methodologies but including the trading commissions. However, debate was yet to come. Since Fama (1970) formed conditions of the efficient market hypothesis it has been in the focus of academic researchers as one after another is trying to prove or disprove the existence of the hypothesis' three forms.

The strong and semi-strong forms of the efficient market hypothesis state that all information and all publicly available information, respectively, are reflected in the asset price. This study focuses on technical analysis used to find mispriced securities that have not yet incorporated all of the information and to predict future performance or a trend of an asset. Such analysis is based on the historical trading data only and therefore the weak form of the efficient market hypothesis is tested in this study. (Fama 1970: 383, 388; Fama 1991: 1576–1577.)

The performance of technical analysis has been one of the most popular and most argued subjects on the academic field of finance. Brock et al. (1992) found that Moving Average rule can generate higher profits than Buy-and-hold while Gençay (1998) observed that moving average performs better in a highly fluctuating market. However, Pukthuanthong-Le and Thomas (2008) showed that in history there used to be greater excess profits using Moving Average rule than nowadays as markets are seen as more developed – more efficient.

Moving Average trading rule is widely used in the market but it is also very often seen in academic studies. Therefore the use of Moving Average is justified as a reference

trading rule as the rule itself is already rather well covered. In this study, however, the Relative Strength Index and its modifications are in the spotlight. There are three modifications used in addition to the original Relative Strength Index suggested by Wilder (1978; 63–70). A major change compared to the original trading rule that links the modifications together is that there are two RSI-indices, short and long, used instead of one. As Thachuk (2000) and Seiler (2001) proposed optimizing parameters also in this study the optimization process is introduced to optimize the parameters of Relative Strength Index trading rule.

Even though interest rate futures are frequently used as data in academic studies the ‘interest rate future’ refers often to the government bond futures, German or US in the most of those contexts. However, the data of this study consists of short term interest rate futures that are futures for a three-month time deposit beginning on delivery date of a future. The instrument is very broadly used in the markets and the most liquid short term interest rate futures contracts are in the same category with German government bond futures in terms of liquidity and open interest. Data is gathered from January 1st 2000 to July 31st 2009 and after filtration it includes 11 future series, 132 futures and 149,212 observations in total. The futures are quoted in 7 currencies: US dollars, euros, British pounds, Japanese yen, Swiss francs, New Zealand dollar and Malaysian ringgit.

Consistent with the majority of previous studies the findings of this study support the view that in the most of the cases technical trading rules cannot consistently generate higher returns versus Buy-and-hold strategy. In terms of return Buy-and-hold rule yields the best daily mean returns in the majority of futures of the most liquid data categories. However, it is interesting that the results of daily mean returns and total returns over the rest of the data period are not too similar as Buy-and hold rule performs much weaker especially in total returns.

RSI and two of its modifications, DRSI and DRSI frequent parameters rules, perform rather badly as a majority of the evidence show Buy-and-hold rule to perform better. Regular DRSI rule has a too short optimization period and therefore the parameters provided by optimization were not reliable enough. With DRSI frequent parameters rule it was tested if a continuous optimization process is needed or is there a set of universal set of parameters that fits for all of the futures. Popularity of different parameters’ combinations is so near to each others that not a single set of parameters are found to consistently generate better returns versus buy-and-hold rule. However, DRSI common optimization rule manages to yield higher daily mean returns than Buy-and-hold rule in

the category of the most liquid futures. Therefore, optimization mechanism has apparently a major effect on the profitability. A mechanism of DRSI rule where optimization is done separately for each of the futures is clearly not working. However, there is solid evidence that a mechanism used in DRSI common optimization rule, where each data category has separately optimized parameters, is working better as it is capable to compete with Buy-and-hold rule.

DRSI common optimization rule generates better daily mean returns in 35 %, better total returns in 39 % and better Sharpe ratios in 56 % of all the futures time series over Buy-and-hold rule whereas the best performance of the trading rule is observed in the categories of the most liquid data, A_1 and A_2 . Even though the returns of DRSI common optimization rule are slightly better than Buy-and-hold rule many results of the futures in A_1 and A_2 data categories' are not statistically significant. However, in 8 out of 14 Malaysian ringgit denominated futures DRSI common optimization rule manages to perform statistically significantly better versus Buy-and-hold rule. This is not much as a whole but it indicates that there are inefficiencies on the Malaysian ringgit denominated short term interest rate futures market. In introduction section it is discussed that reduced individuality of DRSI common optimization rule versus regular DRSI rule may weaken the performance. In fact it does not weaken but the performance improves as more data is used in optimization. This indicates that the optimization period of regular DRSI rule is too short to get a correct set of parameters reliably.

Where DRSI common optimization rule performs in A_1 and A_2 data categories, in terms of return, Moving Average rule is superior versus all other rules, including Buy-and-hold rule, in B_1 and C_1 data categories. Moving Average rule yields better daily mean returns in 72 % and 64 %, better total returns in 77 % and 58 % and better Sharpe ratios in 82 % and 67% of the futures time series in B_1 and C_1 data categories, respectively, versus Buy-and-hold rule. Even though Moving Average rule generates the best returns only few of the returns are statistically significant. Also Moving Average rule performs the best in Malaysian ringgit denominated interest rate futures as in 12 out of 14 futures Moving Average rule generates statistically significantly better returns versus Buy-and-hold rule. Therefore, there is a clear evidence of inefficiency on the Malaysian ringgit denominated short term interest rate futures market allowing one to consistently earn excess returns using Moving Average and DRSI common optimization rules. However, the excess returns are earned subject to trading rule as only three of them generated more better returns than Buy-and-hold rule.

The results on Moving Average trading rule support the findings of Gençay (1998) as he showed that Moving Average can generate significantly better returns versus Buy-and-hold. Kidd and Brorsen (2004), Olson (2004) and Fitfiel et al. (2005) show in their studies that the profits have diminished on the most developed markets as informational function became more efficient. The findings of this study are in line with these studies showing that the trading rules on the emerging and developing markets are still performing relatively better versus developed markets. In addition it is observed that trading rules perform better in a volatile market environment supporting the findings of Kho (1996) and Ruggiero (1998).

While the previous studies show inconsistent results regarding to the trading rules also in this study the results are not obvious. As RSI trading rule cannot consistently generate significantly greater profits versus Buy-and-hold rule in this study the first research hypothesis, H1, must be rejected. But the rejection is not that clear regarding to the two other hypothesis as there are some statistically significant excess returns observed. The second and third research hypotheses, H2 and H3, could be approved partially only regarding to DRSI common optimization and Moving Average rules on the Malaysian ringgit denominated interest rate futures market. However, as the approval is market specific and the trading rules cannot consistently generate higher returns versus Buy-and-hold rule the research hypotheses H2 and H3 must also be rejected.

In this study there are also risk adjusted returns observed using Sharpe ratio. Performance in terms of Sharpe ratios is rather well in line with the performance of daily mean returns and total returns. In most of the cases technical trading rules performed slightly better while Sharpe ratios are considered. This indicates that technical trading rules can generate the same return with a smaller amount of risk compared to Buy-and-hold strategy. However, also in this case only DRSI common optimization rule and Moving Average trading rules can challenge Buy-and-hold rule providing better risk adjusted returns. These results support the findings of Shik and Chong (2007) that some of the technical trading rules generate excess returns if the risk is taken into account.

The modifications of RSI rule, especially DRSI common optimization, proves to be a success if compared to regular RSI, the returns are higher, some of the returns are statistically significant and higher versus Buy-and-hold rule, the returns are more constant from a data category to another and also Sharpe ratios indicate better balance

between risk and return. Though, if further studies are considered it would be interesting to study how similar optimization process, used in this study, would affect the returns generated by the regular RSI rule. As regular RSI with parameters optimized for stocks does not perform very well in this study the problem might be in parameters.

In this study optimization is observed to be one of the key issues regarding to the profitability of DRSI rules. Therefore, it is desired to consider the optimization process again in case of issues that could improve the profitability of the trading rules. Such issues to consider could be a separate optimization process for each of the future series while in this study it is done either within a data category or individually. Also, a process where the parameters are optimized commonly for each maturity could be worthwhile to study while in this study all the maturities are mixed and together in the same categories without any arrangements.

Without a question Moving Average yields in absolute terms the highest returns of all technical trading rules included in this study. As there is only one Moving Average rule used it would probably add value if other parameters, such as 1-100, 1-150 or 5-200, of Moving Average rule were tested with the same data used in this study.

As modifications to the trading rules are considered the data should be discussed as well. Some of the markets may still be uncovered by academic studies but the most of them have been studied using technical analysis in general. However, the combination of the trading rules and optimization process combined with those markets are less covered. Without touching the data itself the properties of the data would be fascinating to go through too. The way that how trends and changes in a trend of underlying interest rates affect the use of trading rules with short term interest rate futures is not that obvious as it is with stocks or currencies. Issues that are not covered in this study and would need a proper analysis are the changes in the shape of interest rate curve and how do they change the profitability of trading rules and is it volatility that makes the trading rules to generate higher profits? The current credit crisis has provided a lot of interesting and volatile market data to study this further. In addition it is observed that the number of executed signals and returns of trading rules are not in a close relationship while a connection between the number of days in the ownership periods, meaning the period between buy and sell, and trading rule profitability is found which encourages studying it further.

A noteworthy issue that is excluded from this study to not to increase the complexity in the study is shorting. A problem why shorting is not often applied is that the most of the security prices tend to rise as time passes. Therefore, a short position might be very expensive if the interest rates decrease towards delivery date as they normally do. However, in a case of volatile market shorting has a better chance to provide extra returns for the investor. While also technical trading rules are found to perform better in more volatile market conditions there were probably the best conditions during the recent years for technical trading rules to perform if also shorting were applied providing an interesting basis to another study.

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APPENDICES

Appendix 1. Returns of the trading rules

Table 24. Returns of the A₁ data category (1st part).

A1 data set	N _O	Buy-and-hold				DRSI							DRSI common optimization							RSI (14)							Moving average (1-50)							DRSI frequent parameters						
		μ _R	r	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	
EDU9	2143	0.00211	15.69	0.0287	0.00195	7.67	22	44	0.94	0.20	0.0331	0.00165	8.80	25	47	0.81	0.46	0.0259	0.00082	0.50	19	46	0.54	0.14	0.0102	0.00031	11.96	65	21	0.38	0.66	0.0029	0.00165	12.67	20	78	0.81	0.52	0.0263	
EDM0	2055	0.00229	15.40	0.0432	0.00162	7.06	23	46	0.65	0.38	0.0341	0.00178	10.87	20	66	0.75	0.71	0.0317	0.00111	2.44	19	43	0.55	0.10	0.0139	0.00219	9.51	74	18	0.95	0.83	0.0453	0.00192	13.22	22	65	0.79	0.54	0.0445	
EDH0	2124	0.00212	14.98	0.0303	0.00227	4.77	13	89	0.94	0.47	0.0352	0.00105	10.81	22	57	0.58	0.75	0.0152	0.00105	2.54	21	42	0.59	0.31	0.0145	0.00164	11.24	69	20	0.82	0.95	0.0220	0.00150	13.91	22	69	0.74	0.74	0.0260	
EDU0	1990	0.00211	11.85	0.0363	0.00097	6.06	18	58	0.55	0.44	0.0132	0.00177	12.56	21	58	0.82	0.24	0.0489	0.00077	1.92	19	43	0.50	0.11	0.0093	0.00199	6.87	77	16	0.95	0.80	0.0357	0.00169	10.14	19	74	0.78	0.47	0.0393	
EDZ9	2143	0.00206	15.08	0.0281	0.00181	11.82	23	46	0.90	0.55	0.0260	0.00162	10.85	22	64	0.82	0.73	0.0256	0.00097	2.48	20	44	0.58	0.31	0.0142	0.00035	11.30	72	19	0.41	0.78	0.0035	0.00165	11.97	20	77	0.83	0.70	0.0264	
EDZ0	1926	0.00202	12.35	0.0515	0.00187	8.92	19	47	0.92	0.56	0.0352	0.00156	11.32	18	67	0.64	0.30	0.0633	0.00136	2.44	18	42	0.66	0.11	0.0228	0.00174	5.16	76	16	0.83	0.85	0.0367	0.00154	7.48	19	70	0.66	0.56	0.0466	
EDH1	1864	0.00203	11.00	0.0503	0.00146	5.35	14	58	0.70	0.39	0.0266	0.00172	14.08	14	78	0.76	0.32	0.0691	0.00099	0.55	18	42	0.56	0.09	0.0130	0.00173	4.43	70	16	0.82	0.63	0.0400	0.00151	4.77	19	66	0.66	0.47	0.0415	
EDM1	1798	0.00239	9.04	0.0406	0.00174	3.65	15	63	0.70	0.42	0.0378	0.00185	15.06	16	75	0.71	0.37	0.0675	0.00130	1.60	19	41	0.55	0.22	0.0225	0.00165	2.15	69	16	0.69	0.71	0.0275	0.00234	2.43	19	65	0.98	0.88	0.0345	
EDU1	1735	0.00129	6.90	0.0183	-0.00197	-1.64	13	50	0.14	0.04	-0.0315	0.00233	11.17	14	93	0.57	0.52	0.0517	0.00150	1.27	18	40	0.92	0.22	0.0232	0.00071	0.75	64	16	0.80	0.42	0.0092	0.00135	3.95	18	67	0.98	0.52	0.0157	
EDZ1	1672	0.00206	7.11	0.0331	0.00164	8.95	16	57	0.81	0.27	0.0394	0.00206	9.28	14	82	1.00	0.79	0.0339	0.00149	1.63	17	41	0.78	0.15	0.0235	0.00191	1.12	65	15	0.94	0.35	0.0305	0.00148	2.67	19	60	0.81	0.39	0.0173	
EDH2	1611	0.00159	6.02	0.0241	0.00005	0.05	4	294	0.53	0.73	-0.0007	0.00177	8.11	12	86	0.92	0.55	0.0325	0.00163	1.88	16	43	0.98	0.26	0.0258	0.00179	0.29	66	14	0.93	0.29	0.0250	0.00117	3.08	16	71	0.87	0.51	0.0136	
EDM2	1546	0.00162	3.78	0.0215	0.00098	4.66	20	40	0.78	0.28	0.0161	0.00178	11.24	14	81	0.94	0.38	0.0435	0.00096	0.87	14	45	0.80	0.38	0.0121	-0.00022	-0.23	68	13	0.48	0.42	-0.0044	0.00011	2.19	15	69	0.53	0.07	0.0001	
EDU2	1482	0.00231	6.78	0.0484	0.00190	3.36	11	71	0.81	0.63	0.0399	0.00161	3.21	14	69	0.65	0.62	0.0409	0.00066	0.44	14	41	0.43	0.20	0.0084	0.00065	-0.24	65	14	0.48	0.60	0.0069	0.00235	5.18	14	75	0.98	0.97	0.0439	
EDM3	1294	0.00218	5.37	0.0516	0.00061	-0.70	13	55	0.52	0.63	0.0064	0.00219	6.34	11	77	1.00	0.72	0.0576	0.00019	-0.05	12	44	0.38	0.25	0.0011	0.00189	0.99	60	13	0.88	0.49	0.0338	0.00224	1.73	14	63	0.98	0.82	0.0288	
EDM0	2143	0.00188	13.24	0.0288	0.00113	6.19	23	48	0.64	0.28	0.0237	0.00092	1.14	19	56	0.58	0.32	0.0149	0.00060	0.39	19	45	0.50	0.20	0.0077	0.00053	11.72	63	22	0.45	0.69	0.0075	0.00136	7.73	18	84	0.76	0.56	0.0245	
EDZ2	1418	0.00217	6.16	0.0462	-0.00313	-2.64	13	60	0.03	0.02	-0.0411	0.00145	3.18	13	65	0.72	0.68	0.0214	0.00139	0.83	14	43	0.72	0.19	0.0187	0.00204	0.87	63	13	0.95	0.59	0.0318	0.00228	1.79	14	74	0.96	0.93	0.0346	
EDH3	1357	0.00237	4.09	0.0379	0.00166	2.91	6	113	0.73	0.57	0.0335	0.00208	9.36	13	75	0.88	0.77	0.0549	0.00071	0.52	14	43	0.51	0.31	0.0083	0.00083	-0.07	61	13	0.57	0.57	0.0090	0.00209	2.81	13	75	0.91	0.99	0.0298	
EDU3	1232	0.00283	3.81	0.0473	0.00118	4.63	11	31	0.46	0.07	0.0201	0.00238	5.24	9	91	0.83	0.81	0.0537	-0.00015	-1.04	11	53	0.29	0.22	-0.0034	0.00047	-0.74	58	12	0.39	0.45	0.0046	0.00205	2.08	13	66	0.78	0.68	0.0250	
EDH4	1108	0.00304	2.65	0.0399	-0.00154	-1.43	7	82	0.19	0.08	-0.0182	0.00241	4.70	9	70	0.81	0.89	0.0525	-0.00083	-0.92	9	50	0.21	0.11	-0.0133	-0.00072	-1.23	53	11	0.23	0.27	-0.0115	0.00122	1.02	13	59	0.61	0.36	0.0120	
EDZ3	1169	0.00294	2.89	0.0394	0.00218	5.07	11	59	0.74	0.78	0.0581	0.00201	3.32	9	90	0.75	0.79	0.0273	0.00038	-0.72	10	57	0.40	0.39	0.0035	-0.00018	-0.99	53	12	0.31	0.38	-0.0039	0.00163	1.17	13	63	0.70	0.35	0.0170	
EDM4	1041	0.00126	1.03	0.0103	-0.00101	-0.53	11	41	0.62	0.76	-0.0118	0.00264	6.60	7	110	0.72	0.55	0.0445	-0.00220	-1.59	9	48	0.39	0.41	-0.0350	-0.00227	-2.27	51	11	0.38	0.49	-0.0352	-0.00072	0.50	11	71	0.66	0.77	-0.0090	
EDU4	980	0.00066	0.72	0.0048	0.00139	0.54	15	31	0.87	0.73	0.0148	0.00294	7.72	7	108	0.55	0.51	0.0676	0.00159	4.08	9	54	0.81	0.79	0.0268	-0.00236	-2.30	53	10	0.47	0.65	-0.0346	0.00048	0.88	10	74	0.97	0.90	0.0039	
EDH5	855	0.00355	1.34	0.0313	-0.00204	-0.90	8	61	0.28	0.90	-0.0209	0.00293	3.21	5	93	0.89	0.67	0.0460	0.00185	4.29	8	49	0.68	0.60	0.0321	-0.00117	-1.82	46	10	0.30	0.65	-0.0171	0.00190	1.50	10	60	0.73	0.83	0.0198	
EDZ4	917	0.00349	1.38	0.0314	0.00243	1.56	10	48	0.80	0.73	0.0362	0.00265	6.28	9	54	0.83	0.61	0.0561	0.00180	4.20	9	46	0.67	0.59	0.0313	-0.00102	-1.91	51	10	0.30	0.62	-0.0153	0.00049	0.85	9	72	0.52	0.68	0.0039	
EDM5	791	0.00438	2.00	0.0482	0.00056	0.13	9	31	0.41	0.71	0.0046	0.00273	1.93	4	86	0.69	0.93	0.0347	0.00291	5.66	8	40	0.69	1.00	0.0512	-0.00187	-1.89	45	10	0.14	0.27	-0.0251	0.00359	2.93	10	52	0.84	0.77	0.0499	
EDZ5	658	0.00189	0.66	0.0135	-0.00317	-0.57	9	31	0.42	0.74	-0.0362	0.00401	4.55	5	71	0.71	0.69	0.0582	0.00332	5.31	6	46	0.80	0.84	0.0551	-0.00300	-1.98	36	9	0.40	0.36	-0.0434	0.00352	2.21	7	72	0.79	0.73	0.0358	
EDU5	721	0.00452	1.08	0.0383	0.00282	0.98	9	34	0.75	0.83	0.0300	0.00376	3.22	5	91	0.88	0.89	0.0468	0.00306	5.27	8	38	0.76	0.91	0.0511	-0.00270	-2.05	40	10	0.16	0.28	-0.0360	0.00373	2.46	10	51	0.88	0.80	0.0453	
EDH6	602	0.00225	0.46	0.0158	0.00401	3.31	6	42	0.78	0.67	0.0547	0.00425	4.01	3	96	0.74	0.69	0.0715	0.00372	6.16	6	55	0.81	0.81	0.0614	-0.00326	-2.15	32	9	0.38	0.39	-0.0438	0.00392	1.90	7	63	0.81	0.73	0.0389	
EDM6	534	0.00583	1.84	0.0610	0.00365	1.46	7	50	0.66	0.91	0.0507	0.00481	4.33	3	99	0.83	0.81	0.0796	0.00456	5.49	6	47	0.78	0.86	0.0938	-0.00294	-1.46	28	10	0.12	0.13	-0.0341	0.00492	2.83	6	68	0.86	0.99	0.0640	
Average		0.00246	6.37	0.0345	0.00093	3.13	13	61			0.0175	0.00230	7.33	12	78			0.0461	0.00129	2.01	13	45			0.0208	0.00002	1.97	58	14			0.0023	0.00189	4.42	14	68			0.0276	
Average, set A		0.00310	4.97	0.0398	0.00148	2.83	10	72			0.0253	0.00282	5.76	8.3	109			0.0490	0.00079	1.75	10	46			0.0110	0.00004	1.20	48	13			0.0055	0.00236	3.65	12	64			0.0313	

N_O = Number of trading days includedμ_R = Daily mean return

r = Total return during the whole trading period

n = number of buy-signals

T = Average number of days while investor was long in the future

t = t-test probability

MW = MW-test probability

Table 25. Returns of the A₁ data category (2nd part).

A1 data set	Buy-and-hold				DRSI					DRSI common optimization					RSI (14)					Moving average (1-50)					DRSI frequent parameters														
	N_O	μ_R	r	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S							
GEU9	936	0.00273	7.52	0.0470	0.00258	5.49	6	93	0.95	0.83	0.0548	0.00297	5.54	3	249	0.93	0.97	0.0435	-0.00158	-1.66	6	61	0.04	0.01	-0.0509	0.00288	7.52	26	24	0.95	0.93	0.0744	0.00174	4.28	8	67	0.73	0.39	0.0246
GEM0	865	0.00319	6.65	0.0562	0.00244	3.78	2	156	0.75	0.97	0.0532	0.00326	6.84	6	99	0.98	0.79	0.0524	-0.00021	0.80	8	47	0.20	0.14	-0.0062	0.00252	3.75	35	16	0.77	0.93	0.0603	0.00279	4.72	10	52	0.89	0.96	0.0403
GEH0	883	0.00313	6.93	0.0530	0.00175	1.53	6	66	0.58	0.85	0.0345	0.00314	6.84	6	102	1.00	0.80	0.0515	-0.00076	-0.13	7	54	0.09	0.09	-0.0240	0.00282	6.05	29	19	0.89	0.86	0.0730	0.00245	5.96	10	54	0.81	0.96	0.0356
GEU0	856	0.00321	5.82	0.0532	0.00265	4.23	7	56	0.82	0.83	0.0557	0.00239	3.76	4	135	0.73	0.85	0.0546	0.00014	1.15	8	45	0.28	0.36	0.0002	0.00239	3.08	41	13	0.73	0.87	0.0562	0.00243	3.56	8	64	0.79	0.79	0.0362
GEZ9	906	0.00290	7.13	0.0486	0.00070	1.07	4	70	0.44	0.63	0.0090	0.00173	2.27	3	189	0.65	0.87	0.0314	-0.00102	-0.47	6	62	0.08	0.06	-0.0326	0.00289	6.87	31	19	1.00	0.74	0.0728	0.00284	5.19	8	68	0.98	0.99	0.0397
GEZ0	853	0.00316	5.23	0.0517	0.00275	5.49	5	125	0.89	0.90	0.0406	0.00234	3.43	4	139	0.74	0.94	0.0537	-0.00033	0.60	8	45	0.21	0.21	-0.0081	0.00210	1.61	44	12	0.68	0.77	0.0431	0.00191	2.28	9	58	0.69	0.99	0.0253
GEH1	859	0.00308	4.78	0.0509	0.00192	2.37	1	342	0.63	0.56	0.0443	0.00226	3.02	3	192	0.74	0.99	0.0505	-0.00196	-0.57	8	46	0.07	0.10	-0.0353	0.00212	0.92	39	13	0.73	0.64	0.0350	0.00181	0.96	10	51	0.69	0.81	0.0226
GEM1	849	0.00306	4.17	0.0491	0.00257	3.04	5	98	0.88	0.99	0.0358	0.00285	5.39	5	132	0.94	0.91	0.0550	-0.00204	-0.67	8	46	0.08	0.13	-0.0371	0.00133	-0.03	39	12	0.56	0.55	0.0190	0.00195	1.24	9	61	0.72	0.94	0.0275
GEU1	846	0.00306	3.64	0.0470	0.00253	3.60	4	105	0.87	0.72	0.0353	0.00289	5.29	6	93	0.95	0.98	0.0628	-0.00143	-0.26	8	42	0.15	0.12	-0.0242	0.00045	-0.16	35	13	0.40	0.41	0.0048	0.00250	3.90	9	64	0.85	0.84	0.0431
GEZ1	846	0.00306	3.22	0.0458	0.00262	4.92	5	149	0.87	0.86	0.0554	0.00268	4.97	7	69	0.88	0.85	0.0635	0.00028	0.27	8	41	0.38	0.16	0.0022	0.00026	-0.31	35	13	0.38	0.39	0.0020	0.00228	2.84	11	50	0.79	0.71	0.0387
GEH2	844	0.00293	3.05	0.0449	0.00235	3.41	10	44	0.83	0.76	0.0521	0.00266	4.65	5	114	0.91	0.77	0.0705	0.00013	0.37	8	40	0.36	0.21	0.0000	-0.00055	-0.71	37	13	0.28	0.37	-0.0099	0.00237	3.06	9	61	0.85	0.78	0.0390
GEM2	839	0.00279	2.92	0.0434	-0.00009	-0.71	6	96	0.37	0.52	-0.0032	0.00304	3.81	4	171	0.93	0.84	0.0589	-0.00080	-0.01	8	40	0.24	0.16	-0.0144	0.00045	-0.07	38	12	0.47	0.44	0.0046	0.00246	3.44	10	54	0.91	0.76	0.0416
GEU2	841	0.00294	2.55	0.0433	0.00226	3.05	6	102	0.80	0.68	0.0518	0.00239	3.00	5	124	0.85	0.89	0.0405	-0.00133	-0.26	8	39	0.17	0.23	-0.0234	-0.00018	-0.40	40	12	0.35	0.47	-0.0043	0.00273	3.09	9	68	0.95	0.94	0.0417
GEM0	949	0.00224	6.88	0.0383	0.00100	1.36	3	144	0.60	0.59	0.0186	0.00126	1.24	4	160	0.70	0.85	0.0206	-0.00161	-1.50	6	71	0.07	0.12	-0.0477	0.00281	8.34	24	24	0.79	0.65	0.0742	0.00037	0.76	7	78	0.51	0.43	0.0037
GEM3	837	0.00412	3.38	0.0458	0.00274	5.08	11	38	0.70	0.80	0.0451	0.00436	3.86	3	227	0.95	0.96	0.0513	-0.00152	-0.91	7	51	0.21	0.24	-0.0173	0.00044	-0.35	43	11	0.44	0.50	0.0029	0.00276	2.29	11	49	0.75	0.78	0.0290
GEZ2	839	0.00283	2.46	0.0417	0.00251	3.12	8	71	0.91	0.90	0.0455	0.00299	3.51	3	247	0.95	0.97	0.0575	0.00018	0.39	8	46	0.41	0.43	0.0007	0.00114	0.08	42	11	0.61	0.58	0.0139	0.00243	0.62	9	68	0.91	0.97	0.0290
GEH3	839	0.00395	3.61	0.0452	0.00289	7.72	9	50	0.76	0.87	0.0531	0.00342	6.14	5	115	0.88	0.86	0.0522	-0.00104	0.20	8	47	0.26	0.41	-0.0121	-0.00002	-0.51	44	11	0.39	0.51	-0.0014	0.00308	3.23	10	57	0.83	0.97	0.0356
GEU3	836	0.00427	3.16	0.0461	0.00102	1.22	11	40	0.51	0.71	0.0080	0.00370	4.44	4	169	0.89	1.00	0.0501	-0.00151	-0.98	7	51	0.20	0.28	-0.0173	0.00010	-0.94	44	10	0.37	0.46	-0.0003	0.00272	3.27	11	51	0.72	0.91	0.0302
GEZ3	837	0.00508	2.73	0.0495	0.00486	1.34	7	69	0.97	0.88	0.0441	0.00440	3.43	4	175	0.89	0.89	0.0467	0.00016	-0.87	7	58	0.31	0.49	0.0003	-0.00082	-1.05	42	11	0.22	0.45	-0.0099	0.00327	2.92	11	51	0.69	0.84	0.0379
GEH4	837	0.00520	2.48	0.0478	-0.00062	-0.88	4	112	0.31	0.47	-0.0059	0.00341	4.19	4	144	0.68	1.00	0.0485	-0.00087	-0.53	7	42	0.21	0.58	-0.0111	-0.00097	-1.01	43	10	0.20	0.45	-0.0122	0.00333	2.69	11	51	0.69	0.88	0.0371
GEM4	836	0.00521	2.37	0.0476	0.00297	4.32	15	30	0.61	0.82	0.0421	0.00385	3.70	5	136	0.77	1.00	0.0452	-0.00087	-0.60	7	42	0.21	0.55	-0.0112	-0.00050	-1.06	44	10	0.24	0.45	-0.0068	0.00278	2.11	10	58	0.63	0.66	0.0263
GEU4	836	0.00509	1.94	0.0457	0.00339	3.66	12	46	0.71	0.87	0.0437	0.00375	3.38	5	123	0.77	0.99	0.0448	0.00275	5.93	8	43	0.60	0.81	0.0396	-0.00120	-1.89	46	10	0.20	0.38	-0.0146	0.00314	2.57	10	59	0.68	0.79	0.0355
GEH5	836	0.00502	1.69	0.0425	0.00346	1.25	12	38	0.75	0.77	0.0399	0.00458	2.83	5	127	0.93	0.99	0.0450	0.00265	6.22	8	46	0.61	0.97	0.0381	-0.00145	-2.33	46	10	0.19	0.50	-0.0181	0.00275	2.14	10	58	0.66	0.84	0.0268
GEZ4	837	0.00523	2.02	0.0447	0.00349	1.36	13	44	0.72	0.81	0.0424	0.00366	4.25	5	122	0.73	0.75	0.0499	0.00252	5.76	8	43	0.55	0.87	0.0360	-0.00118	-2.11	48	9	0.20	0.47	-0.0150	0.00224	2.10	9	67	0.57	0.78	0.0203
GEM5	780	0.00458	2.54	0.0508	0.00148	0.95	10	30	0.54	0.91	0.0124	0.00323	2.60	4	91	0.75	0.89	0.0393	0.00325	6.72	8	40	0.73	0.92	0.0489	-0.00124	-1.78	43	10	0.20	0.33	-0.0150	0.00419	3.26	10	52	0.93	0.80	0.0517
GEZ5	650	0.00156	0.49	0.0095	-0.00639	-3.97	4	108	0.29	0.38	-0.0549	0.00502	4.61	3	114	0.62	0.61	0.0541	0.00374	6.43	6	46	0.74	0.71	0.0541	-0.00406	-3.24	38	8	0.40	0.31	-0.0541	0.00409	2.38	7	71	0.73	0.69	0.0358
GEU5	713	0.00567	1.30	0.0413	0.00015	-0.33	11	30	0.41	0.99	0.0002	0.00432	4.47	5	95	0.82	0.73	0.0545	0.00322	5.92	8	34	0.66	0.96	0.0469	-0.00348	-2.96	40	9	0.12	0.18	-0.0431	0.00447	2.98	10	50	0.84	0.78	0.0476
GEH6	595	0.00213	0.52	0.0129	0.00487	3.45	10	31	0.72	0.53	0.0452	0.00504	4.72	3	90	0.68	0.63	0.0728	0.00346	5.59	5	47	0.85	0.84	0.0483	-0.00383	-2.54	32	9	0.42	0.47	-0.0443	0.00475	2.30	7	63	0.74	0.68	0.0408
GEM6	528	0.00689	2.27	0.0655	0.00418	2.33	6	42	0.61	0.93	0.0630	0.00548	5.26	3	98	0.79	0.81	0.0826	0.00498	6.09	6	42	0.70	0.93	0.0936	-0.00351	-2.34	30	9	0.10	0.09	-0.0360	0.00551	3.72	6	64	0.80	1.00	0.0750
Average		0.00373	3.57	0.0451	0.00204	2.52	7.3	84			0.0332	0.00335	4.19	4.3	139			0.0519	0.00030	1.48	7.3	47			0.0012	0.00006	0.43	39	13			0.0087	0.00283	2.89	9.3	59			0.0351
Average, set A		0.00310	4.97	0.0398	0.00148	2.83	10	72			0.0253	0.00282	5.76	8.3	109			0.0490	0.00079	1.75	10	46			0.0110	0.00004	1.20	48	13			0.0055	0.00236	3.65	12	64			0.0313

Table 26. Returns of the B₁ data category.

B1 data set	Buy-and-hold			DRSI								DRSI common optimization								RSI (14)								Moving average (1-50)								DRSI frequent parameters							
	N_O	μ_R	r	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S				
ERU9	1002	0.00139	5.89	0.0254	-0.00162	-0.95	8	44	0.19	0.54	-0.0333	0.00249	6.53	15	29	0.68	0.55	0.0342	-0.00158	-1.84	8	66	0.12	0.33	-0.0490	0.00261	10.99	23	25	0.61	0.70	0.0447	0.00010	2.01	10	67	0.56	0.61	-0.0004				
ERZ9	937	0.00114	6.88	0.0168	-0.00166	-0.69	7	75	0.28	0.53	-0.0356	0.00109	6.05	14	42	0.99	0.98	0.0160	-0.00147	-0.72	8	52	0.29	0.70	-0.0360	0.00320	11.01	21	26	0.44	0.42	0.0580	-0.00035	0.98	8	67	0.59	0.82	-0.0081				
ERM0	808	0.00306	7.71	0.0341	0.00231	3.04	6	72	0.84	0.79	0.0349	0.00333	8.06	10	50	0.94	0.93	0.0506	0.00168	2.08	8	39	0.71	0.67	0.0245	0.00387	9.65	16	32	0.81	0.85	0.0809	0.00270	4.13	10	47	0.92	0.78	0.0397				
ERH0	872	0.00137	7.46	0.0159	0.00043	1.06	6	41	0.78	0.86	0.0053	0.00309	8.07	14	32	0.61	0.49	0.0483	-0.00076	0.16	7	57	0.51	0.78	-0.0160	0.00349	10.71	16	32	0.49	0.52	0.0708	0.00108	3.41	8	68	0.94	0.87	0.0136				
ERU0	738	0.00159	5.84	0.0185	0.00238	4.55	6	48	0.82	0.83	0.0441	0.00396	5.92	7	55	0.50	0.55	0.0704	0.00082	1.39	8	37	0.84	0.93	0.0108	0.00360	6.91	15	30	0.57	0.64	0.0609	-0.00076	0.18	8	50	0.53	0.45	-0.0139				
ERZ0	704	0.00152	4.91	0.0185	-0.00066	0.13	6	51	0.55	0.83	-0.0131	0.00152	4.03	7	68	1.00	0.72	0.0174	0.00038	0.92	8	35	0.76	0.88	0.0039	0.00357	5.21	18	23	0.56	0.59	0.0619	0.00072	2.24	9	47	0.83	0.78	0.0095				
ERH1	673	0.00126	3.96	0.0161	0.00048	0.72	11	27	0.84	0.86	0.0051	0.00098	1.94	5	108	0.95	0.81	0.0100	-0.00089	0.15	7	39	0.55	0.80	-0.0164	0.00370	5.36	17	23	0.46	0.48	0.0723	-0.00012	1.31	6	77	0.72	0.71	-0.0035				
ERM1	614	0.00178	3.72	0.0211	-0.00219	-2.03	3	56	0.24	0.03	-0.0827	-0.00210	-1.54	3	44	0.26	0.06	-0.0626	-0.00150	-0.30	7	32	0.39	0.20	-0.0309	0.00378	4.75	16	23	0.59	0.96	0.0794	0.00069	0.54	5	82	0.81	0.58	0.0068				
ERU1	547	0.00494	5.37	0.0702	0.00290	2.43	11	22	0.60	0.41	0.0465	0.00156	0.52	3	84	0.41	0.25	0.0217	0.00255	1.97	6	32	0.53	0.23	0.0418	0.00398	4.14	18	20	0.79	0.55	0.0864	0.00400	3.50	5	84	0.82	0.73	0.0580				
ERM9	1008	0.00092	6.36	0.0119	-0.00171	-2.03	6	114	0.30	0.31	-0.0398	0.00224	5.51	15	47	0.69	0.71	0.0258	-0.00240	-4.23	8	63	0.21	0.38	-0.0506	0.00280	11.34	27	21	0.53	0.49	0.0406	-0.00166	-1.18	9	73	0.35	0.41	-0.0322				
ERZ1	482	0.00314	3.58	0.0322	0.00237	3.37	5	37	0.88	0.35	0.0384	0.00100	0.09	1	252	0.70	0.41	0.0117	0.00217	0.73	4	41	0.85	0.33	0.0320	0.00373	2.35	17	19	0.91	0.50	0.0531	0.00423	2.26	3	127	0.85	0.71	0.0521				
ERH2	356	0.00313	2.13	0.0342	0.00429	3.41	3	37	0.83	0.50	0.0911	0.00011	0.04	1	1	0.52	0.09	-0.0063	-0.00128	-0.06	3	36	0.45	0.17	-0.0209	0.00306	1.22	12	18	0.99	0.57	0.0403	0.00156	0.88	2	141	0.83	0.76	0.0141				
ERM2	355	0.00292	1.72	0.0299	0.00203	1.48	3	42	0.89	0.56	0.0273	0.00011	0.04	1	1	0.57	0.16	-0.0063	-0.00178	-0.23	3	35	0.45	0.20	-0.0275	0.00046	-0.09	13	16	0.72	0.47	0.0040	0.00027	0.56	2	141	0.73	0.77	0.0016				
ERU2	292	0.00511	2.71	0.0563	0.00499	2.52	4	27	0.98	0.44	0.0970	0.00379	1.55	1	26	0.81	0.22	0.1064	0.00344	1.26	2	28	0.77	0.22	0.0793	0.00390	0.50	16	11	0.86	0.45	0.0528	0.00616	2.68	2	120	0.88	0.71	0.0813				
ERZ2	163	0.00998	1.17	0.0824	0.00007	-0.15	2	30	0.40	0.25	0.0003	0.00005	0.01	1	1	0.29	0.13	-0.0013	-0.00343	-0.68	1	63	0.27	0.20	-0.0365	-0.00278	-1.11	10	11	0.34	0.24	-0.0236	0.00922	1.09	1	158	0.95	0.94	0.0774				
ERH3	161	0.00687	0.77	0.0511	-0.00176	-0.58	1	64	0.52	0.29	-0.0174	0.00005	0.01	1	1	0.52	0.20	-0.0013	0.00309	0.49	1	14	0.73	0.32	0.0855	-0.00381	-1.14	12	9	0.46	0.29	-0.0311	0.00282	0.20	1	129	0.78	0.73	0.0210				
Average		0.00313	4.39	0.0334	0.00079	1.02	5.5	49			0.0105	0.00145	2.93	6.2	53			0.0209	-0.00006	0.07	5.6	42			-0.0004	0.00245	5.11	17	21			0.0470	0.00192	1.55	5.6	92			0.0198				
L H0	862	0.00148	7.65	0.0200	0.00113	2.18	8	41	0.91	0.29	0.0190	0.00345	9.25	18	24	0.46	0.04	0.0831	-0.00182	-2.12	7	55	0.20	0.38	-0.0606	0.00294	9.36	26	19	0.59	0.19	0.0654	0.00122	1.88	9	66	0.94	0.41	0.0167				
L M0	800	0.00231	7.08	0.0296	0.00147	2.56	5	58	0.79	0.74	0.0283	0.00356	8.89	17	28	0.68	0.13	0.0808	-0.00159	-1.81	6	59	0.18	0.33	-0.0451	0.00313	7.54	27	18	0.79	0.35	0.0705	0.00190	2.69	9	58	0.91	0.38	0.0270				
L Z9	927	0.00166	8.41	0.0222	-0.00230	-4.39	6	55	0.11	0.06	-0.0770	0.00110	2.36	16	34	0.85	0.96	0.0183	-0.00172	-2.27	9	45	0.18	0.21	-0.0568	0.00295	10.42	26	21	0.63	0.25	0.0632	0.00129	2.52	11	54	0.90	0.78	0.0191				
L U0	731	0.00246	5.92	0.0313	-0.00014	0.30	4	49	0.44	0.20	-0.0052	0.00221	3.80	12	28	0.94	0.28	0.0514	-0.00184	-1.70	7	40	0.16	0.65	-0.0550	0.00322	6.51	18	24	0.81	0.14	0.0784	0.00149	1.14	7	71	0.80	0.42	0.0188				
L U9	989	0.00119	8.38	0.0163	-0.00133	-2.20	6	46	0.26	0.19	-0.0571	0.00255	7.04	13	22	0.58	0.09	0.0624	-0.00166	-2.49	9	51	0.24	0.54	-0.0463	0.00277	11.12	29	20	0.53	0.36	0.0621	-0.00087	-0.21	11	57	0.42	0.85	-0.0210				
L Z0	699	0.00234	4.90	0.0291	-0.00157	-1.07	4	51	0.21	0.99	-0.0517	0.00202	2.59	8	38	0.92	0.40	0.0448	-0.00154	-1.06	7	35	0.21	0.59	-0.0521	0.00348	6.33	17	24	0.73	0.09	0.0823	0.00077	0.38	7	64	0.70	0.36	0.0082				
L H1	610	0.00289	4.05	0.0352	0.00264	2.40	7	50	0.95	0.18	0.0386	0.00302	4.77	5	61	0.97	0.23	0.0710	-0.00206	-1.51	6	37	0.15	0.33	-0.0648	0.00388	5.10	15	24	0.79	0.28	0.0802	0.00119	0.59	6	63	0.70	0.42	0.0140				
L M9	1008	0.00127	7.68	0.0161	0.00125	2.36	8	48	0.99	0.09	0.0255	0.00165	3.09	13	24	0.89	0.05	0.0312	-0.00183	-3.79	10	44	0.23	0.85	-0.0499	0.00252	10.55	28	20	0.64	0.10	0.0548	-0.00094	-0.60	10	66	0.44	0.57	-0.0186				
L M1	544	0.00445	5.17	0.0724	0.00120	0.71	2	22	0.26	0.90	0.0337	0.00062	0.00	3	46	0.27	0.96	0.0089	-0.00251	-1.40	4	42	0.05	0.37	-0.0440	0.00418	4.91	17	20	0.93	0.85	0.0949	0.00221	0.49	6	52	0.54	0.86	0.0351				
L U1	543	0.00412	4.19	0.0650	0.00002	-0.29	2	52	0.20	0.61	-0.0023	0.00235	2.04	4	32	0.54	1.00	0.0802	-0.00282	-1.96	4	42	0.06	0.24	-0.0501	0.00417	4.30	17	20	0.99	0.77	0.0853	0.00215	0.37	5	62	0.60	0.83	0.0331				
L H2	414	0.00208	0.99	0.0215	-0.00134	-1.43	2	61	0.53	0.92	-0.0238	0.00044	0.18	1	3	0.72	0.59	0.0307	-0.00418	-2.67	5	32	0.25	0.45	-0.0675	0.00335	2.48	15	14	0.82	0.93	0.0462	-0.00123	-0.54	6	46	0.60	0.82	-0.0152				
L Z1	479	0.00325	1.84	0.0361	-0.00374	-2.26	2	60	0.13	0.50	-0.0729	0.00055	0.24	2	5	0.50	0.81	0.0261	-0.00341	-2.69	4	34	0.16	0.40	-0.0633	0.00265	2.68	17	17	0.91	0.70	0.0351	0.00261	0.62	6	53	0.90	0.71	0.0357				
L M2	352	0.00108	0.36	0.0106	-0.00610	-3.29	1	168	0.23	0.32	-0.0948	0.00054	0.06	1	35	0.92	0.87	0.0119	-0.00508	-2.38	4	39	0.33	0.53	-0.0697	0.00495	3.03	10	17	0.52	0.77	0.0754	-0.00234	-1.37	4	60	0.62	0.97	-0.0270				
L U2	290	0.00586	2.94	0.1042	0.00357	0.97	6	26	0.60	0.95	0.0699	0.00009	0.03	1	1	0.08	0.61	-0.0136	-0.00142	-0.49	2	61	0.20	0.96	-0.0189	0.00571	2.65	9	18	0.98	0.62	0.0931	0.00267	0.35	4	46	0.53	0.96	0.0393				
L Z2	225	0.00491	0.77	0.0625	-0.00752	-2.92	1	130	0.08	0.50	-0.1047	0.00055	-0.01	1	35	0.46	0.75	0.0109	-0.00655	-2.59	1	124	0.12	0.68	-0.0859	0.00662	2.42	5	23	0.80	0.88	0.0959	-0.00193	-0.97	3								

Table 27. Returns of the C₁ data category.

C1 data set	Buy-and-hold			DRSI							DRSI common optimization							RSI (14)							Moving average (1-50)							DRSI frequent parameters							
	N_O	μ_R	r	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S
ESU9	227	0.01099	7.48	0.1532	0.00105	0.22	1	70	0.04	0.42	0.0472	0.00197	0.45	4	18	0.08	0.42	0.0639	0.00053	0.12	1	22	0.03	0.38	0.0351	0.01083	7.02	5	41	0.98	0.97	0.1444	0.00691	2.70	2	37	0.48	0.40	0.1338
ESZ9	162	0.00892	2.58	0.1881	0.00326	0.61	4	13	0.18	0.79	0.1243	0.00485	1.01	3	23	0.37	0.78	0.1449	0.00147	0.24	1	29	0.07	0.54	0.0639	0.00732	1.77	4	38	0.76	0.88	0.1604	0.00542	1.04	1	99	0.50	0.69	0.1188
ESM9	258	0.01029	10.43	0.2154	0.00147	0.40	1	10	0.01	0.73	0.0721	0.00454	1.95	4	24	0.09	0.87	0.1664	0.00188	0.53	2	31	0.01	0.80	0.0816	0.01037	8.74	3	64	0.99	0.73	0.1674	0.00788	5.68	4	35	0.51	0.90	0.2177
Average		0.01006	6.83	0.1856	0.00193	0.41	2	31			0.0812	0.00379	1.13	3.7	22			0.1251	0.00129	0.30	1.3	27			0.0602	0.00951	5.84	4	48			0.1574	0.00674	3.14	2.3	57			0.1568
ZBU9	285	0.00940	11.57	0.2417	0.00457	2.22	2	18	0.10	0.09	0.1429	0.00603	3.55	7	9	0.31	0.06	0.1479	0.00390	1.72	2	19	0.05	0.09	0.1331	0.00922	10.55	7	36	0.96	0.88	0.2325	0.00518	2.72	4	28	0.17	0.21	0.1476
ZBH0	336	0.00902	11.06	0.1544	0.00219	0.60	2	48	0.10	0.12	0.0410	0.00619	4.41	5	28	0.50	0.12	0.1208	0.00458	2.26	3	24	0.29	0.05	0.0881	0.00780	8.29	10	27	0.79	0.56	0.1329	0.00495	2.47	4	34	0.34	0.17	0.0936
ZBU0	228	0.00998	6.35	0.2000	0.00266	0.39	2	26	0.16	0.19	0.0417	0.00954	2.72	3	48	0.95	0.86	0.1059	0.00323	0.93	3	11	0.19	0.23	0.0532	0.00888	5.04	4	42	0.80	0.56	0.1976	-0.00395	-0.73	3	27	0.02	0.13	-0.0534
ZBZ9	284	0.00942	11.27	0.2623	0.00141	0.57	1	39	0.04	0.02	0.0237	0.00864	8.78	5	25	0.79	0.51	0.2445	0.00316	1.20	3	10	0.02	0.02	0.1077	0.00899	9.93	8	31	0.88	0.69	0.2516	0.00670	4.74	3	51	0.37	0.27	0.1787
ZBM0	398	0.00742	10.93	0.1487	0.00364	3.86	5	35	0.33	0.17	0.0590	0.00639	7.96	9	24	0.75	0.58	0.1440	0.00439	3.73	5	24	0.34	0.16	0.1052	0.00689	7.99	13	24	0.88	0.63	0.1291	0.00441	3.02	6	31	0.42	0.38	0.0757
ZBZ0	163	0.00829	0.77	0.0582	-0.00662	-0.61	5	23	0.35	0.86	-0.0452	0.00017	0.25	3	18	0.56	0.90	0.0011	0.00368	0.85	3	11	0.72	0.80	0.0442	0.00422	0.53	4	25	0.73	0.66	0.0725	-0.00748	-1.66	3	27	0.22	0.26	-0.0902
Average		0.00892	8.66	0.1776	0.00131	1.17	2.8	31			0.0439	0.00616	4.61	5.3	25			0.1274	0.00382	1.78	3.2	16			0.0886	0.00767	7.06	7.7	31			0.1694	0.00163	1.76	3.8	33			0.0587
FPM9	505	0.00747	14.03	0.0658	0.00047	-0.29	3	54	0.25	0.01	0.0043	0.00331	4.77	14	17	0.52	0.14	0.0342	-0.00216	-2.82	4	40	0.10	0.00	-0.0322	0.00778	16.32	8	45	0.96	0.36	0.1082	0.00139	1.63	6	40	0.35	0.11	0.0130
FPU9	474	0.00525	13.53	0.0427	0.00222	1.00	2	74	0.66	0.02	0.0226	0.00776	9.68	13	24	0.74	0.36	0.0702	0.00340	4.48	4	43	0.80	0.13	0.0327	0.00716	16.99	8	45	0.77	0.29	0.0922	0.00498	3.65	6	35	0.97	0.08	0.0456
FPZ9	409	0.00763	13.64	0.0586	0.00878	12.22	6	38	0.87	0.40	0.1182	0.00461	7.30	10	22	0.71	0.31	0.0458	0.00673	6.62	3	38	0.90	0.18	0.1087	0.00831	16.19	4	76	0.92	0.37	0.1563	0.00413	2.94	4	40	0.66	0.14	0.0422
FPH0	347	0.00480	10.09	0.0497	0.00511	4.88	3	72	0.97	0.45	0.0441	0.00662	8.99	9	21	0.78	0.47	0.0810	0.00546	4.63	2	50	0.93	0.17	0.0566	0.00939	12.96	4	62	0.46	0.40	0.1369	0.00338	3.87	3	50	0.85	0.20	0.0335
FPM0	286	0.01324	15.12	0.1500	0.00441	0.83	3	13	0.19	0.00	0.0598	0.01081	12.82	6	34	0.75	0.55	0.1163	0.00811	6.20	2	40	0.48	0.02	0.0917	0.01076	12.13	4	60	0.69	0.62	0.1757	0.00892	8.10	4	26	0.56	0.07	0.1009
FPU0	221	0.01062	9.49	0.0993	0.00767	3.68	1	28	0.70	0.07	0.1950	0.01196	7.91	5	20	0.88	0.24	0.1589	0.00855	3.05	2	17	0.81	0.05	0.1100	0.00801	6.56	6	33	0.79	0.84	0.0780	0.00894	3.27	2	29	0.85	0.10	0.1205
FPZ0	155	0.01453	4.42	0.1607	0.00637	1.09	3	11	0.35	0.40	0.1079	0.01038	0.95	1	106	0.74	0.81	0.0806	0.00616	1.29	2	12	0.30	0.48	0.1424	0.01149	1.87	3	44	0.79	0.61	0.1091	-0.00615	-1.11	2	14	0.04	0.24	-0.0692
Average		0.00908	11.47	0.0895	0.00500	3.34	3	41			0.0788	0.00792	7.49	8.3	35			0.0838	0.00518	3.35	2.7	34			0.0728	0.00898	11.86	5.3	52			0.1223	0.00366	3.19	3.9	33			0.0409
EYU9	1008	0.00239	11.06	0.0206	-0.00279	-4.09	6	90	0.21	0.72	-0.0406	0.00256	4.78	19	29	0.97	0.01	0.0216	0.00223	6.54	13	29	0.98	0.00	0.0184	0.00322	22.82	27	23	0.86	0.09	0.0318	0.00239	10.75	17	35	1.00	0.64	0.0267
EYM0	821	0.00551	21.27	0.0889	0.00056	2.21	6	12	0.10	0.91	0.0070	0.00578	8.71	18	28	0.95	0.56	0.0592	0.00481	8.92	12	27	0.83	0.09	0.0642	0.00690	21.59	23	27	0.70	0.37	0.0829	0.00451	15.49	13	39	0.73	0.26	0.0745
EYM9	1008	0.00020	7.93	0.0007	-0.00122	0.97	8	58	0.76	0.85	-0.0155	-0.00259	-4.60	18	28	0.51	0.06	-0.0439	0.00087	6.97	14	29	0.90	0.03	0.0061	0.00356	14.90	32	19	0.49	0.08	0.0356	0.00204	7.97	18	32	0.72	0.62	0.0182
EYZ9	952	0.00222	14.96	0.0178	-0.00005	2.46	6	43	0.63	0.75	-0.0021	0.00243	9.68	20	22	0.97	0.02	0.0242	0.00215	7.07	12	31	0.99	0.11	0.0194	0.00356	22.04	28	22	0.78	0.33	0.0411	0.00070	6.88	14	40	0.77	0.26	0.0053
Average		0.00258	13.80	0.0320	-0.00088	0.39	6.5	51			-0.0128	0.00204	4.64	19	27			0.0153	0.00251	7.38	13	29			0.0270	0.00431	20.34	28	23			0.0479	0.00241	10.27	16	37			0.0312
MYU9	977	0.00192	7.24	0.0232	0.00052	3.73	7	106	0.70	1.00	0.0048	0.00265	3.70	22	17	0.82	0.00	0.0385	-0.00154	0.64	11	38	0.37	0.09	-0.0180	0.00305	13.21	25	25	0.73	0.03	0.0458	-0.00171	-0.13	15	38	0.24	0.08	-0.0312
KKU2	209	0.00858	0.86	0.0691	0.00013	0.34	1	21	0.41	0.00	0.0007	-0.00557	-0.94	6	13	0.17	0.90	-0.0691	0.00504	1.54	3	20	0.71	0.00	0.0802	0.00884	2.83	3	36	0.98	0.03	0.1179	0.00925	1.32	5	29	0.96	0.01	0.0749
KKM2	274	0.00771	4.97	0.0880	0.00833	4.68	2	34	0.93	0.20	0.1152	0.00578	2.69	8	17	0.79	0.31	0.0666	0.00682	3.25	3	27	0.89	0.02	0.1102	0.01035	4.54	5	31	0.76	0.44	0.0920	0.01002	7.51	5	40	0.74	0.13	0.1336
KKU9	957	0.00183	5.31	0.0249	-0.00193	-2.81	9	51	0.15	0.15	-0.0462	0.00027	1.37	20	25	0.61	0.00	0.0023	0.00117	1.90	13	27	0.81	0.00	0.0199	0.00254	9.85	16	36	0.77	0.00	0.0758	-0.00144	-0.54	13	40	0.22	0.09	-0.0336
KKZ9	896	0.00250	6.56	0.0350	0.00261	5.56	9	52	0.97	0.00	0.0411	0.00294	5.85	17	26	0.88	0.00	0.0510	0.00216	3.66	10	25	0.90	0.00	0.0														

Table 28. Returns of the A₂ data category.

A2 data set	N _O	Buy-and-hold				DRSI							DRSI common optimization							RSI (14)							Moving average (1-50)							DRSI frequent parameters						
		μ _R	r	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	μ _R	r	n	T	t	MW	S	
EDU9	993	0.00252	10.07	0.0351	0.00268	6.38	10	57	0.96	0.51	0.0336	0.00273	9.57	5	176	0.95	0.97	0.0359	-0.00219	-2.56	6	71	0.07	0.04	-0.0535	0.00302	10.27	28	22	0.86	0.94	0.0530	0.00088	4.88	8	80	0.61	0.31	0.0102	
EDM0	799	0.00406	10.27	0.0649	0.00252	2.60	8	26	0.62	0.86	0.0370	0.00376	6.54	6	87	0.92	0.70	0.0588	0.00274	2.36	8	38	0.71	0.53	0.0330	0.00337	5.50	34	16	0.80	0.81	0.0687	0.00406	8.16	10	45	1.00	0.71	0.0600	
EDH0	863	0.00382	10.66	0.0567	0.00111	2.02	8	61	0.46	0.61	0.0113	0.00401	8.18	4	167	0.95	0.96	0.0599	-0.00104	-0.05	7	51	0.08	0.03	-0.0248	0.00347	8.85	29	19	0.89	0.97	0.0756	0.00367	9.28	10	50	0.96	0.88	0.0465	
EDU0	718	0.00475	7.25	0.0629	0.00284	3.44	5	57	0.62	0.76	0.0376	0.00433	5.91	7	65	0.91	0.87	0.0605	0.00019	1.44	8	34	0.24	0.21	0.0008	0.00353	2.99	37	13	0.74	0.66	0.0522	0.00397	5.19	7	63	0.83	0.85	0.0559	
EDZ9	929	0.00368	10.94	0.0522	0.00241	4.07	7	50	0.72	0.81	0.0277	0.00325	12.21	5	169	0.89	0.93	0.0510	-0.00143	-0.72	7	53	0.05	0.01	-0.0369	0.00343	10.15	32	19	0.93	0.82	0.0727	0.00338	7.53	8	73	0.93	0.75	0.0363	
EDZ0	697	0.00498	6.32	0.0615	0.00247	3.80	4	61	0.47	0.72	0.0507	0.00350	4.76	7	85	0.69	0.92	0.0587	-0.00091	0.56	7	37	0.13	0.10	-0.0159	0.00333	1.14	38	11	0.70	0.64	0.0400	0.00301	3.00	8	55	0.66	0.97	0.0324	
EDH1	592	0.00555	5.48	0.0639	0.00033	0.84	3	83	0.29	0.22	0.0024	0.00550	7.82	2	275	0.99	0.91	0.0770	-0.00297	-0.47	5	49	0.09	0.11	-0.0351	0.00157	0.44	30	11	0.44	0.50	0.0159	0.00375	1.39	8	44	0.74	0.94	0.0373	
EDM1	535	0.00507	5.96	0.0793	0.00314	0.60	7	36	0.70	0.28	0.0310	0.00509	5.77	3	158	1.00	0.98	0.0836	0.00198	0.35	5	32	0.53	0.22	0.0195	0.00233	-0.32	24	13	0.59	0.32	0.0221	0.00437	2.42	6	59	0.86	0.80	0.0662	
EDU1	507	0.00559	5.26	0.0870	0.00079	1.51	3	110	0.43	0.41	0.0055	0.00518	5.66	3	157	0.91	0.91	0.0932	0.00341	0.88	5	28	0.63	0.15	0.0406	0.00043	-0.37	20	15	0.32	0.26	0.0031	0.00555	4.77	6	57	0.99	0.76	0.0726	
EDZ1	399	0.00608	2.37	0.0428	0.00678	3.69	5	45	0.94	0.70	0.0621	0.00638	4.71	3	108	0.97	0.72	0.0670	0.00430	1.26	4	28	0.83	0.39	0.0509	-0.00444	-2.38	19	11	0.21	0.11	-0.0501	0.00650	2.61	6	49	0.96	0.72	0.0572	
EDH2	344	0.00036	1.13	0.0018	0.00001	0.19	2	92	0.97	0.77	-0.0008	0.00490	2.76	2	136	0.62	0.99	0.0499	0.00161	0.45	2	45	0.89	0.72	0.0153	-0.00528	-2.27	18	10	0.53	0.18	-0.0612	0.00427	2.46	4	67	0.67	0.99	0.0428	
EDM2	249	0.01019	2.26	0.0863	0.00918	2.09	1	218	0.92	0.93	0.0773	0.00918	2.09	1	218	0.92	0.93	0.0773	-0.00203	-0.17	2	34	0.23	0.53	-0.0194	0.00676	0.80	12	11	0.74	0.73	0.0594	0.00835	2.93	5	30	0.84	0.89	0.1059	
EDU2	218	0.00289	0.56	0.0164	0.00659	0.47	2	90	0.81	0.97	0.0462	-0.00421	-0.93	2	64	0.64	0.75	-0.0300	-0.00517	-0.47	2	32	0.55	0.76	-0.0508	0.00257	-0.02	11	9	0.98	0.77	0.0191	0.00928	2.26	3	54	0.63	0.96	0.1016	
EDM09	1008	0.00210	7.85	0.0314	-0.00020	0.51	10	51	0.37	0.34	-0.0064	0.00201	6.07	5	171	0.97	0.88	0.0278	-0.00189	-1.62	7	66	0.11	0.29	-0.0414	0.00281	9.55	28	21	0.78	0.70	0.0546	0.00040	0.86	9	67	0.59	0.59	0.0036	
EDZ2	153	-0.01374	-3.46	-0.1432	-0.00798	-1.22	1	37	0.58	0.41	-0.0938	-0.01113	-2.20	2	53	0.81	0.65	-0.1165	-0.00985	-1.21	2	43	0.76	0.71	-0.0802	-0.01164	-3.43	9	6	0.84	0.92	-0.1480	-0.01081	-1.81	2	62	0.83	0.81	-0.0794	
Average		0.00319	5.53	0.0399	0.00218	2.06	5.1	71			0.0214	0.00297	5.26	3.8	139			0.0436	-0.00088	0.00	5.1	43			-0.0132	0.00102	2.73	25	14			0.0185	0.00338	3.73	6.7	57			0.0433	
GEU9	482	0.00587	6.69	0.0857	0.00365	3.84	1	230	0.65	0.06	0.0425	0.00567	6.61	1	426	0.96	0.80	0.0903	0.00012	0.06	1	1	0.06	0.00	-0.0112	0.00499	6.02	11	35	0.83	0.41	0.0857	0.00457	5.04	4	68	0.78	0.22	0.0555	
GEM0	354	0.00521	3.64	0.0442	0.00433	1.91	1	120	0.91	0.60	0.0444	-0.00362	-1.77	1	68	0.18	0.04	-0.0781	0.00011	0.04	1	1	0.41	0.16	-0.0067	0.00215	0.82	17	14	0.72	0.41	0.0185	0.00526	4.20	5	46	0.99	0.84	0.0612	
GEH0	448	0.00693	6.10	0.0900	0.00638	4.95	6	60	0.92	1.00	0.0726	0.00664	5.53	1	422	0.96	0.88	0.0764	0.00012	0.05	1	1	0.06	0.02	-0.0154	0.00539	4.76	13	26	0.73	0.56	0.0919	0.00472	4.91	6	48	0.69	0.59	0.0524	
GEU0	352	0.00259	3.03	0.0220	0.00235	1.23	1	133	0.97	0.80	0.0270	-0.00378	-1.06	1	189	0.36	0.24	-0.0585	0.00011	0.04	1	1	0.68	0.45	-0.0066	-0.00125	0.09	22	10	0.64	0.42	-0.0129	0.00438	2.62	3	85	0.82	0.99	0.0478	
GEZ9	466	0.00629	6.74	0.0956	0.00090	0.69	4	42	0.21	0.12	0.0117	0.00661	6.49	1	444	0.94	0.98	0.0957	0.00012	0.06	1	1	0.04	0.01	-0.0106	0.00528	5.73	15	24	0.79	0.56	0.0985	0.00532	4.77	4	73	0.86	0.57	0.0550	
GEZ0	374	0.00264	2.86	0.0221	0.00472	3.16	2	97	0.74	0.85	0.1063	-0.00226	-0.65	1	136	0.49	0.32	-0.0312	0.00011	0.04	1	1	0.67	0.49	-0.0074	-0.00413	-1.18	27	8	0.37	0.24	-0.0458	0.00472	2.04	3	100	0.79	0.96	0.0460	
GEH1	251	0.00910	3.35	0.1009	0.00187	-0.03	2	77	0.43	0.25	0.0158	0.00797	2.76	3	59	0.88	0.80	0.0980	0.00008	0.02	1	1	0.11	0.17	-0.0154	0.00338	0.61	15	11	0.48	0.32	0.0351	0.00566	0.74	3	53	0.69	0.61	0.0540	
GEM1	284	0.00793	3.68	0.1103	0.00404	0.92	4	29	0.48	0.67	0.0666	0.00719	2.85	1	212	0.91	0.94	0.0890	0.00009	0.03	1	1	0.06	0.34	-0.0045	-0.00137	-0.56	16	10	0.21	0.37	-0.0143	0.00568	1.16	3	70	0.72	0.76	0.0694	
GEU1	228	0.00616	1.85	0.0532	0.00917	2.73	1	194	0.76	0.82	0.0957	0.00887	2.40	1	212	0.78	0.89	0.0914	-0.00270	-0.24	2	35	0.36	0.64	-0.0301	-0.00155	-0.44	11	11	0.44	0.65	-0.0166	0.00845	2.70	2	102	0.82	0.89	0.0880	
GEZ1	174	0.00622	0.50	0.0500	-0.00036	-0.06	2	49	0.62	0.94	-0.0034	0.00647	0.86	3	30	0.98	0.75	0.0620	-0.00459	-0.23	2	37	0.38	0.75	-0.0449	-0.00157	-0.45	6	14	0.49	0.79	-0.0199	-0.00743	-1.05	3	39	0.25	0.42	-0.0786	
GEH2	144	-0.01011	-1.36	-0.0901	-0.00973	-1.14	1	125	0.98	0.98	-0.0862	-0.00108	-0.07	1	75	0.49	0.36	-0.0104	-0.00186	-0.01	1	68	0.55	0.38	-0.0158	-0.00802	-1.72	5	10	0.85	0.72	-0.1253	-0.00929	-1.21	2	59	0.95	0.92	-0.0924	
GEM2	138	-0.01151	-2.25	-0.1403	-0.00470	-0.03	2	45	0.57	0.31	-0.0411	-0.00122	-0.06	1	75	0.38	0.18	-0.0113	-0.00298	-0.14	1	68	0.49	0.26	-0.0254	-0.00996	-2.40	6	8	0.85	0.78	-0.2105	-0.01037	-1.31	3	35	0.92	0.73	-0.1087	
GEU2	134	-0.01238	-2.44	-0.1549	-0.01026	-1.16	1	111	0.85	0.71	-0.0985	-0.00427	-0.18	2	21	0.46	0.14	-0.0440	-0.00634	-0.37	1	64	0.61	0.31	-0.0583	-0.01015	-2.33	8	5	0.78	0.70	-0.2078	-0.01218	-1.91	1	116	0.99	0.83	-0.1321	
GEM09	549	0.00474	7.04	0.0821	0.00414	5.77	2	155	0.84	0.50	0.1096	0.00476	6.97	2	225	0.99	0.97	0.1045	0.00018	0.16	2	71	0.21	0.13	0.0008	0.00463	7.89	11	36	0.97	0.64	0.1127	0.00156	1.35	5	51	0.44	0.20	0.0185	
GEZ2	104	-0.00740	-0.88	-0.0560	-0.00860	-0.77	2	21	0.94	0.93	-0.0975	-0.00556	-0.25	3	14	0.91	0.72	-0.0630	-0.01039	-1.27	1	60	0.85	0.82	-0.1227	-0.01086	-1.58	9	3	0.81	0.56	-0.1642	-0.01114	-1.41	1	66	0.81	0.82	-0.1282	
Average		0.00148	2.57	0.0210	0.00053	1.47	2.1	99			0.0177	0.00216	2.03	1.5	174			0.0274	-0.00186	-0.12	1.2	27			-0.0250	-0.00154	1.02	13	15			-0.0250	0.00000	1.51	3.2	67			0.0005	
Average, set A		0.00234	4.05	0.0305	0.00135	1.77	3.6	85			0.0196																													

Table 29. Returns of the B₂ data category.

B2 data set	Buy-and-hold				DRSI								DRSI common optimization								RSI (14)								Moving average (1-50)								DRSI frequent parameters							
	N_O	μ_R	r	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S	μ_R	r	n	T	t	MW	S					
ERU9	486	0.00500	9.54	0.0500	-0.00197	-2.18	3	37	0.16	0.00	-0.0403	0.00453	6.36	8	21	0.92	0.03	0.1272	0.00198	1.69	4	50	0.57	0.08	0.0284	0.00603	11.27	8	46	0.85	0.24	0.0904	0.00500	5.42	7	36	1.00	0.13	0.0601					
ERZ9	400	0.00553	8.43	0.0588	-0.00028	0.58	6	24	0.33	0.01	-0.0052	0.00591	8.23	6	39	0.95	0.35	0.0683	-0.00139	-0.18	2	63	0.20	0.00	-0.0272	0.00745	10.71	3	100	0.72	0.30	0.1432	0.00140	1.27	4	38	0.48	0.03	0.0179					
ERM0	291	0.00913	10.09	0.1185	0.00835	8.04	5	32	0.89	0.10	0.1369	0.00621	4.01	4	16	0.56	0.00	0.1622	0.00655	4.34	2	40	0.66	0.01	0.0975	0.00898	8.40	4	61	0.98	0.55	0.1734	0.00730	6.30	5	20	0.74	0.02	0.1322					
ERH0	347	0.00482	7.65	0.0543	0.00280	1.45	3	14	0.74	0.01	0.0370	0.00561	5.57	2	112	0.91	0.56	0.0591	-0.00128	0.00	1	126	0.28	0.02	-0.0226	0.00790	9.15	4	62	0.57	0.28	0.1535	0.00373	3.51	4	37	0.86	0.14	0.0482					
ERU0	190	0.01121	5.10	0.1934	0.00686	2.19	3	12	0.39	0.08	0.1740	0.00797	2.21	4	15	0.63	0.07	0.1075	0.00482	1.32	2	12	0.17	0.02	0.1621	0.01019	4.03	3	58	0.86	0.70	0.1711	-0.00236	-0.37	2	15	0.03	0.01	-0.0399					
ERZ0	150	0.01134	2.81	0.1545	0.00456	0.70	3	16	0.44	0.54	0.0577	0.00318	0.48	2	16	0.33	0.31	0.0429	0.00579	1.20	2	12	0.40	0.38	0.1693	0.00703	1.10	4	32	0.62	0.59	0.0921	0.00551	0.65	2	28	0.50	0.57	0.0700					
ERH1	107	0.00663	0.31	0.0468	0.00003	0.00	1	1	0.63	0.41	-0.0008	-0.00659	-0.89	2	18	0.44	0.42	-0.0610	0.00519	0.66	2	7	0.92	0.64	0.1623	-0.00487	-0.83	6	12	0.52	0.41	-0.0422	0.00366	0.41	2	10	0.84	0.58	0.0683					
ERM9	504	0.00625	10.79	0.0665	-0.00328	-2.99	4	32	0.06	0.00	-0.0496	0.00427	5.81	11	17	0.65	0.12	0.1204	-0.00120	-0.99	3	45	0.13	0.00	-0.0222	0.00639	12.31	9	40	0.98	0.41	0.1247	0.00207	1.95	6	35	0.44	0.06	0.0247					
Average		0.00749	6.84	0.0929	0.00214	0.98	3.5	21			0.0387	0.00388	3.97	4.9	32			0.0783	0.00256	1.01	2.3	44			0.0685	0.00614	7.02	5.1	51			0.1133	0.00329	2.39	4	27			0.0477					
LH0	297	0.00739	9.91	0.1018	0.00481	2.65	2	21	0.57	0.05	0.1490	0.00577	3.77	5	14	0.74	0.09	0.1388	0.00377	2.36	2	32	0.49	0.10	0.0668	0.00847	8.60	9	27	0.83	0.44	0.1742	0.00541	4.19	3	50	0.71	0.48	0.0917					
LM0	132	0.00555	0.63	0.0374	0.00004	0.00	1	1	0.67	0.66	-0.0011	0.00759	1.21	2	33	0.89	0.91	0.0856	0.00866	1.25	2	33	0.83	0.87	0.1028	-0.00791	-1.39	8	11	0.40	0.10	-0.0748	0.00926	1.07	1	114	0.83	0.76	0.0669					
LZ9	360	0.00513	8.16	0.0586	-0.00321	-1.66	1	47	0.11	0.00	-0.0655	0.00388	1.39	4	22	0.82	0.10	0.0660	-0.00213	-0.35	3	35	0.17	0.01	-0.0418	0.00729	8.71	6	44	0.71	0.34	0.1000	0.00198	1.16	3	57	0.62	0.24	0.0222					
LU0	130	-0.00552	-0.18	-0.0371	0.00526	0.60	1	31	0.45	0.93	0.0868	-0.00251	-0.29	1	19	0.82	0.75	-0.0643	0.00386	0.96	3	20	0.55	0.78	0.0403	-0.01129	-2.22	6	13	0.70	0.14	-0.1295	0.00602	0.42	1	116	0.54	0.62	0.0389					
LU9	365	0.00583	8.87	0.0625	-0.00122	-0.38	1	20	0.18	0.00	-0.0335	0.00436	3.12	4	8	0.77	0.01	0.1322	-0.00331	-1.11	3	46	0.10	0.00	-0.0629	0.00763	9.61	6	46	0.76	0.27	0.1080	-0.00228	-0.65	3	55	0.16	0.00	-0.0404					
LM9	492	0.00637	11.60	0.0953	0.00008	0.04	1	1	0.03	0.03	-0.0458	0.00396	4.85	7	22	0.45	0.30	0.1403	-0.00281	-2.17	3	35	0.02	0.00	-0.0510	0.00581	12.03	9	43	0.87	0.58	0.1632	0.00179	1.23	4	61	0.31	0.66	0.0220					
Average		0.00413	6.50	0.0531	0.00096	0.21	1.2	20			0.0150	0.00384	2.34	3.8	19			0.0831	0.00134	0.16	2.7	33			0.0090	0.00166	5.89	7.3	31			0.0569	0.00370	1.24	2.5	75			0.0336					
YEU9	133	-0.00665	-0.64	-0.0492	0.00032	0.00	2	10	0.56	0.00	0.0118	-0.00059	0.18	3	35	0.70	0.01	-0.0053	0.00906	1.10	2	33	0.26	0.00	0.1046	0.00350	0.28	3	21	0.47	0.00	0.0398	-0.00513	-0.45	2	50	0.92	0.02	-0.0420					
YEM9	145	0.00676	0.85	0.0457	-0.00067	0.22	1	68	0.61	0.01	-0.0077	-0.00730	-1.28	1	45	0.30	0.88	-0.1044	0.01002	2.93	2	39	0.83	0.01	0.0939	-0.00629	-0.64	5	19	0.41	0.41	-0.0510	0.00704	1.21	1	119	0.99	0.12	0.0522					
Average		0.00005	0.10	-0.0018	-0.00017	0.11	1.5	39			0.0020	-0.00394	-0.55	2	40			-0.0549	0.00954	2.01	2	36			0.0993	-0.00140	-0.18	4	20			-0.0056	0.00095	0.38	1.5	85			0.0051					
Average, set B		0.00530	5.87	0.0661	0.00141	0.58	2.4	23			0.0252	0.00289	2.80	4.1	28			0.0635	0.00297	0.81	2.4	39			0.0500	0.00352	5.70	5.8	40			0.0773	0.00315	1.71	3.1	52			0.0371					

Table 32. Statistics of A₁, B₁ and C₁ data categories – DRSI common optimization.

Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error			Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error		
								Skew.	Kurt.	KS									Skew.	Kurt.	KS
EDU9	2143	-0.54	0.35	0.002	0.06	-0.84	14.8	0.05	0.11	0.00	GEU9	936	-0.39	0.37	0.003	0.07	-0.03	7.3	0.08	0.16	0.00
EDM0	2055	-0.49	0.50	0.002	0.05	-0.15	18.9	0.05	0.11	0.00	GEM0	865	-0.33	0.41	0.003	0.06	0.03	7.7	0.08	0.17	0.00
EDH0	2124	-0.50	0.39	0.001	0.06	-1.11	12.8	0.05	0.11	0.00	GEH0	883	-0.33	0.37	0.003	0.06	-0.04	7.3	0.08	0.16	0.00
EDU0	1990	-0.29	0.43	0.002	0.03	2.04	46.4	0.05	0.11	0.00	GEU0	856	-0.20	0.18	0.002	0.04	-0.17	3.1	0.08	0.17	0.00
EDZ9	2143	-0.48	0.43	0.002	0.06	-0.73	12.9	0.05	0.11	0.00	GEZ9	906	-0.23	0.28	0.002	0.05	0.13	3.9	0.08	0.16	0.00
EDZ0	1926	-0.15	0.34	0.002	0.02	2.46	37.3	0.06	0.11	0.00	GEZ0	853	-0.19	0.16	0.002	0.04	-0.14	2.7	0.08	0.17	0.00
EDH1	1864	-0.15	0.34	0.002	0.02	2.46	36.6	0.06	0.11	0.00	GEH1	859	-0.20	0.16	0.002	0.04	-0.15	2.5	0.08	0.17	0.00
EDM1	1798	-0.18	0.50	0.002	0.03	5.04	99.9	0.06	0.12	0.00	GEM1	849	-0.21	0.24	0.003	0.05	0.01	2.1	0.08	0.17	0.00
EDU1	1735	-0.34	0.51	0.002	0.04	0.90	21.6	0.06	0.12	0.00	GEU1	846	-0.17	0.17	0.003	0.04	0.00	2.3	0.08	0.17	0.00
EDZ1	1672	-0.44	0.34	0.002	0.06	-0.51	8.3	0.06	0.12	0.00	GEZ1	846	-0.18	0.17	0.003	0.04	-0.01	3.4	0.08	0.17	0.00
EDH2	1611	-0.45	0.27	0.002	0.05	-0.58	8.6	0.06	0.12	0.00	GEH2	844	-0.14	0.18	0.003	0.04	0.27	3.6	0.08	0.17	0.00
EDM2	1546	-0.40	0.30	0.002	0.04	-0.85	23.0	0.06	0.12	0.00	GEM2	839	-0.21	0.19	0.003	0.05	0.08	2.5	0.08	0.17	0.00
EDU2	1482	-0.21	0.24	0.002	0.04	0.16	6.5	0.06	0.13	0.00	GEU2	841	-0.31	0.28	0.002	0.06	-0.03	4.2	0.08	0.17	0.00
EDM3	1294	-0.18	0.24	0.002	0.04	0.23	4.6	0.07	0.14	0.00	GEM0	949	-0.32	0.23	0.001	0.06	-0.15	3.8	0.08	0.16	0.00
EDM0	2143	-0.46	0.29	0.001	0.05	-0.74	11.7	0.05	0.11	0.00	GEM3	837	-0.45	0.40	0.004	0.08	0.10	3.7	0.08	0.17	0.00
EDZ2	1418	-0.38	0.36	0.001	0.06	-0.15	4.7	0.06	0.13	0.00	GEZ2	839	-0.22	0.21	0.003	0.05	0.00	2.3	0.08	0.17	0.00
EDH3	1357	-0.18	0.24	0.002	0.04	0.13	5.1	0.07	0.13	0.00	GEH3	839	-0.47	0.29	0.003	0.06	-0.40	7.4	0.08	0.17	0.00
EDU3	1232	-0.23	0.20	0.002	0.04	-0.01	3.7	0.07	0.14	0.00	GEU3	836	-0.40	0.33	0.004	0.07	0.01	3.7	0.08	0.17	0.00
EDH4	1108	-0.21	0.22	0.002	0.04	0.25	4.9	0.07	0.15	0.00	GEZ3	837	-0.34	0.49	0.004	0.09	0.50	3.8	0.08	0.17	0.00
EDZ3	1169	-0.37	0.36	0.002	0.07	-0.22	4.3	0.07	0.14	0.00	GEH4	837	-0.41	0.37	0.003	0.07	0.11	5.5	0.08	0.17	0.00
EDM4	1041	-0.36	0.27	0.003	0.06	-0.19	3.8	0.08	0.15	0.00	GEM4	836	-0.36	0.45	0.004	0.08	0.30	3.8	0.08	0.17	0.00
EDU4	980	-0.21	0.20	0.003	0.04	0.19	4.7	0.08	0.16	0.00	GEU4	836	-0.39	0.46	0.004	0.08	0.32	4.6	0.08	0.17	0.00
EDH5	855	-0.30	0.41	0.003	0.06	0.32	7.2	0.08	0.17	0.00	GEH5	836	-0.46	0.64	0.005	0.10	0.60	5.9	0.08	0.17	0.00
EDZ4	917	-0.33	0.23	0.003	0.04	-0.32	9.5	0.08	0.16	0.00	GEZ4	837	-0.37	0.38	0.004	0.07	0.02	4.7	0.08	0.17	0.00
EDM5	791	-0.38	0.79	0.003	0.07	1.75	23.4	0.09	0.17	0.00	GEM5	780	-0.58	0.78	0.003	0.08	1.15	23.4	0.09	0.17	0.00
EDZ5	658	-0.44	0.42	0.004	0.07	0.50	11.1	0.10	0.19	0.00	GEZ5	690	-0.52	0.61	0.005	0.09	0.88	12.3	0.10	0.19	0.00
EDU5	721	-0.41	0.49	0.004	0.08	0.43	7.6	0.09	0.18	0.00	GEU5	713	-0.46	0.43	0.004	0.08	0.20	6.9	0.09	0.18	0.00
EDH6	602	-0.27	0.35	0.004	0.06	1.10	9.0	0.10	0.20	0.00	GEH6	595	-0.33	0.47	0.005	0.07	1.62	12.4	0.10	0.20	0.00
EDM6	534	-0.23	0.33	0.005	0.06	0.58	4.9	0.11	0.21	0.00	GEM6	528	-0.27	0.35	0.005	0.06	0.74	5.3	0.11	0.21	0.00
ERU9	1002	-0.48	0.52	0.002	0.07	0.41	12.9	0.08	0.15	0.00	L U9	989	-0.22	0.43	0.003	0.04	1.35	0.1	22.46	0.16	0.00
ERZ9	937	-0.31	0.78	0.001	0.06	2.31	32.4	0.08	0.16	0.00	L Z0	699	-0.27	0.29	0.002	0.04	1.40	0.1	13.45	0.18	0.00
ERM0	808	-0.58	0.42	0.003	0.06	-0.69	16.8	0.09	0.17	0.00	L H1	610	-0.20	0.19	0.003	0.04	0.54	0.1	5.76	0.20	0.00
ERH0	872	-0.58	0.38	0.003	0.06	-0.64	18.5	0.08	0.17	0.00	L M9	1008	-0.48	0.41	0.002	0.05	-0.53	0.1	30.82	0.15	0.00
ERU0	738	-0.34	0.39	0.004	0.05	0.63	10.6	0.09	0.18	0.00	L M1	544	-0.42	0.47	0.001	0.06	-0.36	0.1	22.26	0.21	0.00
ERZ0	704	-0.38	0.45	0.002	0.08	-0.38	5.1	0.09	0.18	0.00	L U1	543	-0.13	0.18	0.002	0.03	0.74	0.1	8.97	0.21	0.00
ERH1	673	-0.48	0.37	0.001	0.09	-0.33	3.1	0.09	0.19	0.00	L H2	414	-0.08	0.20	0.000	0.01	14.44	0.1	3.00	0.24	0.00
ERM1	614	-0.37	0.15	-0.002	0.04	-4.13	41.1	0.10	0.20	0.00	L Z1	479	-0.14	0.20	0.001	0.02	6.18	0.1	97.05	0.22	0.00
ERU1	547	-0.63	0.30	0.002	0.07	-1.40	16.9	0.10	0.21	0.00	L M2	352	-0.25	0.22	0.001	0.04	-0.37	0.1	23.02	0.26	0.00
ERM9	1008	-0.59	0.65	0.002	0.08	0.70	13.1	0.08	0.15	0.00	L U2	290	0.00	0.00	0.000	0.00	1.92	0.1	3.46	0.29	0.00
ERZ1	482	-0.64	0.34	0.001	0.08	-1.78	17.3	0.11	0.22	0.00	L Z2	225	-0.27	0.25	0.001	0.04	-0.29	0.2	15.70	0.32	0.00
ERH2	356	0.00	0.00	0.000	0.00	1.86	3.6	0.13	0.26	0.00	YEH0	880	-2.00	1.27	0.004	0.12	-3.48	0.1	127	0.16	0.00
ERM2	355	0.00	0.00	0.000	0.00	1.86	3.6	0.13	0.26	0.00	YEU9	950	-1.61	1.09	0.002	0.17	-1.14	0.1	26.49	0.16	0.00
ERU2	292	-0.19	0.25	0.004	0.03	2.01	20.5	0.14	0.28	0.00	YEZ9	890	-1.99	1.27	-0.004	0.13	-4.07	0.1	83.18	0.16	0.00
ERZ2	163	0.00	0.00	0.000	0.00	3.11	13.4	0.19	0.38	0.00	YEM0	888	-1.99	1.35	0.001	0.16	-1.45	0	47.38	0.16	0.00
ERH3	161	0.00	0.00	0.000	0.00	3.10	13.3	0.19	0.38	0.00	YEZ0	888	-1.51	1.15	0.001	0.15	-1.58	0.1	26.79	0.16	0.00
L H0	862	-0.24	0.37	0.003	0.04	0.55	13.1	0.08	0.17	0.00	YEM9	980	-0.88	0.87	0.004	0.08	0.65	0.1	42.14	0.16	0.00
L M0	800	-0.24	0.35	0.004	0.04	0.50	9.8	0.09	0.17	0.00	YEU0	885	-1.85	1.16	0.004	0.11	-3.08	0	107	0.16	0.00
L Z9	927	-0.40	0.45	0.001	0.05	0.20	14.2	0.08	0.16	0.00	YEH1	581	-0.39	1.01	0.005	0.06	7.75	0.1	117	0.20	0.00
L U0	731	-0.20	0.26	0.002	0.04	1.30	10.5	0.09	0.18	0.00											
ESU9	227	-0.12	0.22	0.002	0.03	2.73	23.9	0.16	0.32	0.00	EYM9	1008	-0.94	0.46	-0.003	0.06	-3.60	69.4	0.08	0.15	0.00
ESZ9	162	-0.15	0.22	0.005	0.03	0.95	14.3	0.19	0.38	0.00	EYZ9	952	-1.60	0.61	0.002	0.10	-4.73	91.1	0.08	0.16	0.00
ESM9	258	-0.11	0.18	0.005	0.03	2.68	15.7	0.15	0.30	0.00	MYU9	977	-0.54	0.46	0.003	0.10	0.15	17.0	0.08	0.16	0.00
ZBU9	285	-0.10	0.41	0.006	0.04	5.90	45.8	0.14	0.29	0.00	KKU2	209	-0.74	0.32	-0.006	0.08	-3.94	34.9	0.17	0.33	0.00
ZBH0	336	-0.22	0.40	0.006	0.05	3.22	23.5	0.13	0.27	0.00	KKM2	274	-0.37	0.50	0.006	0.09	1.37	11.8	0.15	0.29	0.00
ZBU0	228	-0.53	0.76	0.010	0.09	2.08	28.7	0.16	0.32	0.00	KKU9	957	-0.66	0.45	0.000	0.06	-0.99	22.7	0.08	0.16	0.00
ZBZ9	284	-0.12	0.24	0.009	0.03	1.97	10.6	0.14	0.29	0.00	KBZ9	896	-0.37	0.63	0.003	0.06	2.16	40.1	0.08	0.16	0.00
ZBM0	398	-0.22	0.40	0.006	0.04	3.78	32.8	0.12	0.24	0.00	KKH0	835	-0.35	0.65	0.003	0.05	2.20	42.7	0.08	0.17	0.00
ZBZ0	163	-0.73	0.36	0.000	0.11	-2.83	20.4	0.19	0.38	0.00	KKM0	773	-0.16	0.38	0.003	0.03	3.64	42.8	0.09	0.18	0.00
FPM9	505	-0.54	0.59	0.003	0.09	0.21	10.4	0.11	0.22	0.00	KKU0	704	-0.60	0.60	0.003	0.07	2.20	24.9	0.09	0.18	0.00
FPU9	474	-0.49	0.73	0.008	0.11	1.19	12.4	0.11	0.22	0.00	KKZ0	642	-0.48	0.69	0.003	0.07	1.33	28.2	0.10	0.19	0.00
FPZ9	409	-0.59	0.55																		

Table 34. Statistics of A₁, B₁ and C₁ data categories – Moving Average.

Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error			Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	KS		
								Skew.	Kurt.	KS											
EDU9	2143	-0.76	0.40	0.000	0.07	-1.95	22.4	0.05	0.11	0.00	GEU9	936	-0.17	0.23	0.003	0.04	0.49	5.6	0.08	0.16	0.00
EDM0	2055	-0.31	0.37	0.002	0.05	0.16	10.1	0.05	0.11	0.00	GEM0	865	-0.23	0.28	0.003	0.04	0.24	7.8	0.08	0.17	0.00
EDH0	2124	-0.60	0.53	0.002	0.07	-0.50	12.0	0.05	0.11	0.00	GEH0	883	-0.20	0.21	0.003	0.04	0.28	6.0	0.08	0.16	0.00
EDU0	1990	-0.40	0.51	0.002	0.05	0.10	14.1	0.05	0.11	0.00	GEU0	856	-0.24	0.31	0.002	0.04	0.31	9.0	0.08	0.17	0.00
EDZ9	2143	-0.64	0.49	0.000	0.07	-1.63	19.3	0.05	0.11	0.00	GEZ9	906	-0.18	0.24	0.003	0.04	0.45	5.9	0.08	0.16	0.00
EDZ0	1926	-0.34	0.29	0.002	0.04	-0.25	9.3	0.06	0.11	0.00	GEZ0	853	-0.27	0.28	0.002	0.05	-0.08	8.7	0.08	0.17	0.00
EDH1	1864	-0.24	0.24	0.002	0.04	-0.03	7.0	0.06	0.11	0.00	GEH1	859	-0.35	0.43	0.002	0.06	0.43	14.2	0.08	0.17	0.00
EDM1	1798	-0.38	0.35	0.002	0.06	-0.17	8.5	0.06	0.12	0.00	GEM1	849	-0.40	0.49	0.001	0.06	0.42	14.4	0.08	0.17	0.00
EDU1	1735	-0.55	0.57	0.001	0.07	-0.28	15.6	0.06	0.12	0.00	GEU1	846	-0.41	0.50	0.000	0.07	-0.01	13.6	0.08	0.17	0.00
EDZ1	1672	-0.49	0.48	0.002	0.06	0.14	13.8	0.06	0.12	0.00	GEZ1	846	-0.44	0.43	0.000	0.07	-0.19	11.7	0.08	0.17	0.00
EDH2	1611	-0.53	0.82	0.002	0.07	1.40	27.6	0.06	0.12	0.00	GEH2	844	-0.57	0.44	-0.001	0.07	-0.68	14.0	0.08	0.17	0.00
EDM2	1546	-0.60	0.52	0.000	0.08	-0.67	13.3	0.06	0.12	0.00	GEM2	839	-0.45	0.48	0.000	0.07	-0.11	13.6	0.08	0.17	0.00
EDU2	1482	-0.55	0.72	0.001	0.08	0.10	18.2	0.06	0.13	0.00	GEU2	841	-0.49	0.50	0.000	0.07	-0.32	13.9	0.08	0.17	0.00
EDM3	1294	-0.39	0.45	0.002	0.05	1.02	17.6	0.07	0.14	0.00	GEM0	949	-0.18	0.23	0.003	0.04	0.36	5.8	0.08	0.16	0.00
EDM0	2143	-0.61	0.36	0.001	0.05	-1.65	19.2	0.05	0.11	0.00	GEM3	837	-0.82	0.91	0.000	0.11	0.31	20.8	0.08	0.17	0.00
EDZ2	1418	-0.40	0.48	0.002	0.06	0.73	15.4	0.06	0.13	0.00	GEZ2	839	-0.55	0.65	0.001	0.07	0.39	20.6	0.08	0.17	0.00
EDH3	1357	-0.67	0.90	0.001	0.08	0.42	26.7	0.07	0.13	0.00	GEH3	839	-0.87	0.87	0.000	0.10	0.19	20.9	0.08	0.17	0.00
EDU3	1232	-0.51	0.56	0.000	0.08	0.06	11.1	0.07	0.14	0.00	GEU3	836	-0.57	0.83	0.000	0.10	0.64	14.5	0.08	0.17	0.00
EDH4	1108	-0.44	0.51	-0.001	0.07	-0.21	8.6	0.07	0.15	0.00	GEH4	837	-0.61	0.59	-0.001	0.10	-0.06	11.4	0.08	0.17	0.00
EDZ3	1169	-0.45	0.50	0.000	0.08	-0.15	9.4	0.07	0.14	0.00	GEZ3	837	-0.43	0.62	-0.001	0.09	-0.07	9.1	0.08	0.17	0.00
EDM4	1041	-0.56	0.42	-0.002	0.07	-0.73	12.1	0.08	0.15	0.00	GEM4	836	-0.49	0.60	-0.001	0.09	0.11	9.7	0.08	0.17	0.00
EDU4	980	-0.60	0.48	-0.002	0.07	-0.67	12.3	0.08	0.16	0.00	GEU4	836	-0.48	0.71	-0.001	0.09	0.20	9.8	0.08	0.17	0.00
EDH5	855	-0.43	0.53	-0.001	0.08	-0.08	8.7	0.08	0.17	0.00	GEH5	836	-0.49	0.57	-0.001	0.09	-0.17	8.1	0.08	0.17	0.00
EDZ4	917	-0.45	0.47	-0.001	0.07	-0.21	7.6	0.08	0.16	0.00	GEZ4	837	-0.48	0.65	-0.001	0.09	0.09	9.3	0.08	0.17	0.00
EDM5	791	-0.59	0.47	-0.002	0.08	-0.48	10.1	0.09	0.17	0.00	GEM5	780	-0.54	0.58	-0.001	0.09	-0.09	8.3	0.09	0.17	0.00
EDZ5	658	-0.40	0.38	-0.003	0.07	-0.23	8.0	0.10	0.19	0.00	GEZ5	650	-0.62	0.45	-0.004	0.08	-0.69	13.7	0.10	0.19	0.00
EDU5	721	-0.51	0.46	-0.003	0.08	-0.43	9.0	0.09	0.18	0.00	GEU5	713	-0.48	0.44	-0.003	0.08	-0.32	7.5	0.09	0.18	0.00
EDH6	602	-0.40	0.42	-0.003	0.08	-0.16	7.6	0.10	0.20	0.00	GEH6	595	-0.50	0.51	-0.004	0.09	-0.19	8.2	0.10	0.20	0.00
EDM6	534	-0.56	0.46	-0.003	0.09	-0.33	7.7	0.11	0.21	0.00	GEM6	528	-0.55	0.64	-0.004	0.10	-0.04	8.3	0.11	0.21	0.00
ERU9	1002	-0.38	0.37	0.003	0.06	0.58	11.0	0.08	0.15	0.00	L U9	989	-0.21	0.24	0.003	0.04	0.26	6.3	0.08	0.16	0.00
ERZ9	937	-0.23	0.34	0.003	0.05	0.55	6.1	0.08	0.16	0.00	L Z0	699	-0.17	0.20	0.003	0.04	0.21	3.5	0.09	0.18	0.00
ERM0	808	-0.18	0.28	0.004	0.05	0.57	4.6	0.09	0.17	0.00	L H1	610	-0.22	0.19	0.004	0.05	0.14	3.8	0.10	0.20	0.00
ERH0	872	-0.19	0.25	0.003	0.05	0.44	4.5	0.08	0.17	0.00	L M9	1008	-0.26	0.22	0.003	0.04	0.05	5.5	0.08	0.15	0.00
ERU0	738	-0.22	0.35	0.004	0.06	0.35	4.8	0.09	0.18	0.00	L M1	544	-0.19	0.17	0.004	0.04	0.17	3.6	0.10	0.21	0.00
ERZ0	704	-0.21	0.23	0.004	0.06	0.22	3.5	0.09	0.18	0.00	L U1	543	-0.24	0.18	0.004	0.05	0.12	4.5	0.10	0.21	0.00
ERH1	673	-0.20	0.21	0.004	0.05	0.19	3.9	0.09	0.19	0.00	L H2	414	-0.42	0.35	0.003	0.07	0.04	8.8	0.12	0.24	0.00
ERM1	614	-0.17	0.20	0.004	0.05	0.28	3.3	0.10	0.20	0.00	L Z1	479	-0.51	0.39	0.003	0.07	-0.31	9.9	0.11	0.22	0.00
ERU1	547	-0.17	0.20	0.004	0.04	0.40	2.8	0.10	0.21	0.00	L M2	352	-0.31	0.27	0.005	0.06	0.37	6.7	0.13	0.26	0.00
ERM9	1008	-0.36	0.44	0.003	0.07	0.46	7.2	0.08	0.15	0.00	L U2	290	-0.27	0.22	0.006	0.06	0.30	5.2	0.14	0.29	0.00
ERZ1	482	-0.27	0.31	0.004	0.07	0.22	3.3	0.11	0.22	0.00	L Z2	225	-0.36	0.32	0.007	0.07	0.39	9.4	0.16	0.32	0.00
ERH2	356	-0.33	0.30	0.003	0.07	-0.09	3.6	0.13	0.26	0.00	YEH0	880	-0.53	0.76	0.006	0.08	3.45	33.6	0.08	0.16	0.00
ERM2	355	-0.26	0.29	0.000	0.09	-0.13	1.3	0.13	0.26	0.00	YEU9	950	-1.05	1.55	0.004	0.11	1.75	52.6	0.08	0.16	0.00
ERU2	292	-0.27	0.34	0.004	0.07	0.37	3.1	0.14	0.28	0.00	YEZ9	890	-0.62	0.85	0.006	0.09	3.18	34.1	0.08	0.16	0.00
ERZ2	163	-0.49	0.42	-0.003	0.12	-0.18	3.5	0.19	0.38	0.00	YEM0	888	-0.62	0.85	0.006	0.09	3.34	35	0.08	0.16	0.00
ERH3	161	-0.53	0.40	-0.004	0.12	-0.53	3.8	0.19	0.38	0.00	YEZ0	888	-0.49	0.68	0.006	0.07	3.74	37.0	0.08	0.16	0.00
L H0	862	-0.24	0.21	0.003	0.04	-0.11	5.1	0.08	0.17	0.00	YEM9	980	-0.97	1.03	0.002	0.11	1.09	22.7	0.08	0.16	0.00
L M0	800	-0.17	0.20	0.003	0.04	0.22	3.3	0.09	0.17	0.00	YEU0	885	-0.59	0.82	0.006	0.09	3.25	33	0.08	0.16	0.00
L Z9	927	-0.27	0.24	0.003	0.04	-0.10	5.8	0.08	0.16	0.00	YEH1	581	-0.92	1.57	0.006	0.10	5.42	103	0.10	0.20	0.00
L U0	731	-0.16	0.20	0.003	0.04	0.24	3.4	0.09	0.18	0.00											
ESU9	227	-0.29	0.50	0.011	0.07	2.90	19.0	0.16	0.32	0.00	EYM9	1008	-0.85	1.34	0.004	0.10	2.90	54.4	0.08	0.15	0.00
ESZ9	162	-0.16	0.21	0.007	0.05	0.67	3.8	0.19	0.38	0.00	EYZ9	952	-0.62	1.54	0.004	0.08	6.42	129	0.08	0.16	0.00
ESM9	258	-0.38	0.29	0.010	0.06	0.45	11.2	0.15	0.30	0.00	MYU9	977	-0.43	0.85	0.003	0.06	2.40	40.1	0.08	0.16	0.00
ZBU9	285	-0.14	0.31	0.009	0.04	2.41	16.0	0.14	0.29	0.00	KKU2	209	-0.29	0.46	0.009	0.07	2.21	14.7	0.17	0.33	0.00
ZBH0	336	-0.36	0.34	0.008	0.06	8.89	13.5	0.13	0.27	0.00	KKM2	274	-0.37	1.07	0.010	0.11	4.16	35.5	0.15	0.29	0.00
ZBU0	228	-0.17	0.20	0.009	0.04	0.92	4.7	0.16	0.32	0.00	KKU9	957	-0.27	0.37	0.003	0.03	1.83	32.2	0.08	0.16	0.00
ZBZ9	284	-0.12	0.24	0.009	0.04	2.07	11.1	0.14	0.29	0.00	KKZ9	896	-0.15	0.35	0.003	0.03	2.93	34.0	0.08	0.16	0.00
ZBM0	398	-0.22	0.33	0.007	0.05	0.61	7.1	0.12	0.24	0.00	KKH0	835	-0.17	0.30	0.003	0.03	2.46	29.4	0.08	0.17	0.00
ZBZ0	163	-0.17	0.23	0.004	0.06	0.89	4.0	0.19	0.38	0.00	KKM0	773	-0.17	0.30	0.003	0.03	2.95	32.0	0.09	0.18	0.00
FPM9	505	-0.35	1.01	0.008	0.07	5.77	84.5	0.11	0.22	0.00	KKU0	704	-0.24	0.27	0.004	0.03	1.27	16.7	0.09	0.18	0.00
FPU9	474	-0.36	0.31	0.007	0.08	0.05	6.0	0.11	0.22	0.00	KKZ0	642	-0.28	0.50	0.004	0.06	2.28	23.0	0.10	0.19	0.00
FPZ9	409	-0.29	0.30	0.008	0.05	1.04	8.4														

Table 36. Statistics of A₂ and B₂ data categories – Buy-and-hold.

Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error				Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	KS	
								Skew.	Kurt.	KS	KS										
EDU9	993	-0.40	0.35	0.003	0.07	0.02	4.4	0.08	0.16	0.00	GEU9	482	-0.28	0.27	0.006	0.07	0.02	3.4	0.11	0.22	0.00
EDM0	799	-0.30	0.26	0.004	0.06	-0.22	3.5	0.09	0.17	0.00	GEM0	354	-0.64	0.74	0.005	0.12	-0.04	11.4	0.13	0.26	0.00
EDH0	863	-0.34	0.28	0.004	0.07	-0.02	2.3	0.08	0.17	0.00	GEH0	448	-0.29	0.34	0.007	0.08	0.20	3.9	0.12	0.23	0.00
EDU0	718	-0.28	0.35	0.005	0.07	0.04	2.6	0.09	0.18	0.00	GEU0	352	-0.82	0.55	0.003	0.11	-1.28	12.6	0.13	0.26	0.00
EDZ9	929	-0.26	0.26	0.004	0.07	0.12	1.7	0.08	0.16	0.00	GEZ9	466	-0.25	0.27	0.006	0.06	0.08	3.1	0.11	0.23	0.00
EDZ0	697	-0.33	0.35	0.005	0.08	0.06	2.9	0.09	0.18	0.00	GEZ0	374	-0.73	0.51	0.003	0.11	-0.72	7.7	0.13	0.25	0.00
EDH1	592	-0.38	0.37	0.006	0.08	0.11	3.4	0.10	0.20	0.00	GEH1	251	-0.38	0.55	0.009	0.09	0.53	9.0	0.15	0.31	0.00
EDM1	535	-0.24	0.22	0.005	0.06	-0.07	1.4	0.11	0.21	0.01	GEM1	284	-0.25	0.31	0.008	0.07	0.47	3.9	0.14	0.29	0.00
EDU1	507	-0.21	0.22	0.006	0.06	0.03	1.4	0.11	0.22	0.05	GEU1	228	-0.52	0.44	0.006	0.11	-0.22	5.6	0.16	0.32	0.00
EDZ1	399	-0.46	0.54	0.006	0.14	0.11	2.5	0.12	0.24	0.00	GEZ1	174	-0.51	0.53	0.006	0.12	-0.01	4.2	0.18	0.37	0.05
EDH2	344	-0.80	0.60	0.000	0.14	-0.71	6.3	0.13	0.26	0.00	GEH2	144	-0.31	0.36	-0.010	0.11	-0.17	0.3	0.20	0.40	0.96
EDM2	249	-0.47	0.60	0.010	0.12	0.62	5.1	0.15	0.31	0.00	GEM2	138	-0.29	0.24	-0.012	0.08	-0.25	0.7	0.21	0.41	0.86
EDU2	218	-0.77	0.69	0.003	0.17	-0.40	5.0	0.16	0.33	0.00	GEU2	134	-0.30	0.23	-0.012	0.08	-0.39	1.1	0.21	0.42	0.75
EDM09	1008	-0.31	0.28	0.002	0.06	0.08	3.3	0.08	0.15	0.00	GEM09	549	-0.22	0.28	0.005	0.06	0.28	2.5	0.10	0.21	0.00
EDZ2	153	-0.47	0.24	-0.014	0.10	-0.97	3.6	0.20	0.39	0.38	GEZ2	104	-0.43	0.44	-0.007	0.13	0.07	2.0	0.24	0.47	0.39
ERU9	486	-0.46	0.80	0.005	0.10	0.70	11.1	0.11	0.22	0.00	L.H0	297	-0.62	0.25	0.007	0.07	-2.66	24.1	0.14	0.28	0.00
ERZ9	400	-0.41	0.47	0.006	0.09	0.07	4.6	0.12	0.24	0.00	L.M0	132	-0.52	0.59	0.006	0.15	0.06	4.1	0.21	0.42	0.22
ERM0	291	-0.35	0.48	0.009	0.08	0.41	11.3	0.14	0.28	0.00	L.Z9	360	-0.56	0.44	0.005	0.09	-0.90	10.4	0.13	0.26	0.00
ERH0	347	-0.34	0.44	0.005	0.09	0.02	4.8	0.13	0.26	0.00	L.U0	130	-0.63	0.54	-0.006	0.15	-0.42	3.7	0.21	0.42	0.08
ERU0	190	-0.25	0.26	0.011	0.06	0.16	4.3	0.18	0.35	0.09	L.U9	365	-0.59	0.34	0.006	0.09	-0.64	8.3	0.13	0.25	0.00
ERZ0	150	-0.25	0.30	0.011	0.07	0.29	3.4	0.20	0.39	0.23	L.M9	492	-0.44	0.43	0.006	0.07	-0.87	15.0	0.11	0.22	0.00
ERH1	107	-0.55	0.42	0.007	0.14	-0.54	2.3	0.23	0.46	0.72	YEU9	133	-0.69	0.31	-0.007	0.14	-1.05	4.9	0.21	0.42	0.00
ERM9	504	-0.71	0.47	0.006	0.09	-0.44	12.5	0.11	0.22	0.00	YEM9	145	-0.74	0.87	0.007	0.15	0.65	11.9	0.20	0.40	0.00

Table 37. Statistics of A₂ and B₂ data categories – DRSI.

Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error				Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	KS	
								Skew.	Kurt.	KS	KS										
EDU9	993	-0.74	0.53	0.003	0.08	-0.06	20.0	0.08	0.16	0.00	GEU9	482	-0.57	0.61	0.004	0.08	0.18	18.4	0.11	0.22	0.00
EDM0	799	-0.50	0.44	0.003	0.06	-0.33	14.6	0.09	0.17	0.00	GEM0	354	-0.47	0.75	0.004	0.10	1.19	17.5	0.13	0.26	0.00
EDH0	863	-0.53	0.49	0.001	0.09	-0.09	9.7	0.08	0.17	0.00	GEH0	448	-0.44	0.46	0.006	0.09	-0.01	5.3	0.12	0.23	0.00
EDU0	718	-0.45	0.43	0.003	0.07	-0.06	9.1	0.09	0.18	0.00	GEU0	352	-0.43	0.60	0.002	0.08	0.72	18.0	0.13	0.26	0.00
EDZ9	929	-0.67	0.85	0.002	0.08	0.24	26.9	0.08	0.16	0.00	GEZ9	466	-0.50	0.68	0.001	0.07	0.65	32.8	0.11	0.23	0.00
EDZ0	697	-0.26	0.31	0.002	0.05	0.57	10.6	0.09	0.18	0.00	GEZ0	374	-0.20	0.34	0.005	0.04	1.57	13.6	0.13	0.25	0.00
EDH1	592	-0.80	0.58	0.000	0.08	-0.89	23.2	0.10	0.20	0.00	GEH1	251	-0.78	0.44	0.002	0.11	-0.97	10.3	0.15	0.31	0.00
EDM1	535	-0.46	0.52	0.003	0.10	0.21	5.9	0.11	0.21	0.00	GEM1	284	-0.31	0.33	0.004	0.06	0.43	9.1	0.14	0.29	0.00
EDU1	507	-0.77	0.48	0.001	0.12	-0.61	7.0	0.11	0.22	0.00	GEU1	228	-0.39	0.53	0.009	0.10	1.07	9.8	0.16	0.32	0.00
EDZ1	399	-0.49	0.57	0.007	0.11	0.51	7.3	0.12	0.24	0.00	GEZ1	174	-0.48	0.49	0.000	0.12	-0.34	4.2	0.18	0.37	0.00
EDH2	344	-0.68	0.58	0.000	0.12	-0.49	7.6	0.13	0.26	0.00	GEH2	144	-0.32	0.43	-0.010	0.11	0.01	1.2	0.20	0.40	0.12
EDM2	249	-0.52	0.70	0.009	0.12	0.84	8.0	0.15	0.31	0.00	GEM2	138	-0.47	0.39	-0.005	0.12	-0.48	3.1	0.21	0.41	0.00
EDU2	218	-0.59	0.64	0.007	0.14	-0.09	5.2	0.16	0.33	0.00	GEU2	134	-0.30	0.37	-0.010	0.10	-0.17	1.8	0.21	0.42	0.02
EDM09	1008	-0.28	0.57	0.000	0.05	1.34	22.1	0.08	0.15	0.00	GEM09	549	-0.15	0.21	0.004	0.04	0.81	5.9	0.10	0.21	0.00
EDZ2	153	-0.46	0.25	-0.008	0.09	-2.41	11.4	0.20	0.39	0.00	GEZ2	104	-0.41	0.23	-0.009	0.09	-1.79	6.3	0.24	0.47	0.00
ERU9	486	-0.37	0.22	-0.002	0.05	-2.05	16.3	0.11	0.22	0.00	L.H0	297	-0.08	0.28	0.005	0.03	5.45	37.7	0.14	0.28	0.00
ERZ9	400	-0.37	0.34	0.000	0.08	-0.85	8.3	0.12	0.24	0.00	L.M0	132	0.00	0.00	0.000	0.00	1.83	2.4	0.21	0.42	0.00
ERM0	291	-0.34	0.40	0.008	0.06	1.26	17.6	0.14	0.28	0.00	L.Z9	360	-0.42	0.21	-0.003	0.05	-3.92	34.4	0.13	0.26	0.00
ERH0	347	-0.48	0.63	0.003	0.07	0.46	28.9	0.13	0.26	0.00	L.U0	130	-0.20	0.36	0.005	0.06	1.60	12.5	0.21	0.42	0.00
ERU0	190	-0.22	0.20	0.007	0.04	1.52	14.5	0.18	0.35	0.00	L.U9	365	-0.52	0.40	-0.001	0.04	-3.64	114	0.13	0.25	0.00
ERZ0	150	-0.55	0.39	0.005	0.08	-1.71	21.8	0.20	0.39	0.00	L.M9	492	-0.02	0.00	0.000	0.00	-21.9	485	0.11	0.22	0.00
ERH1	107	0.00	0.00	0.000	0.00	1.90	3.0	0.23	0.46	0.00	YEU9	133	-0.08	0.09	0.000	0.02	0.37	8.8	0.21	0.42	0.00
ERM9	504	-0.65	0.33	-0.003	0.07	-2.70	22.7	0.11	0.22	0.00	YEM9	145	-0.54	0.31	-0.001	0.09	-1.72	10.4	0.20	0.40	0.00

Table 38. Statistics of A₂ and B₂ data categories – DRSI common optimization.

Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error				Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	KS	
								Skew.	Kurt.	KS	KS										
EDU9	993	-0.30	0.38	0.003	0.07	0.11	2.8	0.08	0.16	0.00	GEU9	482	-0.30	0.25	0.006	0.06	-0.12	4.0	0.11	0.22	0.00
EDM0	799	-0.32	0.41	0.004	0.06	0.35	5.2	0.09	0.17	0.00	GEM0	354	-0.30	0.23	-0.004	0.05	-2.05	16.1	0.13	0.26	0.00
EDH0	863	-0.33	0.45	0.004	0.06	0.51	7.2	0.08	0.17	0.00	GEH0	448	-0.41	0.43	0.007	0.09	-0.03	4.5	0.12	0.23	0.00
EDU0	718	-0.37	0.44	0.004	0.07	0.31	9.4	0.09	0.18	0.00	GEU0	352	-0.44	0.22	-0.004	0.07	-1.43	8.4	0.13	0.26	0.00
EDZ9	929	-0.28	0.28	0.003	0.06	0.11	2.8	0.08	0.16	0.00	GEZ9	466	-0.28	0.30	0.007	0.07	0.18	4.0	0.11	0.23	0.00
EDZ0	697	-0.28	0.24	0.004	0.06	-0.11	2.6	0.09	0.18	0.00	GEZ0	374	-0.33	0.38	-0.002	0.08	-0.24	6.5	0.13	0.25	0.00
EDH1	592	-0.26	0.30	0.005	0.07	0.04	2.3	0.10	0.20	0.00	GEH1	251	-0.39	0.59	0.008	0.08	1.24	16.4	0.15	0.31	0.00
EDM1	535	-0.22	0.23	0.005	0.06	0.01	2.0	0.11	0.21	0.00	GEM1	284	-0.40	0.54	0.007	0.08	1.15	13.8	0.14	0.29	0.00
EDU1	507	-0.19	0.24	0.005	0.05	0.17	1.9	0.11	0.22	0.01	GEU1	228	-0.39	0.53	0.009	0.10	1.03	9.2	0.16	0.32	0.00
EDZ1	399	-0.49	0.45	0.006	0.09	0.27	7.0	0.12	0.24	0.00	GEZ1	174	-0.40	0.49	0.006	0.10	0.28	4.8	0.18	0.37	0.00
EDH2	344	-0.38	0.49	0.005	0.10	0.18	5.0	0.13	0.26	0.00	GEH2	144	-0.52	0.50							

Table 40. Statistics of A₂ and B₂ data categories – Moving Average.

Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error			Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error		
								Skew.	Kurt.	KS									Skew.	Kurt.	KS
EDU9	993	-0.35	0.31	0.003	0.05	0.24	6.8	0.08	0.16	0.00	GEU9	482	-0.27	0.28	0.005	0.06	0.37	5.8	0.11	0.22	0.00
EDM0	799	-0.25	0.31	0.003	0.05	0.28	6.9	0.09	0.17	0.00	GEM0	354	-0.71	0.69	0.002	0.11	-0.56	15.5	0.13	0.26	0.00
EDH0	863	-0.27	0.26	0.003	0.04	0.30	6.6	0.08	0.17	0.00	GEH0	448	-0.26	0.31	0.005	0.06	0.52	5.4	0.12	0.23	0.00
EDU0	718	-0.33	0.50	0.004	0.07	0.48	8.4	0.09	0.18	0.00	GEU0	352	-0.87	0.44	-0.001	0.11	-1.58	16.4	0.13	0.26	0.00
EDZ9	929	-0.24	0.32	0.003	0.05	0.53	6.6	0.08	0.16	0.00	GEZ9	466	-0.22	0.27	0.005	0.05	0.50	5.3	0.11	0.23	0.00
EDZ0	697	-0.57	0.53	0.003	0.08	-0.01	12.2	0.09	0.18	0.00	GEZ0	374	-0.53	0.41	-0.004	0.09	-0.50	6.8	0.13	0.25	0.00
EDH1	592	-0.54	0.51	0.002	0.09	-0.63	10.2	0.10	0.20	0.00	GEH1	251	-0.45	0.53	0.003	0.09	-0.03	9.5	0.15	0.31	0.00
EDM1	535	-0.52	0.75	0.002	0.10	0.85	14.2	0.11	0.21	0.00	GEM1	284	-0.40	0.51	-0.001	0.10	-0.06	6.0	0.14	0.29	0.00
EDU1	507	-0.52	0.54	0.000	0.10	-0.19	8.4	0.11	0.22	0.00	GEU1	228	-0.50	0.44	-0.002	0.10	-0.07	7.7	0.16	0.32	0.00
EDZ1	399	-0.44	0.51	-0.004	0.09	-0.58	6.7	0.12	0.24	0.00	GEZ1	174	-0.36	0.40	-0.002	0.08	0.23	10.0	0.18	0.37	0.00
EDH2	344	-0.41	0.53	-0.005	0.09	-0.13	7.1	0.13	0.26	0.00	GEH2	144	-0.27	0.19	-0.008	0.06	-1.22	4.4	0.20	0.40	0.00
EDM2	249	-0.54	0.68	0.007	0.11	1.30	12.6	0.15	0.31	0.00	GEM2	138	-0.25	0.13	-0.010	0.05	-1.91	7.0	0.21	0.41	0.00
EDU2	218	-0.63	0.89	0.003	0.13	1.25	15.5	0.16	0.33	0.00	GEU2	134	-0.23	0.14	-0.010	0.05	-1.73	6.4	0.21	0.42	0.00
EDM09	1008	-0.29	0.30	0.003	0.05	0.42	6.4	0.08	0.15	0.00	GEM09	549	-0.15	0.25	0.005	0.04	0.98	5.8	0.10	0.21	0.00
EDZ2	153	-0.55	0.20	-0.012	0.08	-2.75	16.5	0.20	0.39	0.00	GEZ2	104	-0.32	0.21	-0.011	0.07	-1.44	6.9	0.24	0.47	0.00
ERU9	486	-0.36	0.31	0.006	0.07	0.18	6.9	0.11	0.22	0.00	LH0	297	-0.26	0.31	0.008	0.05	1.21	11.1	0.14	0.28	0.00
ERZ9	400	-0.27	0.31	0.007	0.05	0.91	8.4	0.12	0.24	0.00	LM0	132	-0.37	0.63	-0.008	0.11	0.92	11.0	0.21	0.42	0.00
ERM0	291	-0.15	0.35	0.009	0.05	1.43	9.5	0.14	0.28	0.00	LZ9	360	-0.50	0.43	0.007	0.07	-0.05	13.2	0.13	0.26	0.00
ERH0	347	-0.17	0.45	0.008	0.05	2.49	19.7	0.13	0.26	0.00	LU0	130	-0.33	0.51	-0.011	0.09	0.55	11.1	0.21	0.42	0.00
ERU0	190	-0.26	0.27	0.010	0.06	0.27	4.7	0.18	0.35	0.04	LU9	365	-0.47	0.43	0.008	0.07	0.14	13	0.13	0.25	0.00
ERZ0	150	-0.27	0.35	0.007	0.08	0.24	4.1	0.20	0.39	0.04	LM9	492	-0.16	0.15	0.006	0.03	0.4	3	0.11	0.22	0.00
ERH1	107	-0.43	0.30	-0.005	0.12	-0.47	2.0	0.23	0.46	0.00	YEU9	133	-0.36	0.36	0.004	0.09	0.25	5.7	0.21	0.42	0.00
ERM9	504	-0.20	0.27	0.006	0.05	0.46	5.3	0.11	0.22	0.00	YEM9	145	-0.70	0.47	-0.006	0.12	-0.76	8.6	0.20	0.40	0.00

Table 41. Statistics of A₂ and B₂ data categories – DRSI frequent parameters.

Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error			Future	N	min.	max.	Mean	Std.	Skew.	Kurt.	Std. Error		
								Skew.	Kurt.	KS									Skew.	Kurt.	KS
EDU9	993	-0.68	0.81	0.001	0.07	1.24	32.8	0.08	0.16	0.00	GEU9	482	-0.61	0.43	0.005	0.08	-0.78	11.6	0.11	0.22	0.00
EDM0	799	-0.44	0.43	0.004	0.07	-0.20	13.5	0.09	0.17	0.00	GEM0	354	-0.42	0.78	0.005	0.08	1.78	26.2	0.13	0.26	0.00
EDH0	863	-0.55	0.39	0.004	0.08	-0.21	8.8	0.08	0.17	0.00	GEH0	448	-0.35	0.63	0.005	0.09	1.01	10.8	0.12	0.23	0.00
EDU0	718	-0.43	0.44	0.004	0.07	-0.01	10.0	0.09	0.18	0.00	GEU0	352	-0.42	0.73	0.004	0.09	1.02	17.0	0.13	0.26	0.00
EDZ9	929	-0.79	0.62	0.003	0.09	-0.25	13.6	0.08	0.16	0.00	GEZ9	466	-0.50	0.64	0.005	0.09	0.21	9.6	0.11	0.23	0.00
EDZ0	697	-0.38	0.66	0.003	0.09	0.14	8.0	0.09	0.18	0.00	GEZ0	374	-0.39	0.65	0.005	0.10	0.42	7.0	0.13	0.25	0.00
EDH1	592	-0.42	0.58	0.004	0.10	0.08	5.4	0.10	0.20	0.00	GEH1	251	-0.45	0.55	0.006	0.10	0.07	6.9	0.15	0.31	0.00
EDM1	535	-0.28	0.28	0.004	0.06	-0.05	3.3	0.11	0.21	0.00	GEM1	284	-0.35	0.32	0.006	0.08	0.05	3.2	0.14	0.29	0.00
EDU1	507	-0.42	0.32	0.006	0.07	0.06	4.9	0.11	0.22	0.00	GEU1	228	-0.35	0.48	0.008	0.10	0.79	7.8	0.16	0.32	0.00
EDZ1	399	-0.41	0.52	0.006	0.11	0.38	3.6	0.12	0.24	0.00	GEZ1	174	-0.30	0.36	-0.007	0.10	-0.26	1.7	0.18	0.37	0.00
EDH2	344	-0.35	0.49	0.004	0.10	0.24	3.9	0.13	0.26	0.00	GEH2	144	-0.29	0.33	-0.009	0.10	-0.22	0.8	0.20	0.40	0.08
EDM2	249	-0.26	0.51	0.008	0.08	1.74	10.4	0.15	0.31	0.00	GEM2	138	-0.29	0.32	-0.010	0.10	-0.30	1.3	0.21	0.41	0.01
EDU2	218	-0.27	0.53	0.009	0.09	1.43	7.9	0.16	0.33	0.00	GEU2	134	-0.28	0.30	-0.012	0.09	-0.29	1.2	0.21	0.42	0.08
EDM09	1008	-0.58	0.69	0.000	0.08	0.36	15.5	0.08	0.15	0.00	GEM09	549	-0.50	0.51	0.002	0.08	-0.31	14.0	0.10	0.21	0.00
EDZ2	153	-0.42	0.53	-0.011	0.14	-0.02	1.9	0.20	0.39	0.01	GEZ2	104	-0.33	0.19	-0.011	0.09	-0.90	1.8	0.24	0.47	0.00
ERU9	486	-0.39	0.53	0.005	0.08	0.62	10.7	0.11	0.22	0.00	LH0	297	-0.41	0.31	0.005	0.06	-0.66	17.0	0.14	0.28	0.00
ERZ9	400	-0.40	0.42	0.001	0.07	0.21	10.4	0.12	0.24	0.00	LM0	132	-0.48	0.64	0.009	0.14	0.33	5.2	0.21	0.42	0.01
ERM0	291	-0.34	0.36	0.007	0.05	1.09	20.7	0.14	0.28	0.00	LZ9	360	-0.57	0.51	0.002	0.08	-0.51	13.5	0.13	0.26	0.00
ERH0	347	-0.33	0.64	0.004	0.08	1.48	17.5	0.13	0.26	0.00	LU0	130	-0.63	0.67	0.006	0.15	0.17	5.7	0.21	0.42	0.03
ERU0	190	-0.58	0.22	-0.002	0.06	-5.36	50.3	0.18	0.35	0.00	LU9	365	-0.61	0.28	-0.002	0.06	-4.02	38	0.13	0.25	0.00
ERZ0	150	-0.34	0.35	0.006	0.08	-0.29	6.8	0.20	0.39	0.00	LM9	492	-0.73	0.36	0.002	0.08	-2.5	24	0.11	0.22	0.00
ERH1	107	-0.24	0.25	0.004	0.05	0.85	10.8	0.23	0.46	0.00	YEU9	133	-0.69	0.33	-0.005	0.12	-1.73	10.3	0.21	0.42	0.00
ERM9	504	-0.40	0.51	0.002	0.08	0.28	9.7	0.11	0.22	0.00	YEM9	145	-0.70	0.93	0.007	0.13	1.38	20.3	0.20	0.40	0.00

Appendix 3. Interest rate universe affecting the short term interest rate futures pricing

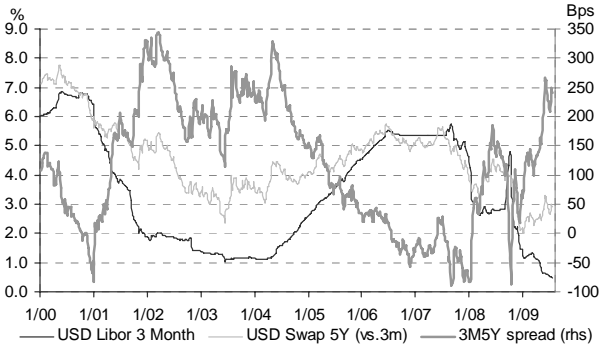


Figure 7. USD interest rates.

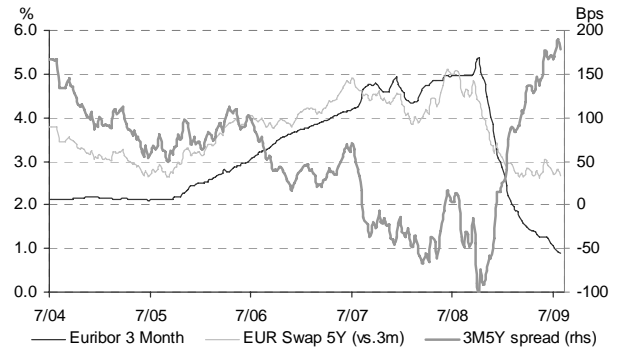


Figure 8. EUR interest rates.

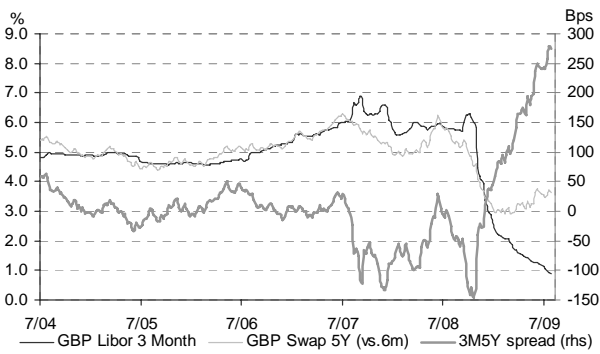


Figure 9. GBP interest rates.

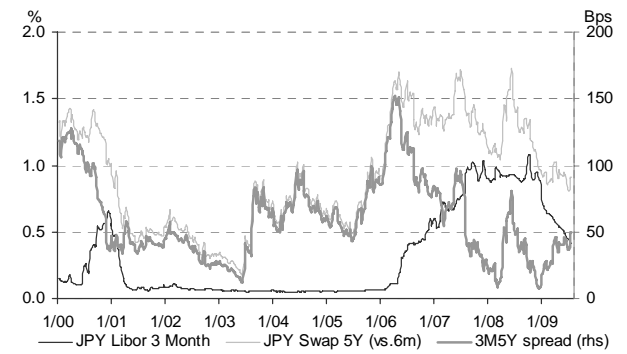


Figure 10. JPY interest rates.

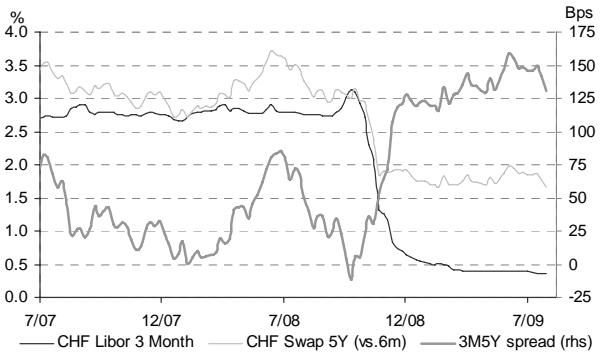


Figure 11. CHF interest rates.

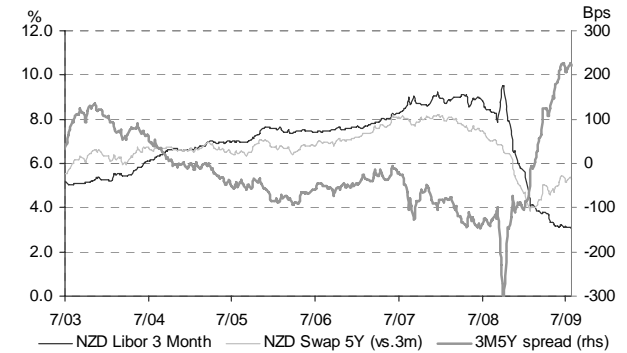


Figure 12. NZD interest rates.

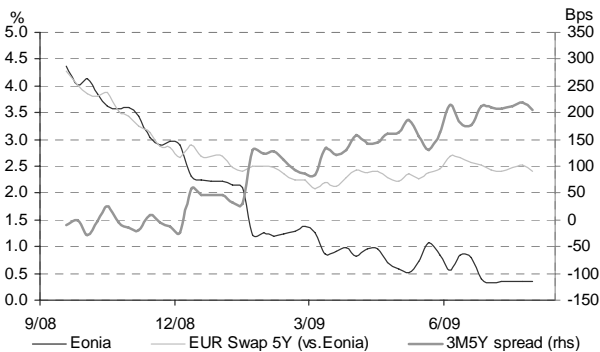


Figure 13. EONIA based interest rates.

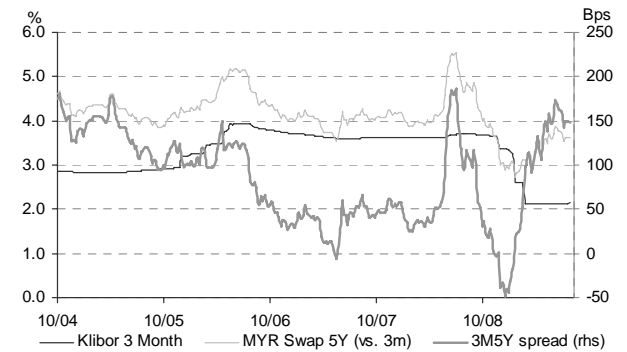


Figure 14. MYR interest rates.

Appendix 4. Descriptive data of the interest rate futures

Table 42. Descriptive data of futures in the A data categories.

Ticker	Unit of Trading	Currency	Initial margin	Value of a percentage point	Value of a minimum price movement	Minimum price movement	First trading date	Delivery date	Exchange	Interest rate basis
EDU9	1 000 000	USD	1013	2500	6.25	0.0025	14.9.1999	14.9.2009	Chicago Mercantile Exchange	ACT/360
EDM0	1 000 000	USD	1013	2500	6.25	0.0025	20.6.2000	14.6.2010	Chicago Mercantile Exchange	ACT/360
EDH0	1 000 000	USD	1013	2500	6.25	0.0025	14.3.2000	15.3.2010	Chicago Mercantile Exchange	ACT/360
EDU0	1 000 000	USD	1148	2500	6.25	0.0025	19.9.2000	13.9.2010	Chicago Mercantile Exchange	ACT/360
EDZ9	1 000 000	USD	1013	2500	6.25	0.0025	14.12.1999	14.12.2009	Chicago Mercantile Exchange	ACT/360
EDZ0	1 000 000	USD	1148	2500	6.25	0.0025	19.12.2000	13.12.2010	Chicago Mercantile Exchange	ACT/360
EDH1	1 000 000	USD	1148	2500	6.25	0.0025	20.3.2001	14.3.2011	Chicago Mercantile Exchange	ACT/360
EDM1	1 000 000	USD	1148	2500	6.25	0.0025	19.6.2001	13.6.2011	Chicago Mercantile Exchange	ACT/360
EDU1	1 000 000	USD	1148	2500	6.25	0.0025	17.9.2001	19.9.2011	Chicago Mercantile Exchange	ACT/360
EDZ1	1 000 000	USD	1148	2500	6.25	0.0025	18.12.2001	19.12.2011	Chicago Mercantile Exchange	ACT/360
EDH2	1 000 000	USD	1148	2500	6.25	0.0025	18.3.2002	19.3.2012	Chicago Mercantile Exchange	ACT/360
EDM2	1 000 000	USD	1148	2500	12.5	0.005	18.6.2002	18.6.2012	Chicago Mercantile Exchange	ACT/360
EDU2	1 000 000	USD	1148	2500	12.5	0.005	17.9.2002	17.9.2012	Chicago Mercantile Exchange	ACT/360
EDM3	1 000 000	USD	1148	2500	12.5	0.005	16.6.2003	17.6.2013	Chicago Mercantile Exchange	ACT/360
EDM9	1 000 000	USD	1215	2500	6.25	0.0025	20.6.2000	15.6.2009	Chicago Mercantile Exchange	ACT/360
EDZ2	1 000 000	USD	1148	2500	12.5	0.005	17.12.2002	17.12.2012	Chicago Mercantile Exchange	ACT/360
EDH3	1 000 000	USD	1148	2500	12.5	0.005	17.3.2003	18.3.2013	Chicago Mercantile Exchange	ACT/360
EDU3	1 000 000	USD	1148	2500	12.5	0.005	16.9.2003	16.9.2013	Chicago Mercantile Exchange	ACT/360
EDH4	1 000 000	USD	1148	2500	12.5	0.005	15.3.2004	17.3.2014	Chicago Mercantile Exchange	ACT/360
EDZ3	1 000 000	USD	1148	2500	12.5	0.005	15.12.2003	16.12.2013	Chicago Mercantile Exchange	ACT/360
EDM4	1 000 000	USD	1148	2500	12.5	0.005	15.6.2004	16.6.2014	Chicago Mercantile Exchange	ACT/360
EDU4	1 000 000	USD	1148	2500	12.5	0.005	14.9.2004	15.9.2014	Chicago Mercantile Exchange	ACT/360
EDH5	1 000 000	USD	1148	2500	12.5	0.005	14.3.2005	16.3.2015	Chicago Mercantile Exchange	ACT/360
EDZ4	1 000 000	USD	1148	2500	12.5	0.005	13.12.2004	15.12.2014	Chicago Mercantile Exchange	ACT/360
EDM5	1 000 000	USD	1148	2500	12.5	0.005	13.6.2005	15.6.2015	Chicago Mercantile Exchange	ACT/360
EDZ5	1 000 000	USD	1148	2500	12.5	0.005	19.12.2005	14.12.2015	Chicago Mercantile Exchange	ACT/360
EDU5	1 000 000	USD	1148	2500	12.5	0.005	20.9.2005	14.9.2015	Chicago Mercantile Exchange	ACT/360
EDH6	1 000 000	USD	1148	2500	12.5	0.005	13.3.2006	14.3.2016	Chicago Mercantile Exchange	ACT/360
EDM6	1 000 000	USD	1148	2500	12.5	0.005	19.6.2006	13.6.2016	Chicago Mercantile Exchange	ACT/360
GEU9	1 000 000	USD	1485	2500	6.25	0.0025	14.9.1999	14.9.2009	Chicago Mercantile Exchange	ACT/360
GEM0	1 000 000	USD	1485	2500	12.5	0.005	20.6.2000	14.6.2010	Chicago Mercantile Exchange	ACT/360
GEH0	1 000 000	USD	1485	2500	12.5	0.005	14.3.2000	15.3.2010	Chicago Mercantile Exchange	ACT/360
GEU0	1 000 000	USD	1485	2500	12.5	0.005	19.9.2000	13.9.2010	Chicago Mercantile Exchange	ACT/360
GEZ9	1 000 000	USD	1485	2500	6.25	0.0025	14.12.1999	14.12.2009	Chicago Mercantile Exchange	ACT/360
GEZ0	1 000 000	USD	1485	2500	12.5	0.005	19.12.2000	13.12.2010	Chicago Mercantile Exchange	ACT/360
GEH1	1 000 000	USD	1485	2500	12.5	0.005	20.3.2001	14.3.2011	Chicago Mercantile Exchange	ACT/360
GEM1	1 000 000	USD	1485	2500	12.5	0.005	19.6.2001	13.6.2011	Chicago Mercantile Exchange	ACT/360
GEU1	1 000 000	USD	1485	2500	12.5	0.005	18.9.2001	19.9.2011	Chicago Mercantile Exchange	ACT/360
GEZ1	1 000 000	USD	1485	2500	12.5	0.005	17.12.2001	19.12.2011	Chicago Mercantile Exchange	ACT/360
GEH2	1 000 000	USD	1485	2500	12.5	0.005	19.3.2002	19.3.2012	Chicago Mercantile Exchange	ACT/360
GEM2	1 000 000	USD	1485	2500	12.5	0.005	18.6.2002	18.6.2012	Chicago Mercantile Exchange	ACT/360
GEU2	1 000 000	USD	1485	2500	12.5	0.005	17.9.2002	17.9.2012	Chicago Mercantile Exchange	ACT/360
GEM9	1 000 000	USD	1485	2500	6.25	0.0025	20.6.2000	15.6.2009	Chicago Mercantile Exchange	ACT/360
GEM3	1 000 000	USD	945	2500	12.5	0.005	17.6.2003	17.6.2013	Chicago Mercantile Exchange	ACT/360
GEZ2	1 000 000	USD	1485	2500	12.5	0.005	17.12.2002	17.12.2012	Chicago Mercantile Exchange	ACT/360
GEH3	1 000 000	USD	945	2500	12.5	0.005	18.3.2003	18.3.2013	Chicago Mercantile Exchange	ACT/360
GEU3	1 000 000	USD	945	2500	12.5	0.005	16.9.2003	16.9.2013	Chicago Mercantile Exchange	ACT/360
GEZ3	1 000 000	USD	945	2500	12.5	0.005	16.12.2003	16.12.2013	Chicago Mercantile Exchange	ACT/360
GEH4	1 000 000	USD	945	2500	12.5	0.005	16.3.2004	17.3.2014	Chicago Mercantile Exchange	ACT/360
GEM4	1 000 000	USD	945	2500	12.5	0.005	15.6.2004	16.6.2014	Chicago Mercantile Exchange	ACT/360
GEU4	1 000 000	USD	945	2500	12.5	0.005	14.9.2004	15.9.2014	Chicago Mercantile Exchange	ACT/360
GEH5	1 000 000	USD	945	2500	12.5	0.005	15.3.2005	16.3.2015	Chicago Mercantile Exchange	ACT/360
GEZ4	1 000 000	USD	945	2500	12.5	0.005	14.12.2004	15.12.2014	Chicago Mercantile Exchange	ACT/360
GEM5	1 000 000	USD	945	2500	12.5	0.005	14.6.2005	15.6.2015	Chicago Mercantile Exchange	ACT/360
GEZ5	1 000 000	USD	945	2500	12.5	0.005	20.12.2005	14.12.2015	Chicago Mercantile Exchange	ACT/360
GEU5	1 000 000	USD	945	2500	12.5	0.005	17.9.2005	14.9.2015	Chicago Mercantile Exchange	ACT/360
GEH6	1 000 000	USD	945	2500	12.5	0.005	13.3.2006	14.3.2016	Chicago Mercantile Exchange	ACT/360
GEM6	1 000 000	USD	945	2500	12.5	0.005	19.6.2006	13.6.2016	Chicago Mercantile Exchange	ACT/360

Table 43. Descriptive data of futures in the B data categories.

Ticker	Unit of Trading	Currency	Initial margin	Value of a percentage point	Value of a minimum price movement	Minimum price movement	First trading date	Delivery date	Exchange	Interest rate basis
ERU9	1 000 000	EUR	900	2500	12.5	0.005	14.9.2004	14.9.2009	NYSE LIFFE - London	ACT/360
ERZ9	1 000 000	EUR	900	2500	12.5	0.005	14.12.2004	14.12.2009	NYSE LIFFE - London	ACT/360
ERM0	1 000 000	EUR	900	2500	12.5	0.005	14.6.2005	14.6.2010	NYSE LIFFE - London	ACT/360
ERH0	1 000 000	EUR	900	2500	12.5	0.005	15.3.2005	15.3.2010	NYSE LIFFE - London	ACT/360
ERU0	1 000 000	EUR	900	2500	12.5	0.005	20.9.2005	13.9.2010	NYSE LIFFE - London	ACT/360
ERZ0	1 000 000	EUR	900	2500	12.5	0.005	7.11.2005	13.12.2010	NYSE LIFFE - London	ACT/360
ERH1	1 000 000	EUR	900	2500	12.5	0.005	7.11.2005	14.3.2011	NYSE LIFFE - London	ACT/360
ERM1	1 000 000	EUR	900	2500	12.5	0.005	14.3.2006	13.6.2011	NYSE LIFFE - London	ACT/360
ERU1	1 000 000	EUR	900	2500	12.5	0.005	7.11.2005	19.9.2011	NYSE LIFFE - London	ACT/360
ERM9	1 000 000	EUR	800	2500	12.5	0.005	15.6.2004	15.6.2009	NYSE LIFFE - London	ACT/360
ERZ1	1 000 000	EUR	900	2500	12.5	0.005	7.11.2005	19.12.2011	NYSE LIFFE - London	ACT/360
ERH2	1 000 000	EUR	900	2500	12.5	0.005	20.3.2007	19.3.2012	NYSE LIFFE - London	ACT/360
ERM2	1 000 000	EUR	900	2500	12.5	0.005	20.3.2007	18.6.2012	NYSE LIFFE - London	ACT/360
ERU2	1 000 000	EUR	900	2500	12.5	0.005	19.6.2007	17.9.2012	NYSE LIFFE - London	ACT/360
ERZ2	1 000 000	EUR	900	2500	12.5	0.005	17.12.2007	17.12.2012	NYSE LIFFE - London	ACT/360
ERH3	1 000 000	EUR	900	2500	12.5	0.005	18.12.2007	18.3.2013	NYSE LIFFE - London	ACT/360
LH0	500 000	GBP	550	1250	12.5	0.01	17.3.2005	17.3.2010	NYSE LIFFE - London	ACT/365
LM0	500 000	GBP	550	1250	12.5	0.01	16.6.2005	16.6.2010	NYSE LIFFE - London	ACT/365
LZ9	500 000	GBP	550	1250	12.5	0.01	16.12.2004	16.12.2009	NYSE LIFFE - London	ACT/365
LU0	500 000	GBP	550	1250	12.5	0.01	22.9.2005	15.9.2010	NYSE LIFFE - London	ACT/365
LU9	500 000	GBP	550	1250	12.5	0.01	16.9.2004	16.9.2009	NYSE LIFFE - London	ACT/365
LZ0	500 000	GBP	550	1250	12.5	0.01	7.11.2005	15.12.2010	NYSE LIFFE - London	ACT/365
LH1	500 000	GBP	550	1250	12.5	0.01	16.3.2006	16.3.2011	NYSE LIFFE - London	ACT/365
LM9	500 000	GBP	550	1250	12.5	0.01	17.6.2004	17.6.2009	NYSE LIFFE - London	ACT/365
LM1	500 000	GBP	550	1250	12.5	0.01	22.6.2006	15.6.2011	NYSE LIFFE - London	ACT/365
LU1	500 000	GBP	550	1250	12.5	0.01	22.6.2006	21.9.2011	NYSE LIFFE - London	ACT/365
LH2	500 000	GBP	550	1250	12.5	0.01	21.12.2006	21.3.2012	NYSE LIFFE - London	ACT/365
LZ1	500 000	GBP	550	1250	12.5	0.01	21.9.2006	21.12.2011	NYSE LIFFE - London	ACT/365
LM2	500 000	GBP	550	1250	12.5	0.01	22.3.2007	20.6.2012	NYSE LIFFE - London	ACT/365
LU2	500 000	GBP	550	1250	12.5	0.01	21.6.2007	19.9.2012	NYSE LIFFE - London	ACT/365
LZ2	500 000	GBP	550	1250	12.5	0.01	20.9.2007	19.12.2012	NYSE LIFFE - London	ACT/365
YEH0	100 000 000	JPY	13750	250000	1250	0.005	15.3.2005	16.3.2010	Tokyo Financial Exchange	ACT/360
YEU9	100 000 000	JPY	13750	250000	1250	0.005	14.9.2004	15.9.2009	Tokyo Financial Exchange	ACT/360
YEZ9	100 000 000	JPY	13750	250000	1250	0.005	14.12.2004	16.12.2009	Tokyo Financial Exchange	ACT/360
YEM0	100 000 000	JPY	13750	250000	1250	0.005	14.6.2005	15.6.2010	Tokyo Financial Exchange	ACT/360
YEZ0	100 000 000	JPY	15000	250000	1250	0.005	20.12.2005	14.12.2010	Tokyo Financial Exchange	ACT/360
YEM9	100 000 000	JPY	17500	250000	1250	0.005	15.6.2004	16.6.2009	Tokyo Financial Exchange	ACT/360
YEU0	100 000 000	JPY	15000	250000	1250	0.005	20.9.2005	14.9.2010	Tokyo Financial Exchange	ACT/360
YEH1	100 000 000	JPY	15000	250000	1250	0.005	14.3.2006	15.3.2011	Tokyo Financial Exchange	ACT/360

Table 44. Descriptive data of the futures in the C₁ data category.

Ticker	Unit of Trading	Currency	Initial margin	Value of a percentage point	Value of a minimum price movement	Minimum price movement	First trading date	Delivery date	Exchange	Interest rate basis
ESU9	1 000 000	CHF	750	2500	25	0.01	18.9.2007	14.9.2009	NYSE LIFFE - London	ACT/360
ESZ9	1 000 000	CHF	750	2500	25	0.01	18.12.2007	14.12.2009	NYSE LIFFE - London	ACT/360
ESM9	1 000 000	CHF	750	2500	25	0.01	19.6.2007	15.6.2009	NYSE LIFFE - London	ACT/360
ZBU9	1 000 000	NZD	1010	2500	25	0.01	26.6.2007	17.9.2009	ASX Trade24	ACT/365
ZBH0	1 000 000	NZD	1010	2500	25	0.01	26.6.2007	11.3.2010	ASX Trade24	ACT/365
ZBU0	1 000 000	NZD	1010	2500	25	0.01	13.9.2007	16.9.2010	ASX Trade24	ACT/365
ZBZ9	1 000 000	NZD	1010	2500	25	0.01	26.6.2007	17.12.2009	ASX Trade24	ACT/365
ZBM0	1 000 000	NZD	1010	2500	25	0.01	26.6.2007	17.6.2010	ASX Trade24	ACT/365
ZBZ0	1 000 000	NZD	1010	2500	25	0.01	13.12.2007	16.12.2010	ASX Trade24	ACT/365
FPM9	1 000 000	EUR	625	2500	12.5	0.005	20.6.2006	15.6.2009	Eurex	ACT/360
FPU9	1 000 000	EUR	625	2500	12.5	0.005	19.9.2006	14.9.2009	Eurex	ACT/360
FPZ9	1 000 000	EUR	625	2500	12.5	0.005	19.12.2006	14.12.2009	Eurex	ACT/360
FPH0	1 000 000	EUR	625	2500	12.5	0.005	20.3.2007	15.3.2010	Eurex	ACT/360
FPM0	1 000 000	EUR	625	2500	12.5	0.005	19.6.2007	14.6.2010	Eurex	ACT/360
FPU0	1 000 000	EUR	625	2500	12.5	0.005	18.9.2007	13.9.2010	Eurex	ACT/360
FPZ0	1 000 000	EUR	625	2500	12.5	0.005	18.12.2007	13.12.2010	Eurex	ACT/360
EYU9	100 000 000	JPY	16200	250000	1250	0.005	14.9.2004	14.9.2009	Singapore Exchange	ACT/360
EYM0	100 000 000	JPY	20250	250000	625	0.0025	14.6.2005	15.6.2010	Singapore Exchange	ACT/360
EYM9	100 000 000	JPY	16200	250000	1250	0.005	15.6.2004	15.6.2009	Singapore Exchange	ACT/360
EYZ9	100 000 000	JPY	17550	250000	1250	0.005	14.12.2004	15.12.2009	Singapore Exchange	ACT/360
MYU9	100 000 000	JPY	29700	250000	1250	0.005	13.9.2004	14.9.2009	Chicago Mercantile Exchange	ACT/360
KKU2	1 000 000	MYR	1000	2500	25	0.01	20.9.2007	19.9.2012	Bursa Malaysia	ACT/365
KKM2	1 000 000	MYR	1000	2500	25	0.01	21.6.2007	20.6.2012	Bursa Malaysia	ACT/365
KKU9	1 000 000	MYR	1000	2500	25	0.01	16.9.2004	16.9.2009	Bursa Malaysia	ACT/365
KKZ9	1 000 000	MYR	1000	2500	25	0.01	16.12.2004	16.12.2009	Bursa Malaysia	ACT/365
KKH0	1 000 000	MYR	1000	2500	25	0.01	17.3.2005	17.3.2010	Bursa Malaysia	ACT/365
KKM0	1 000 000	MYR	1000	2500	25	0.01	16.6.2005	16.6.2010	Bursa Malaysia	ACT/365
KKU0	1 000 000	MYR	1000	2500	25	0.01	22.9.2005	15.9.2010	Bursa Malaysia	ACT/365
KKZ0	1 000 000	MYR	1000	2500	25	0.01	22.12.2005	15.12.2010	Bursa Malaysia	ACT/365
KKH1	1 000 000	MYR	1000	2500	25	0.01	16.3.2006	16.3.2011	Bursa Malaysia	ACT/365
KKM1	1 000 000	MYR	1000	2500	25	0.01	22.6.2006	15.6.2011	Bursa Malaysia	ACT/365
KKU1	1 000 000	MYR	1000	2500	25	0.01	21.9.2006	21.9.2011	Bursa Malaysia	ACT/365
KKZ1	1 000 000	MYR	1000	2500	25	0.01	21.12.2006	21.12.2011	Bursa Malaysia	ACT/365
KKH2	1 000 000	MYR	1000	2500	25	0.01	22.3.2007	21.3.2012	Bursa Malaysia	ACT/365
KKZ2	1 000 000	MYR	1000	2500	25	0.01	21.12.2007	19.12.2012	Bursa Malaysia	ACT/365