Department of Business Studies

Master Thesis

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The Profitability of Simple Technical Trading Rules Applied on Value and Growth Stocks

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Executive Summary

This thesis studies the efficacy of the most simple and commonly used technical trading rules when applied on American growth and value stocks. The period under investigation goes from 1986 to 2005. A famous study conducted by Brock, Lakonishok and LeBaron in 1992 showed that technical analysis could indeed create abnormal profit compared to a buy-and-hold strategy. Later studies tested Brock et al's results in the subsequent period (from 1986 and onwards) and reached the conclusion that the technical trading rules in question could no longer outperform a passive investment management strategy. This thesis is inspired by Brock et al's study and uses same methodology. Eight moving average trading rules are tested on a growth and value portfolio respectively. The earnings-to-price and book-to-market ratios are used to classify the stocks as growth or value stocks. The short moving average is the actual price and the long moving average varies in length from 10 to 50 days. Furthermore, the rules are tested with a 1% band. A bootstrap procedure is applied in order to increase the reliability of the tests. However, further investigation is added as to increase the practical relevance. The results are tested in an environment where traders face transaction costs. This allows that the implications for the Efficient Market Hypothesis can be discussed. Transaction costs are set to 0.25% per transaction.

The results show that the trading rules are able to identify periods with positive and negative returns. For both portfolios the mean return following buy signals is positive for all trading rules while it is negative following a sell signal. Furthermore, sell periods are characterized by higher volatility than buy periods. This is consistent with the leverage effect. Moreover, it is showed that the use of simple technical trading gives a better return compared to a buy-and-hold strategy also when adjusting for risk before transaction costs are accounted for. This is valid for all trading rules and for both portfolios. For the growth portfolio, three of the eight trading rules generate a return that is above and statistically significantly different from the buy-and-hold at the five percent significance level using a two-tailed test. For the value portfolio five of the trading rules generate a return that is above and statistically significantly different from the buy-and-hold strategy.

Due to the fact that the growth portfolio generates a very poor return, the bootstrap methodology and effects of transaction costs are only applied to the value portfolio.

As it is well known that stock returns present a number of features that violates the assumptions behind the t-test, bootstrap simulations, as applied in BLL, are performed to check whether the previous results are due to these features. This is strongly rejected for all the four null models tested, even though features such as autocorrelation, volatility clustering and the leverage effect are present in the return series. Thus, the results are in general consistent with those reported by BLL for the DJIA confirming that simple technical trading rules have predictability power for value stocks.

The seemingly superiority of the technical trading rules must however, be seen in the light of the fact that the assumptions made about the investment environment are not realistic. When transaction costs are introduced the trading rules does not generate a return that is statistically significantly different from the buy-and-hold return. This is true for all trading rules. This implies that investors cannot be certain they will earn an abnormal return by using the tested trading rules on value stocks.

The fact that at least some forecasting power is documented, need not to be a violation of the EMH. The introduction of transaction costs causes that equality, between the return generated by the trading rules and the return obtained through a buy-and-hold strategy, cannot be rejected. Thus, the weak form efficiency cannot be rejected for value stocks

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1 Introduction

The efficiency of capital markets is among the most fundamental as well as most disputed doctrines in financial theory. Many attempts have been made to define financial market efficiency and perhaps the most famous definition was formulated by Eugene F. Fama in 1970 called the Efficient Market Hypothesis (EMH). The cornerstone of the hypothesis is that the price of a security always fully reflects all available information. Due to their practical relevance and favorable data conditions, empirical studies of market efficiency have been extremely popular among academics.

Numerous studies have been conducted to explore the vast area of capital markets seeking out for anomalies and patterns of return predictability, evaluating the validity of various return generating processes and assessing the accuracy and reliability of miscellaneous market models. As a result of this extensive research, two different camps have emerged: those who believe in market efficiency and those who argue markets are inefficient. Efficiency advocates trust that markets entail all information available properly. Consequently, mispricing in entire markets or single assets cannot occur and hence, it is impossible to systematically earn any abnormal profit. This stance leads them to acquire a preference for passive portfolio management strategies. In contrast, believers of inefficient markets maintain that security prices do not always reflect information correctly. Building their activities on historical empirical research, predictive models, studies of human behavior or simply pure belief, they actively seek mispricing or recursively occurring patterns in order to realize improved returns.

Perhaps the most used active trading strategy is the use of technical trading rules. A famous study conducted by Brock, Lakonishok and LeBaron in 1992 (‘BLL’ henceforth) showed that simple forms of technical analysis could indeed create abnormal profit compared to a buy-and-hold strategy. Later studies, however, tested Brock et al’s results in the subsequent period (from 1986 and onwards) and reached the conclusion that the technical trading rules in question could no longer outperform a passive investment management strategy.

1.1 Problem Specification

Technical analysis is widely used in practice, but the method has not gained much support in academic circles. In these circles the theory of market efficiency is the preferred theory. The purpose of this thesis is to contribute to the ongoing battle between advocates of efficient markets and inefficient markets accordingly. Numerous studies have tested the profitability of technical trading rules and through this questioned market efficiency. Many of these studies analyze the trading rules on the basis of stock indices such as the Dow-Jones Industrial Average (DJIA) and the FT-SE 100. Not much has been said about the behavior of technical trading strategies across market segments based on valuation parameters. This thesis will add a new perspective to the discussion by combining technical analysis with a well-known stock market anomaly: the value premium puzzle. Thus, the central question is the following:

Is it possible to earn a significantly better return than the return generated by a buy-and-hold strategy through the use of simple technical trading rules when applied on growth and value stocks respectively?

By investigating technical trading rules a hypothesis about the efficiency of the financial market in its weak form as defined by Fama *(1970)* is indirectly examined. If the technical trading rules prove to be able to generate a statistical and economical significant better return, the EMH can be rejected. Due to this fact, the theory of efficient markets will also be covered in the thesis.

1.2 Limitations

In the empirical analysis of technical trading rules only moving average rules will be used. The reason for this is that it is possible to use these rules mechanically and thus, they are easy testable due to the clear signals produced. Other trading rules such as e.g. the head-and-shoulder pattern are based on subjective beliefs and ideas and cannot be defined mechanically. This makes such rules much more complicated to test on and therefore this will not be done.

The classification of stocks into the growth or value portfolio is based on two measures: the earnings-to-price (E/P) and book-to-market (B/M) ratio. These two measures are commonly used when classifying stocks as value or growth stocks. Other measures such as cash flow-to-price and growth in sales are also frequently used. However, it has been found that the division of stocks based on the E/P and B/M ratio is sufficient for the purpose of this thesis.

The test period is limited to a 19-year period spanning from 1986 to 2004. The reason why this period is of interest for this study is that BLL in their 1992 study show that a technical analysis approach can earn a higher return than a simple buy-and-hold strategy when testing on the DJIA from 1897 to 1986. However, later studies *(e.g. Sullivan, Timmerman & White, 1999)* have showed that from 1986 and onwards the technical trading rules tested by BLL *(1992)* have not outperformed the simple buy-and-hold strategy. Hence, it is of interest to test whether there are investment strategies that enables technical analysts to earn abnormal profits in the period following BLL's *(1992)* test period.

1.3 Structure

The thesis consists of two parts. In part one the theoretical background for the thesis is presented and discussed. In the second part the empirical analysis and the results hereof are presented.

Part one contains the chapters 2-4. Chapter 2 entails a general description of what technical analysis is. In this chapter the trading rules used in the empirical part will be emphasized. Chapter 3 covers the EMH and discusses this in detail. The hypothesis has always been subject for great attendance and the most important attacks on it are presented in a chronological order. In chapter 4 growth and value stocks are defined and discussed.

The empirical analysis is presented in part two. This part consists of the chapters 5 through 8. The second part starts out with a short presentation of earlier important studies of technical analysis. In chapter 6 the dataset is described. The chapter will emphasize the portfolio construction and methods for calculating risk and returns. Chapter 7 reports the results of the analysis. The chapter is divided into three parts.

First, the results are tested in a traditional way through the use of a t-test. Secondly, the bootstrap procedure is applied as used in BLL *(1992)*. The starting point in a bootstrap analysis is to find relevant null models to test against. To find these null models, time series theory must be consulted, and this theory is therefore described in this part of the chapter. In the last part of the chapter the effect of introducing transaction costs is analyzed. By examining the results on an after transaction costs basis it is possible to comment on the implications for the EMH. Finally, the implications of the results are discussed in chapter 8.

As round off, the main findings of the thesis will be summarized in chapter 9.

Part One: Theoretical Background

2 Technical Analysis

Many speculators are used to trade from a fundamental perspective. They use economic data such as P/E ratios, cash flows, book value and general business environment, to determine whether a stock or a market is over- or undervalued. Technical analysis is, on the other hand, the study of historic price movements or patterns to recognize investments yielding abnormal profit. Unlike fundamental analysis no economical theory lies behind technical analysis and hence no theoretical explanation can be found as to why it should work. This is also the reason why many theorists are not fond of technical analysis and simply do not accept it. However, studies show that using simple technical trading rules, such as Moving Averages and Trading Range Breakout, can give higher return than a buy-and-hold strategy. The study of technical analysis is also of interest because it is an important part of investment behavior. Finally, technical analysis is interesting in a historical view. Today, free and valuable information is easy accessible. Until recently, there was no Internet or any other source where you could easily get information. In the early years of stock trading, information was often limited to ticker tape with the latest price and volume on a given stock or index. These facts made it very hard, not to say impossible, to conduct fundamental analysis on stocks and investors and brokers were forced to make use of technical analysis. This explains why technical analysis is a much older profession than fundamental analysis.

The following chapter is based on several books on technical analysis. Since the books are used interchangeably there will be no references in the text as such. The books used are:

Brown *(1999),* Kamich *(2003),* Hirschey & Nofsinger *(2005),* Murphy *(1986),* Pring *(1998)* and Tvede *(2002).*

2.1 Definition

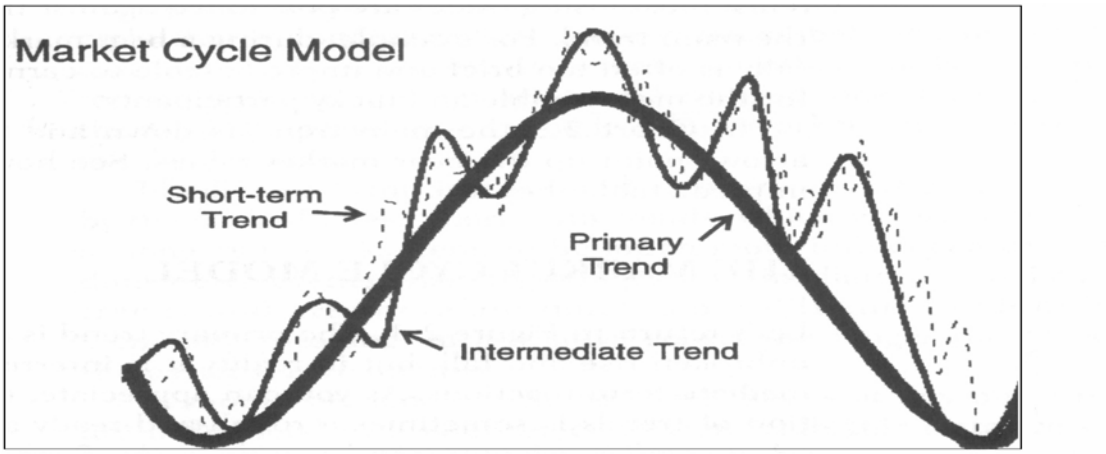
Technical analysis can be defined as the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends. The technician uses three sources to forecast the market action namely, price, volume and open interest. This information is per definition historical and readily available for everybody. Technical analysis is based on three premises:

1. Market action discounts everything.
2. Prices move in trends.
3. History repeats itself

The basic idea in the first premise is as follows. Technicians, or chartists, believe that anything that affects the market price of a commodity is contained in the price already. All a technician need to study is therefore the price action of the security. This price action reflects a shift in supply and demand where a situation with demand exceeding supply leads to an increase in price and vice versa. Chartists are not concerned with the reasons for price changes, they just react on them. Likewise, the actual price of the stock is also of no concern to the chartists, he just wants to know whether it is rising or falling.

The second premise deals with the idea of price moving in trends. If one does not agree with the thought that market prices move in trends there is no point in studying technical analysis. The purpose of analyzing charts is of course to identify trends as early as possible and then trade in the direction of the trend. Technical analysts simply believe in the idea of Newton's first law of motion; a trend in motion is more likely to continue than to reverse. Of course, trends differ in many ways and chartists normally divide them up in time units. This is also known as The Dow Theory, which will be covered below. A main tenet of this theory is, however, that there are three levels of market trends: primary, secondary and tertiary. In short, primary trends are the long-term trends, secondary trends are intermediate-term and tertiary trends are the short-term or daily fluctuations.

Figure 2.1 The Market Cycle Model



Source: Pring (2002).

The last premise deals with the view that the key to predict the future lies in understanding the past. This implies that the human psychology plays an important factor in technical analysis. Many years of charting have resulted in many trading rules, which are believed to repeat themselves. It is believed that since these patterns have performed well in the past they will also perform well in the future.

All in all, the art of technical analysis is to identify trend changes in early stages and stay in the position you have taken until there are enough indications of a trend reversal.

2.2 Technical Trading Rules

The principles behind technical analysis are the same. It does not matter whether you focus on short-term or long-term investments, follow a conservative or speculative strategy, the basic principles are still the same. Prices are determined by changes in mass psychology and psychology is just as relevant in short-term charts as in longer-term charts. Also, the basic principles of technical analysis are the same no matter what investment opportunities you look at, and no matter where you do it.

Markets are formed by human actions and people tend to make the same mistakes. Since human nature is more or less constant, these mistakes or emotional swings keep reoccurring which technical analysts exploit.

As mentioned earlier, no economical theory lies behind technical analysis. Hence, there are no limitations of the number of trading rules you can make use of. You can, more or less, make your own trading rules by studying the price of a given index or stock why an exhaustive description of the topic is impossible to give.

Below, the most important issues within the area of technical trading are described. Chartists do not only focus on prices when making decisions but also include several other indicators, which will be described in this part.

2.2.1 Dow Theory

Charles Dow, one of the founders of The Wall Street Journal and its first editor, developed Dow Theory in the late 1890s. Dow was the first to create a stock market average, which he published on July 3rd, 1884. The first average consisted of only 11 stocks of which 9 were railroad companies. In 1897, the original index was split into two indices, a railroad index and an industrial index with 20 and 12 stocks respectively. In 1928, the industrial index was increased to 30 stocks and a utility index was created. It was not until after Dow's death, however, that his theory was formulated. His successor as editor, William Hamilton, published more than 250 stock-market predictions using theories proposed by Dow. Dow's technical basis for stock market forecasts came to be known as Dow Theory and was articulated in the book *The Stock Market Barometer*, published in 1922.

Dow theory is therefore a natural starting point in the study of technical analysis. This theory can be considered as the granddaddy of the art of technical analysis and most of what is accepted under the broad heading of technical analysis today derives from Dow Theory. Dow Theory tries to identify long-term trends in stock market prices. Six of the most important and basic tenets of the theory are:

1. The Averages Discounts Everything.
2. The Market Has Three Trends.
3. Major Trends Have Three Phases.
4. The Averages Must Confirm Each Other.
5. Volume Must Confirm the Trend.
6. A Trend Is Assumed to Be in Effect Until It Gives Definite Signals That It Has Reversed.

Ad 1. This is one of the basic premises of technical analysis. It simply means that all the market participants combined possesses the required information needed for assessing the value of a stock and this knowledge is discounted in the price movements of the market.

Ad 2. Maybe the most important principle of Dow Theory is that the market has three trends: primary, secondary and tertiary. The definition of a trend according to Dow was that an uptrend had to have a pattern of rising peaks and troughs and a downtrend had to have a pattern of successively lower peaks and troughs.

The major long-term trend is called the primary trend and lasts anywhere from less than one year up to several years. Secondary, or intermediate, trends are a short-term move that usually runs contrary to the primary trend. Secondary trends in a bull market are called *market corrections* whereas in a bear market they are referred to as *bear traps*. A market correction is a temporary decline in an otherwise increasing market, while a bear trap is seen when prices temporarily increase followed by a sharp decline in the market. A secondary trend lasts usually from three weeks to three months. A tertiary movement lasts less than three weeks and is relatively sensitive towards random disturbances and has no or only limited influence on the two other trends. Thus, it also has very little long-term forecasting value under Dow Theory.

Ad 3. The primary trend can be divided into three phases. The first phase is when the initial revival of confidence is created. In this phase the informed investors recognize that the market has finally discounted all bad economic news. The second phase is where most technical traders begin to participate. In this phase prices begin to move rapidly and the economy actually shows signs of improvement. The last phase is characterized by rampant speculation. In this last phase newspapers begin to print bullish stories and economic news is better than ever. At this point of time the informed investors begin to sell out of their stocks since they realize that the trend is about to reverse. Another reason why the informed investors begin to sell their stocks is the fact that no one else seems to be willing to sell and hence they can charge a higher price.

Ad 4. Before a trend can be considered as such, it must be confirmed by another index. In practice, the DJIA and Dow Jones Transportation Average (DJTA) must both confirm either the bull or bear trend. For a bull market to begin both averages have to exceed the previous secondary peak and vice versa for a bear market. If only one of the averages gives the signal conclusions often seems to be erroneous. Signals do not have to be given at exactly the same time but the closer they are the better.

Figure 2.2 Confirmation of reversals of the primary trend in the DJIA and DJTA

Source: Hirschey & Nofsinger (2005).

In the figure above, three situations are shown. The green line represents the DJIA while the gray represents the DJTA. At point 1 the DJTA fails to confirm the bear trend indicated by the DJIA and thus the bull market is intact. At point 2, however, the end of the bull market is confirmed. The lower high and lower low on the DJTA confirms the trend reversal. Point 3 confirms that the bull market has resumed. The higher highs and higher lows on both averages indicate this resumption.

Ad 5. Another important factor in confirming a trend is to look at volume. In an uptrend volume must expand when prices are rising and drop when prices are falling. In a downtrend it is the other way around. Volume increases as prices fall and shrink as prices increase. In general terms, volume should follow the direction of the major trend. It should however, be noticed that this tenet is only a secondary indicator that confirms the trend. It is not useful for identifying the trend in the first place according to Dow Theory.

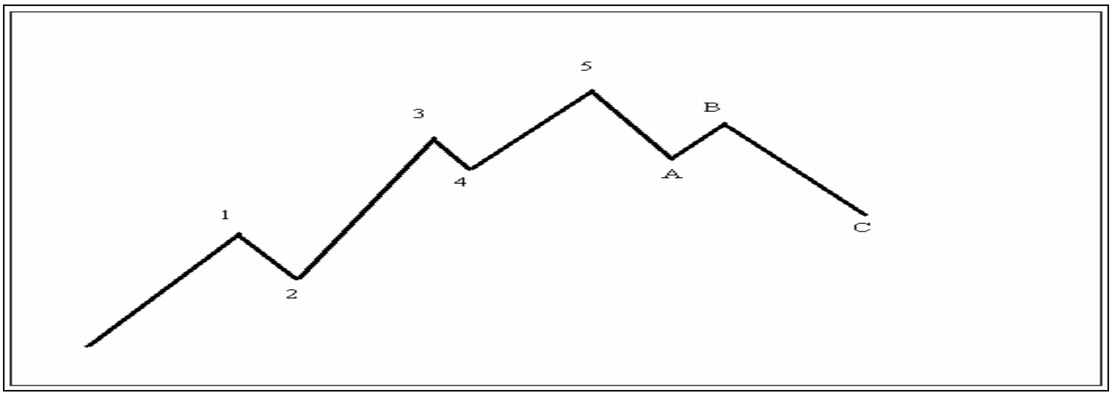
Ad 6. As mentioned earlier, technical analysts believe in the idea of Newton's first law of motion. The art is then to be able to spot the reversal of a trend. This is not as easy as it sounds, but chartists have some methods for identifying these reversals. Among some of the best known are support and resistance levels, moving averages, trendlines etc. Technical analysts must be able to distinguish between a normal secondary correction in an existing trend and true reversal of the primary trend. This can be very difficult and users of the theory disagree about when the actual reversal signal is given.

2.2.1.1 Market Cycle Model

The business cycle is a well-known phenomenon in the economy. Economists believe that the economy moves in a rhythmic cycle from boom to recession. Among technical analysts there is a widespread belief that stock markets also move in rhythmic cycles from boom to recession and back to boom again or, in other words, they believe that there is a tendency for prices to rotate from market peak to market trough in a rhythmic cycle. Some of the factors that cause this cyclical movement are the underlying political and economic forces and crowd behavior among humans. It can take months or even years for crowd behavior to rise to the level of irrational exuberance, decline to despondent pessimism and back to irrational exuberance again. Some of the famous episodes of irrational exuberance in the U.S. occurred in the late 60's with technology stocks, late 80's with energy stocks and finally in the late 90's with technology stocks again. The corresponding lows occurred in 1974, 1982 and 1990 when investors where unusually pessimistic.

One of the best-known market cycle models is The Elliot Wave Pattern, after Ralph Nelson Elliot. He believed that crowd behavior, trends and reversals occur in recognizable patterns. The basic principle of the Elliot Wave Theory is that stock prices are governed by the Fibonacci numbers (1, 2, 3, 5, 8, 13, 21, 34, 55….) and the upside market moves in five waves and three on the downside. Within these waves there can, however, be minor waves and these also show the same pattern as the major wave with five waves on the upside and three on the downside.

Figure 2.3 The Elliot Wave Pattern



Source: Own creation with inspiration from Murphy (1986).

As it was the case in Dow Theory, the waves can be divided in accordance with their size. The major wave decides the major or primary trend of the market and the minor waves the minor trend. As can be seen in figure 2.3, peak 1 is a part of the major trend whereas the first trough, marked number 2, is only corrective and therefore only a secondary trend.

2.2.2 Other Technical Indicators

While price is the most used signal for technical analysts other indicators are also used. Some of these indicators are used for confirming the signal generated by the price, but they can also be used as a primary signal.

2.2.2.1 Volume

As described in section 2.2.1, volume is often used as a confirmation of the trend. Volume has, however, the potential to provide useful information. When investors are uncertain of the future they normally do nothing. This means that when volume decreases a reversal can be underway. Therefore, volume can give indications of the future direction of prices by measuring the level of confidence among buyers and sellers. Most of the time volume is, however, used as a secondary indicator in connection with price movements as described above.

2.2.2.2 Money flows

Another way of measuring conviction among buyers and sellers is to look at the money flows. Money flow is the relative buying and selling pressure on stock prices and is measured on a daily basis. Technical analysts try to figure out what the “smart money” is doing. Investors talk about uptick and downtick trades where an uptick trade is a trade at a higher price than the previous day and vice versa. To get the money flow of a stock or a portfolio, the share price is multiplied by the number of shares traded. The net gain or net loss is then the money flow. The interpretation of the money flow is quite logical. A buyer requires a seller but they have different opinions of the price. It is, however, the supply and demand that determines the market price. If a larger number of stocks changes hands in an uptick trade buyers are more willing to buy at the price suggested by sellers than sellers are willing to dump prices. The “buy” investors can then be classified as more-aggressive investors and they are expected to carry the price trend over time. Hence, positive money flow figures are a sign of a bullish market.

Finally, it should be mentioned that money flow data are reported for both institutional trades and individual trades. Block trades, which is trades that consists of 10.000 or more shares, reflects institutional investors while nonblock trades indicates individual stocks and various major stock indices.

2.2.2.3 Market breadth

In a bull market it is not necessarily all stocks that are rising in price. Neither stocks nor markets rise or fall in straight lines. Some fluctuations will always occur and some stocks will go against the major trend. Identifying the major trend can be done by calculating the market breadth. The market breadth measures how many stocks are increasing in price relative to the number of stocks decreasing in price. One of the most used ways to determine the market breadth is probably the advance/decline ratio. Technical analysts consider this ratio as a good indication of the overall direction of the market and can be determined by dividing the number of stocks rising in price by the number of stocks declining in price. If the ratio is above 1 the market is considered bullish and if the ratio is below 1 it is bearish.

Another way to measure the breadth of the market is to use the advance/decline line. This method is very similar to the advance/decline ratio, but differs in the way that it uses the ongoing sum of the difference between rising and declining stocks. For the breadth to be healthy the line has to rise indicating that there are more positive price movements than negative. Normally, the overall market and the advance/decline line moves together but at times a so-called divergence emerges. This occurs when the overall market continues to move higher while the advance/decline line drops. Technicians see this as a warning of a pending reversal of the trend.

2.2.2.4 Market imbalance

More than 30 years ago, Sherman McClellan and his wife invented the McClellan Oscillator. This indicator of the market trend, smooth the advance/decline data by using moving averages[1]. The oscillator graphs the difference between the 19-day moving average and the 39-day average of net number of advancing stocks. A positive McClellan Oscillator indicates a bullish market is in progress. If the oscillator however, gets too high, the market is considered as overbought by technicians. When the number gets too low the market is thought of as oversold and the market may be at its bottom.

The Arms Index, also known as the trading index (TRIN), is probably an even more used indicator of market imbalance. To derive TRIN, the ratio of rising stocks to declining stocks is divided by the ratio of the volume of advancing stocks to the volume of declining stocks. If TRIN is below one the market is considered bullish and above one bearish. Generally, technicians believe that if TRIN is below 0.65 the

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[1] See section 2.2.3.1 for a detailed description of moving averages.

market is very bullish and if it is above 1.35 it is very bearish. For detecting market imbalances technicians believe that the higher the smoothed or averaged TRIN reading is the more oversold it is, and the lower the reading the more overbought the stock or the market is. Hence, extreme oversold readings indicate a potential market bottom and extreme overbought readings is interpreted as potential market peaks.

2.2.3 Simple Trading Rules

In the following part, two simple trading rules will be described. The moving average trading rules, that will be empirically tested, will be emphasized.

2.2.3.1 Moving Average

Probably the most versatile and used trading rule is the moving average trading rule. The rule has been used for at least 50 years and belongs to category of indicators called trend-following indicators. These indicators are meant to smooth the price pattern of indices or stocks making it easier to identify beginnings and end of trends and identify the underlying trend. The reason why moving average is so widely used may be because buy and sell signals can easily be computed into a computer. Chart analysis is largely subjective and difficult to test. Technicians may disagree whether a price pattern is a head-and-shoulder pattern or a flag pattern while moving averages is a mathematical calculated pattern leaving no issues open for debate.

As the term implies, moving average is a technique where the data of a certain stock or an index is averaged over a time period. There are no specific demands to the length of the time period, but it has to fit the trading issue. Also, different prices can be used. Normally, however, the closing price is used, but there is no rule that says you cannot use other prices such as highs, lows or maybe even a combination of more prices.

2.2.3.1.1 Simple Moving Average

The most commonly type of average used is the simple moving average. The calculation of this average is very simple. If a 20-day average is needed, the price of each day for the last 20 days is added and then divided by 20. To make it a moving average, the oldest observation is subtracted and a new is added. To find out what length the average should have, logic sense must be applied. If you need weekly data a 4-week data may seem reasonable. If monthly data is needed a 12-month moving average is more useful.

The simple moving average has, however, two major drawbacks. The first is the fact that it only covers the period under observation. It totally excludes earlier data, which might contain useful information. The second criticism is that each observation is given equal weight. The oldest observation is in other words regarded just as important as the newest. Some analysts argue that more recent observations should be given more weight in the average. This drawback makes perfect logical sense especially for moving averages with longer time span such as 50-day and 200-day moving averages. To correct for this, the linearly weighted moving average and exponential moving average have been created.

2.2.3.1.2 The Linearly Weighted Moving Average

The easiest way to correct for the second of the above-mentioned problem is to use the linear weighted average. By using this average more recent observations are given more weight than old ones. If a 5 day moving average is used, the observation on the fifth day is multiplied by five; the observation on the fourth day is multiplied by four etc. The total is added up and divided by the sum of the multipliers. In this little example, the sum of the observations is divided by 15 (5+4+3+2+1=15). The linear weighted moving average method does, however, not help with the so-called drop-off effect. To correct for both problems, analysts must turn to the exponentially smoothed moving average.

2.2.3.1.3 The Exponential Moving Average

The exponential moving average is also a weighted average assigning more weight to recent observations. The oldest price observations are never removed from the data but the further back they are, the less weight they are given in the calculations. The formula for the exponential moving average is:

(2-1) $$EMA_t = \alpha \times price(1-\alpha) \times EMA_{t-1}$$

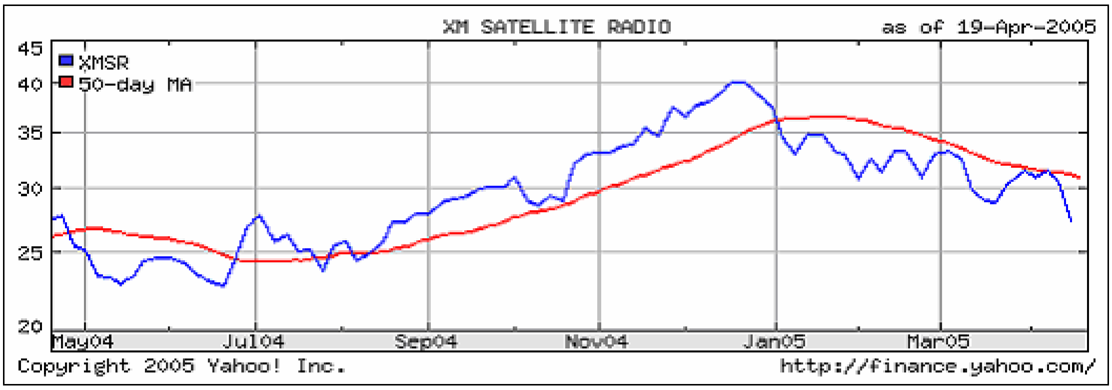
where $\alpha = \dfrac{2}{N+1}$.

Advocates of the exponential moving average argue that this kind of moving average is relatively easy to maintain by hand day by day. The only data needed is the previous day's exponential moving average data and today's closing data.

2.2.3.1.4 One Moving Average

The moving average is just a line on a piece of paper or a computer screen and is not by itself a signal that can be used for making buy or sell decisions. To make signals out of the average, analysts benchmark either one or more against the actual price or each other. The simplest way to generate a signal is by using one moving average and compare it to the actual price. The idea behind this is that in an uptrend, the moving average tends to lag the price action and trails below the prices. If the actual price moves above the moving average a buy signal is generated and conversely, if the price moves below the average a sell signal is generated.

Figure 2.4 Simple one moving average



Source: http://finance.yahoo.com, April 19 2005.

As can be seen in the figure several buy and sell signals for the XM Satellite Radio stock are generated. The first signal is a sell signal, which occurs in late April 2004. Around July 20th a buy signal is generated as the price of the stock breaks the moving average line from below. An unfortunate characteristic of the one moving average technique is that in a trading-range market it is a money-losing indicator. If you react on all signals, the transaction costs will eat up the gains. With this trading rule, you are always in the market, either short or long. The problem is illustrated at the end of July and beginning of August. Here the price crosses the moving average line four times. The three first crossovers are false signals while the last one is a “true” signal. Even though the shorter averages generate more false signals they also have the advantage of giving trend signals earlier in the move. Hence, analysts must make a trade-off whether to react early in the trend or save some transaction costs.

There are various ways of dealing with the problem of too many signals. The easiest is to adjust the length of the moving average. By doing that, only significant price violations are given. This gives later buy and sell signals but it also gives rise to another problem. With a short moving average it is possible to react early in the trend whereas a long moving average result in fewer so-called whipsaws but the signals are late. Another way to correct the problem is to add a filter on the moving average. There are numerous filters that can be used helping analysts to react only on real buy signals. Some common filters are:

- *Closing price:* The price must close above or below the moving average line to be a valid crossover. Some analysts even require that the entire day’s price range clear the average.
- *Time filters:* Because most false signals correct themselves relatively quickly, some traders require the crossover to remain in force for a certain time period. The time period can last from a couple of days to a week.
- *Percentage bands:* This is a very popular filter and will also be used in the empirical analysis. For a signal to be generated the price of the stock must cross the moving average by a certain percentage of the price of the moving average. The percentage band creates a buffer zone around the moving average line. As long as the price lies within this buffer zone, no action is taken. Action is first taken when the price crosses either the upper or lower percentage band. The question how large the buffer zone should be is again a trade-off. If it is decided to use small percentages the risk of trading on false signals is greater, but the chance of getting early in on a trend is also greater. In the empirical analysis the band will be a 1 percent band.
- *High-low band:* Instead of using closing price as indicator the high and low price of each day is can be used. This result in two moving averages: one

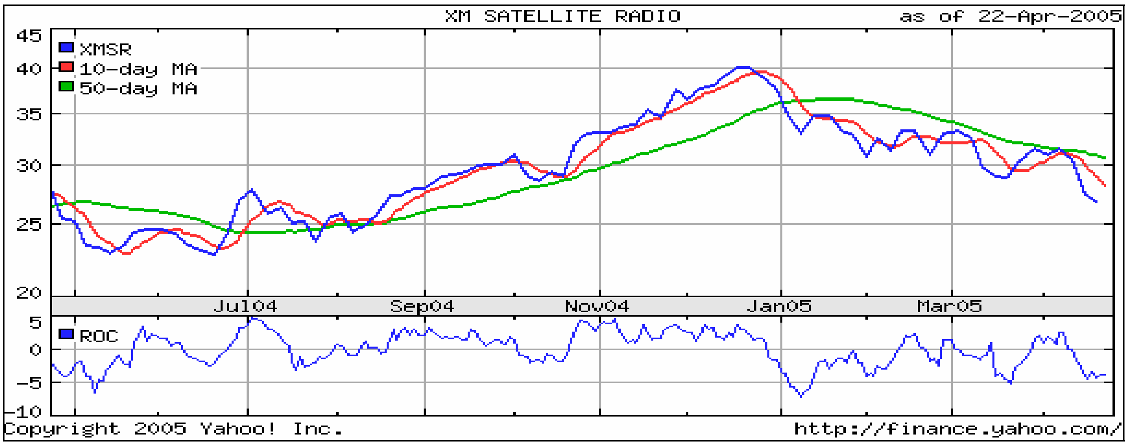
for the highest price and one for the lowest. A buy signal is generated when the closing price lies above the line for the highest average. Similarly, a sell signal is given when the closing price is below the lower average.

2.2.3.1.5 Two Moving Averages

Technicians also have other possibilities for making better decisions besides the use of filters. An effective and common method is to use two moving averages simultaneously. The averages are of different lengths with the shortest of them used instead of the actual price and the longest to identify the underlying trend. There are numerous combinations of averages that can be used, but some very common combinations are the 5- and 20-day averages and 10- and 40-day averages. For a signal to be given the shorter average must cross the longer average. If the shorter moving average crosses from below a buy signal is given and if it crosses from above a sell signal is given. The use of two moving averages lags the signal a little bit, but the advantage is that it produces fewer whipsaws than by the use of only one moving average. It should be noticed that it is the simple moving average that lies behind the method described above.

Another way to make use of a two moving average method is to create an oscillator. The oscillator is the mathematical difference between the short and long moving average. It measures whether a market is overbought or oversold. When a security lies too far above the longer moving average it is overbought and technicians believe that the price will fall. Another way of interpreting the oscillator is to look at crossovers on the zero line. If it crosses from below, a buy signal is given and vice versa.

Figure 2.5 Simple Two Moving Averages



Source: http://finance.yahoo.com, April 22 2005.

In figure 2.5 some of the problems from the one moving average method are corrected. The issue with the whipsaws around august 2004 is corrected since the shorter moving average does not cross the longer moving average and hence, no false signals are given. Below the price curves, the oscillator is shown.

2.2.3.1.6 Three Moving Averages

To make even fewer mistakes, technicians make use of three moving averages. The analogy is, if two averages resulted in fewer false signals than one, three must result in fewer than two. Technicians choose the length of the three moving averages in different ways. Probably the most used way is to use cycle length as a deciding factor. The first moving average is a 5-day moving average representing a week. The second is a 21-day average representing a month and finally a 63-day moving average for a quarter. Another way is to use harmonic numbers. If this strategy is used, you simply multiply the next longer average with a factor of two. This means that if the first moving average is a 10-day average the next moving average will be a 20-day moving average and so forth. Lastly, some also make use of the Fibonacci numbers described earlier. A popular three moving average system based on these numbers is a 5-, 13- and 34-day moving average.

The trading rules with three moving averages are similar to those under one and two moving averages. The general principle is that the longer moving average must cross the shorter to generate a signal. A sell signal is generated when the e.g. 5-day average crosses the 21- day average *and* the 21-day average crosses the 63-day average from above. With three averages there is an in-between. The period from the fastest moving average crosses the medium until the medium average crosses the slowest moving average is a period with no clear signals. This is one of the important differences between using a one or two moving average method and a three moving average method. With one and two moving average methods you are always in the market. These methods tell you only whether to take a short or a long position. With three moving averages there is a period in-between where you are out of the market. The first sign of a reversal of a trend is that the fastest moving average crosses the medium average. As soon as this happens the position is liquidated and a position out of the market is taken. When the medium average then crosses the longest average a new position is taken again.

Of course there is a catch by using three moving averages. The method results in fewer whipsaws but at the same time the first part of the trend is missed. The more averages taken into consideration the less risk is taken and hence, the lower return you will get.

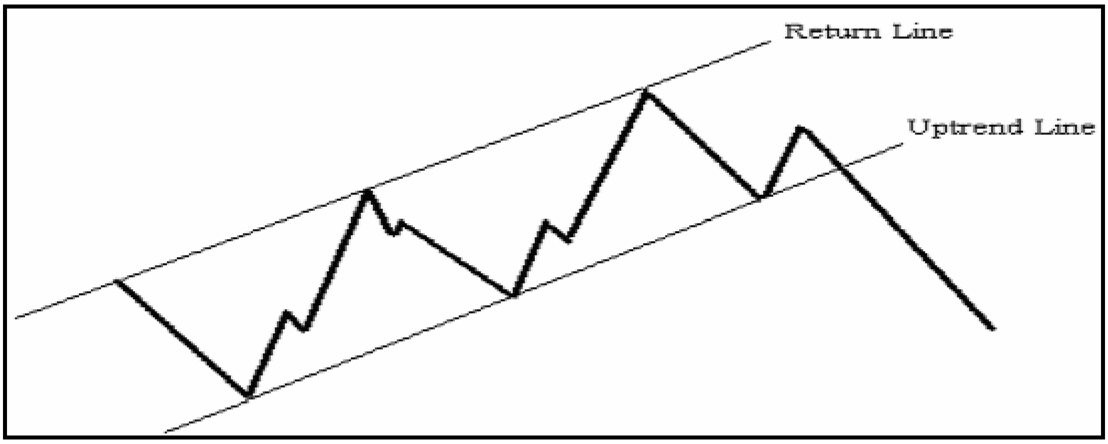
2.2.3.2 Trading Range Breakout

As described earlier, technical analysis builds on the belief that price moves in trends. A trend can move in three directions, sideways, upwards and downwards. To be able to use these trends and easier react on them, technicians often draw trend lines. Trend lines can be drawn from either the lows in an uptrend and highs in a downtrend or through some key closes. The time issue is very important when using trend lines. If you have a very short time horizon, a 10-year trend line is of very little use. Similar a two-week trend line will trigger too many signals for a trader with a five-year time horizon.

The technique of drawing trend lines is subjective. This means that no formula can be used to help you draw the line; you must simply draw what you think you see. The fact that it is a subjective technique makes it hard to use for buy and sell signals. If the price crosses the trend line from either below or above it should be a signal. However, the line is drawn from your own believes and it is very hard to say whether the line has been drawn correctly. Maybe the line ought to have been drawn more steep or flatter. To help making better decisions some analysts use bands around the line. Typically these bands are 1% or 3% bands. The idea is, in case of a 1% band, that the security must trade more than 1% above or below the line before action is taken. If the band approach is taken the signals that are generated must be used as mechanical signals; if the price reaches the 1% or 3% level action is required without any extra hesitation.

Another way to use trend lines is to draw what is referred to as channels. Basically, two trend lines are drawn; one up or downtrend line and a return line also called channel line. To be able to draw a channel in an uptrend, two bottoms with an intervening high followed by another high at a level higher than the intervening high is needed. In a channel four possible kind of signals are generated, two in uptrend and two in a downtrend. If the price in an uptrend does not reach the uptrend line analysts believe that the price accelerates and a steeper trend has begun. If the price, however, fails to reach the return line it may be a signal of a reversal of the trend. The signals in a downtrend are of course similar to those in an uptrend just the opposite way.

Figure 2.6 Uptrend Channel



Source: Own creation with inspiration from Murphy (1998).

The idea of a channel is illustrated in the figure above. As can be seen there are two troughs and two peaks with the latter of them above the prior. This makes it possible to draw the channel, which in this illustration is an uptrend channel. A signal is generated where the last peak fails to reach the return line. Hereafter, the price crosses the uptrend line and analysts believe that a trend reversal has occurred.

2.2.3.2.1 Support and Resistance

When the price of a stock keeps bouncing back and forth between two price levels and no clear trend can be observed, analysts make use of support and resistance levels. The support level refers to the troughs of a price curve. After a certain period of declining prices, the price will hit the support level. At that point the buying pressure is sufficiently strong to overcome the selling pressure and the price will begin to rise again. The previous trough normally defines the support level. Conversely, after a period with rising prices, the resistance level is reached. At this level selling pressure overcomes buying pressure and prices will start to fall again. As with support level a previous peak defines the resistance level. In the range between support and resistance there is so to say a war between buyers and sellers. At one point, however, one of the sides will win and the support or resistance level is broken. At this point the trend reveals itself. If the trend is an uptrend the price will cross the resistance level while in a downtrend the support level is crossed. When one of the lines is crossed the roles of them are reversed. This means that if the support level is crossed from above it becomes the new resistance level and if the original resistance level is broken it becomes the new support level. The reason for this is that investors have the price in mind. Investors want to get out of losing trades at break-even. Similarly, traders seek to increase winning positions by buying more stocks at or near the support level.

Another psychological aspect of support and resistance levels is the role of round numbers as support and resistance. Round numbers has a tendency to stop advances or declines. Investors tend to see round numbers such as 50, 100, 1.000 10.000 etc. as price objectives and act accordingly. Hence, round numbers often act as psychological support or resistance levels.

2.2.4 Complicated Patterns

Price patterns consists of two categories, namely reversal and continuation patterns. Reversal patterns generate signals of reversing trends whereas continuation patterns are only a short pause of a trend, maybe to correct for overbought or oversold conditions. After the pause the existing trend will be resumed. In the following some reversal patterns will be described followed by a description of a few continuation patterns. These patterns all belong to what can be classified as complicated trading rules, which refers to the fact that they build on subjective opinions and are impossible to calculate mathematically.

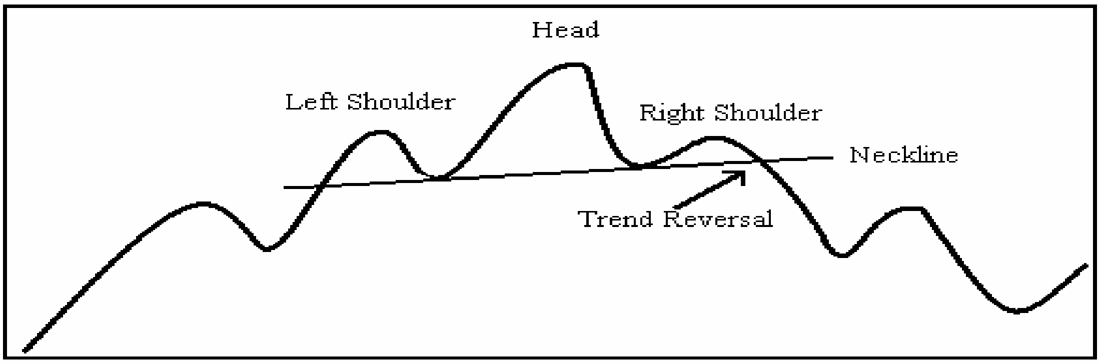
2.2.4.1 Reversal Patterns

As the name indicates the following patterns indicate an important change in the existing trend. Most changes in trend are not abrupt affairs but evolve over a longer period. The art is then to identify these trend changes as early as possible in order to profit as much as possible.

2.2.4.1.1 Head and Shoulders

The most famous of the reversal patterns is without doubt the head-and-shoulders pattern. In its simplest form the pattern consists of three peaks, when looking at pattern with tops. The middle of the three, also called the head, is the highest and is surrounded by two lower peaks. The two lower peaks are known as the left and right shoulder. It is possible to draw a trend line in the pattern as well. The line joins the troughs immediately to the left and right of the head and is called the neckline. In an uptrend the neckline generally has a slight upward slope but can also be horizontal and sometimes even downward sloping. As with all trend lines, the signal is generated when there is a crossover of the line, in the case of a head-and-shoulder pattern, the neckline. The breaking of the neckline is a signal that the series of rising peaks and troughs has reversed and a series of declining peaks and troughs is now in force. The pattern is shown in figure 2.7.

Figure 2.7 The Head and Shoulder pattern



Source: Own creation with inspiration from Pring (2002).

A head-and-shoulder pattern can take form in a matter of weeks or might evolve over a year. The logical time span of the pattern when dealing with stocks is, however, a period of around three or four months. This is due to the fact that public held companies are tied to quarterly reports and thus, reversals in trends tend to evolve in such cycles.

The head-and-shoulder pattern in a downtrend is referred to as the inverse head-and-shoulder pattern. This pattern has three troughs instead of three peaks with the middle being the lowest of them. The neckline in the inverse pattern is generally downward sloped. The breaking of the neckline in the inverse head-and-shoulder signals a reversal of a downtrend and a beginning of new uptrend.

2.2.4.1.2 Double and Triple Tops and Bottoms

The second most common reversal pattern is probably the double tops or bottoms pattern, also referred to as “M” or “W” patterns. A double top formation consists of two peaks separated by a trough. Normally, the second peak is lower than the first. However, the two peaks have approximately the same level. Volume is normally heavier during the first peak and often shrinks to almost nothing at the second peak. During the second peak volume and trend goes in opposite directions. Price goes up even though volume is declining which is an abnormal situation and hence a bearish signal.

Similar to the head-and-shoulder pattern, the double top/bottom pattern has a trend

line from which signals are generated. In the case of a double top pattern the line is drawn horizontally along the lowest point of the valley between the two tops and is called the valley line. Analysts believe that when the price crosses the valley line a signal is generated.
The double bottom pattern is just a mirror image of the double top formation with one exception, however: when the price crosses the signal generating line volume must expand. If it does not do so, the signal is looked upon as being suspicious. As with double top formations, the volume plays an important role. To generate a valid signal the volume must be higher during the first bottom also indicating that the first bottom marks the selling climax.

The double top/bottom formation can extend itself to triple top/bottom formations but these are much rarer. Triple tops or bottoms patterns tend to be more unstable than double top/bottom patterns and indicates that the battle between buyers and sellers is much greater. As a result the bear market that follows a "top" pattern is often more forceful. The same goes for the bull market following a "bottom" formation.

2.2.4.2 Continuation Patterns

Continuation patterns are, as the name indicates, just a signal of a small pause in the existing trend after which the trend will continue in the same direction as before. Another difference between reversal and continuation patterns is the duration of these. Whereas reversal patterns often evolve over a considerable time span continuation patterns are normally shorter-term in duration. Below, three continuation patterns are shortly described.

2.2.4.2.1 Triangles

There are three different types of triangles: the symmetrical, the ascending and finally the descending triangle. To differentiate the triangles from one another the trendlines are examined. The symmetrical triangle has a descending upper trendline and an ascending lower trendline, while an ascending triangle has an ascending lower trendline but horizontal upper trendline. The descending triangle has a declining upper trendline and a horizontal bottom trendline.

The symmetrical triangle is usually a continuation pattern. The prevailing trend just pauses for a short while before resuming the trend. This means that if the trend was an uptrend, the symmetrical triangle has bullish implications and vice versa. Because the two trendlines meet at some point, time is also an important issue when interpreting the pattern. The breakout must occur between the one-half and three-quarters of the horizontal width of the triangle. If the breakout does not occur it looses it strength. Thus, the symmetrical triangle pattern gives both an indication of the price boundaries but also provides investors with a time target.

The ascending and descending triangle are variations of the symmetrical triangle. However, they differ in a very important sense. Both the ascending and descending triangle has very clear forecasting implications. The ascending triangle is a bullish pattern while the descending triangle has bearish implications. The symmetrical triangle is more neutral, but also has forecasting implications. Investors must, however, look at the prevailing trend to decide the implications of the symmetrical triangle.

2.2.4.2.2 Flags and Pennants

Flags and pennants are quite common and among the most trustworthy continuation patterns. They are treated together due to the fact that they are very similar in appearance.

Flags take the form of a rectangle marked by an upper and a lower trendline that usually goes against the existing trend. Flags occur after a steep advance or decline in the price. This drastic movement has caused the market to go ahead of itself and as a result there is a short pause in the price movement. After this short break the trend continues in the same direction. The signal that the trend has reassumed is given when the price breaks the upper trendline in an uptrend and the lower trendline in a downtrend.

Pennants have the form of a small symmetrical triangle and are also marked by two trendlines. However, whereas the trendlines go against the prevailing trend in a flag pattern they seem to move more horizontally in a pennant pattern. Both of the patterns usually lasts no longer than three weeks and in a downtrend they are often developed over a shorter period, often no longer than one or two weeks. A pennant pattern is also a triangle but differs from the three above-mentioned in that there is a drastic price movement prior to the sideways movement.

The volume during the two patterns is also similar. During the initial sharp movement volume is very high. During the consolidation pattern the activity dies out only to recover dramatically at the point of breakout.

2.2.4.2.3 Wedges

The wedge formation is much similar to the symmetrical triangle pattern described above. Two converging trendlines meeting at an apex forms it. The duration of the wedge pattern is between one and three months. What differentiate the pattern from the symmetrical triangle pattern is that the two trendlines moves in the same direction. All other characteristics are the same. As a countercyclical pattern the direction of the wedge pattern is rising when a bear market is in place while falling during a bull market. In both market situations volume is declining during the wedge formation only to expand when the breakout occurs.

2.3 Recapitulation

Only the basic foundation of what is known as technical analysis has been touched upon in preceding section. One should bear in mind that there are innumerable ways of combining trend-following systems and thus, an exhaustive description of technical analysis is almost impossible and also not of interest in this thesis. The comprehensive area technical analysis covers is also one of its greatest criticisms. Often empirical studies are criticized for finding patterns ex-post and thus, the way of making stock market analysis is not valid when investors make decisions ex-ante.
The next section will look at a competing theory, the efficient market theory. Technical analysis and the efficient market theory are mutually exclusive. Thus, if it can be proven empirically that one can earn an abnormal return by following technical trading rules, markets can be considered as inefficient.

3 Efficient market hypothesis

Many studies have been conducted to obtain a theoretical foundation to understand the price movements on the financial market. The research has resulted in a number of different definitions and hypothesis of the efficient market. Perhaps the most famous and widely used hypothesis was defined by Fama *(1970)* and known as the EMH. The EMH states that security prices fully reflect all available information. Any new information will thereby immediately be incorporated in the price, making the quoted stock price a fair value. You cannot expect to gain any abnormal profit for a given risk for a longer period of time[2]. The stock return will fluctuate randomly, while the stock price only will respond to any new information. New information is by definition unpredictable, making the stock price and the return unpredictable and random *(Christensen & Pedersen, 2003)*.

The theory of efficient markets is very closely associated with a random walk. Actually, the forerunner for the EMH was known as the Random Walk Hypothesis. The pioneer, the French mathematician Louis Bachelier, concluded as early as in 1900 that French government bonds followed a random walk model. Unfortunately, Bachelier's insight was so far ahead of his time that his thoughts went largely unnoticed for more than fifty years, until his work was rediscovered and translated into English. The random walk hypothesis stands in sharp contrast to fundamental analysis. If stock prices follows a random walk, it seems that fundamental analysis is worthless. Stock prices will no longer be controlled by the law of supply and demand, but instead be completely random and unpredictable. The neglecting of the law of supply and demand created skepticism among the academics and the search for crucial evidence towards the random walk model hypothesis was set in motion.

However, the random walk model left as many questions unanswered as it resolved and it did not take long for the skeptics to find it weaknesses. They found that the weakness of the random walk hypothesis was the error term. The assumptions behind the error term were too restrictive to describe the stock price movements. To

[2] Jensen (1978) definition of market efficiency states that it is impossible to gain any abnormal profit by trading on the basis of the information set. This was considered, at the given point in time, as a vague rewriting of Fama's definition.

follow a random walk the error term should, besides being uncorrelated, also be completely independent with earlier period's error terms. Studies soon showed autocorrelation and the random walk hypothesis was shot down. A new less restrictive model still containing the characteristics of the random walk model was needed. The answer was the martingale model. Paul Samuelson's *(1965)* paper was the first to develop the link between capital market efficiency and martingales. Unlike the random walk model, the martingale model does not assume fully independency between the error terms, but only that they are uncorrelated. Thus, it can be seen that the random walk model is a special case of the martingale. Fama picked up the insights from Samuelson and formed the EMH.

After a short definition and a presentation of EMH and its background it seems reasonable to introduce the econometrics behind the above discussion. Next section will seek to elaborate the martingale model and present the EMH in a more technical language.

3.1 The Econometrics Behind the EMH

Before getting any deeper into the EMH, it is found necessary to introduce the econometrics behind stock prices, returns and EMH. The purpose of this section is not only to introduce the fundamental econometrics behind stock prices and returns but also to derive an econometrical definition of the EMH, which can be used as a starting point, when going deeper into the discussion of market efficiency. This section is mainly build upon two sources of literature; Cuthbertson *(2004)* and Christensen & Pedersen *(2003)*.

As mentioned, the EMH assumes stocks prices incorporate all relevant information. Consequently, the only reason a price change can occur between t and $t+1$ is the arrival of news or unanticipated events. Forecast errors $\varepsilon_{t+1} = P_{t+1} - E_t P_{t+1}$ should therefore be zero on average and uncorrelated with any information available at the time of the forecast. The latter is often referred to as the rational expectations element (RE) of the EMH and can be represented as:

(3-1) $$P_{t+1} = E_t P_{t+1} + \varepsilon_{t+1}$$

Taking the expectation of (3-1) and rearranging the expected value of the forecast errors leads to:

(3-2) $$E_t \varepsilon_{t+1} \equiv E_t (P_{t+1} - E_t P_{t+1}) \equiv E_t P_{t+1} - E_t P_{t+1} \equiv 0$$

The fact that the expected value of the forecast error is zero implies that the forecast of P_{t+1} is unbiased i.e. actual prices on average equals expected prices. Often, the EMH is applied on stock returns instead of stock prices and due to close link between stock prices and stock returns (3-2) can be written as follows:

(3-3) $$E_t \varepsilon_{t+1} = E_t R_{t+1} - E_t R_{t+1} = 0$$

Under EMH one cannot earn abnormal profit by buying and selling stock. This is referred to as the fair game property. A fair game is also known as a martingale difference, which can easily be shown.

A stochastic process X_t is a martingale with respect to a sequence of information sets Ω_t if X_t has the property:

(3-4) $$E(X_{t+1} | \Omega_t) = X_t$$

Thus, the best forecast of all future values X_{t+j} is the current X_t, hence no additional information in Ω_t can be used to improve the forecast once the agent knows X_t. A stochastic process is a fair game if:

(3-5) $$E(y_{t+1} | \Omega_t) = 0$$

The property of a fair game is that the expected return is zero given Ω_t. Using (3) and (4) it is obviously that if X_t is a martingale then $y_{t+1} = X_{t+1} - X_t$ is a fair game. Hence, fair game is martingale difference. Turning to the EMH it furthermore embodies the fair game property for unexpected stock returns, so that abnormal return (or excess return) on average is zero. Combining the fair game property with a simple model, where stocks pay no dividends and investors are willing to hold stocks as long as it is expected to earn a constant return, k :

(3-6) $$E_t R_{t+1} = k \qquad k > 0$$

This form is known as the fair game of excess return. Now assume another simple model where returns are still constant but now the stock pays dividends, then the expected returns can be defined as:

(3-7) $$E_t R_{t+1} = \frac{E_t V_{t+1} - V_t + D_{t+1}^e}{V_t}$$

where V_t is the value of the stock at the end of time t and D_{t+1} are dividends paid between the period t and $t+1$. Using (3-6) and (3-7) a differential (Euler) equation is obtained, which shows the movement in value over time:

(3-8) $$V_t = \delta E_t (V_{t+1} + D_{t+1})$$

where δ is the discount factor $\frac{1}{(1+k)}$. By leading (3-5) one period.

(3-9) $$V_{t+1} = \delta E_t (V_{t+2} + D_{t+2})$$

Taking the expectation of (3-9) under the assumption that information is only available up to time t.

(3-10) $$E_t V_{t+1} = \delta E_t (V_{t+2} + D_{t+2})$$

In deriving (3-10) the *law of iterated expectations* has been used. The concept of this law is that the expectation formed today (t) of what one's expectation will be tomorrow ($t+1$), of the value at time $t+2$ equals today expectation of the value at time $t+2$. The rationale behind this is that one cannot know how one's expectations will alter in the future. Hence, equation (3-9) contains the rational expectation element mentioned earlier. If Equation (3-9) holds for all period then:

(3-11) $$E_t V_{t+2} = \delta E_t (V_{t+3} + D_{t+3})$$ etc.

Substituting (3-11) in (3-9)

(3-12) $$V_t = \delta\left[\delta E_t (V_{t+2} + D_{t+2})\right] + \delta(E_t D_{t+1})$$

By successive substitution

(3-13) $$V_t = \delta D_{t+1}^e + \delta^2 D_{t+2}^e + \delta^3 D_{t+3}^e + ... + \delta^n (D_{t+n}^e + V_{t+n}^e)$$

As can be seen in equation (3-13), V_t is a function of the future expected stock value, thus no unambiguous solution can be derived. To resolve this (3-13) is imposed a transversality condition:

(3-14) $$\lim_{n\to\infty} E_t\left[\delta^n (D_{t+n} + V_{t+n})\right] \to 0$$

then (3-13) becomes:

(3-15) $$V_t = \sum_{k=1}^{\infty} \delta^k D_{t+k}^e$$

The interpretation of (3-15) is that the fundamental value V_t of a stock is the discounted present value (DPV) of expected future dividends. In an efficient market investors set the actual market price P_t equal to fundamental value. Thus, the rational valuation formula (RVF) with a constant discount rate can be written as follows:

(3-16) $$P_t = \sum_{k=1}^{\infty} \delta^k D_{t+k}^e$$

The above equation is derived under the assumption that investors require a constant rate of return thus, a constant discount rate. Now, suppose investors require a different expected return, i.e. a time varying discount rate. To make such a transaction, a simple dividend equilibrium model is no longer optimal to determine the stock price but a more sophisticated equilibrium model is needed. A better-suited model is the intertemporal consumption CAPM (C-CAPM). Here, the investor maximizes expected utility with current and future consumption as the only variables. With the RVF in mind and the use of intertemporal utility maximization Christensen & Pedersen *(2003)* arrive at following expression for the stock price:

(3-17) $$P_t = \sum_{k=1}^{\infty} \delta^k E(\frac{U^/(c_{t+k})}{U^/(c_t)} \times D_{t+k}) + \delta^n E(\frac{U^/(c_{t+n})}{U^/(c_t)} \times P_{t+n})$$

By imposing the transversality condition

(3-18) $$\lim_{n \to \infty} \delta^n E(\frac{U^/(c_{t+n})}{U^/(c_t)} \times P_{t+n})$$

(3-17) becomes:

(3-19) $$P_t = \sum_{k=1}^{\infty} \delta^k E(\frac{U^/(c_{t+k})}{U^/(c_t)} \times D_{t+k})$$

Comparing (3-19) and (3-16) the only difference is the $U^/(c_{t+k})/U^/(c_{t+k})$ part of the formula, which expresses the relationship between marginal utility of the future consumption and the marginal utility of current consumption also known as the marginal rate of substitution. The marginal rate of substitution can here be seen as a time varying weight, which relates to future dividends and thereby works as a time varying discount rate. Equation (3-19) is often referred to as the efficiency hypothesis of stock price determination *(Christensen & Pedersen, 2003)*.

By introducing the C-CAPM in the RVF for stock prices, a model that can be used as theoretical starting point for the further discussion of the EMH is finally arrived at. By incorporating the fair game properties in a dividend model the apparent paradox that returns cannot be forecasted yet, prices are still determined by fundamentals (i.e. dividends), is resolved, a paradox that initially was triggered by the limitations of the random walk theory.

3.2 Information Paradox

Although the EMH theoretically is said to take all relevant information into account, the question is why people tend to spend time and money to gather information in an attempt to beat the market? The reason for this can be found in a famous article written by George A. Akerlof *(1970)* where he identified what is known as 'The Lemon Problem'. In this article Akerlof formulated the asymmetric information and free rider problem within the used car dealer business. In the same way asymmetric information and free rider problems destroys the efficiency in the used car dealer market, the two aspects also play a significant role on the efficiency of the stock market. If gathering information is not free, no one will do so, because you cannot gain any abnormal profit to cover the costs, due to the fact that all relevant information is already incorporated in the price and freely available. But if everybody ´free rides´ there is no one to collect the information and surely the price cannot reflect all relevant information and the market can thereby not be efficient. However, it is worth remembering that every transaction involves both buyers and sellers. Through their activity they behave like they somehow know more than the person acting on the other side of the transaction. It is obvious that if asymmetric information is present, the market cannot be efficient, because once again if all available information is fully incorporated, then neither the buyer nor the seller will have an information advantage *(Grossman & Stiglitz, 1980).*

Acknowledging the information paradox Fama *(1970)* sat up some conditions, which should be sufficient but not necessary for market efficiency:

1. All relevant information is freely available to all agents.
2. No transaction costs.
3. All agents have homogeneous expectations.

As discussed above these conditions do not hold in practice. However, Fama states that the lack of fulfilling these condition is not tantamount to market inefficiency. Even though not all agents interpret the information the same way, the market is still efficient as long as no investors systematically gain any abnormal profit, due to the fact that they continuously interpret the information better than the market. Furthermore, even though the transactions costs reduce the number of transactions, it has no effect on market efficiency. Finally, Fama states that the cost of information is not synonymous with market efficiency, as long as a sufficient amount of agents have access to the information. Grossman & Stiglitz *(1980)* disagree and state that no information cost is not only sufficient but also necessary. They argue that even though information is readily available there is still a cost combined with interpretation of the information. Grossman & Stiglitz *(1980)* end up with a solution contradicting Fama's definition that prices fully reflect all relevant information. In their model agents paying to be informed will be awarded with higher return than the uninformed because of better market timing (knowing when to buy and sell). The award offset the cost of information so the informed and uninformed agents receive the same net return. In that way, prices do not fully reflect all relevant information but do have the effect that no agents can earn an abnormal profit. This conclusion entails that a distinction can be made between Fama's *(1970)* definition and Jensen's *(1978)* definition that were earlier considered almost synonymous.

The information paradox and the EMH can be seen as the real world versus a theoretical world. To help the transition between the two worlds Fama divided the market efficiency into three levels.

3.3 Levels of Market efficiency

Fama *(1970)* distinguishes between three different degrees of market efficiency – labeled weak form, semi-strong form and strong form respectively. The different levels are classified by the amount of information, which is incorporated in the current prices.

The weak form involves the lowest hurdle that must be met for one to argue that the stock market is efficient. In the weak form the only information reflecting the current prices is the historical prices. This means that any examination of the past prices is redundant and cannot be used to create any abnormal profit. This statement, due to the definition of technical analysis, undermines the usefulness of technical analysis making fundamental analysis and insider information the only tools for creating superior profit.

In the semi-strong form all public available information is incorporated in the price. It means that besides historical information everything read in the news, heard on the radio, seen on the television and Internet is already incorporated in the price. This have the effect that fundamental analysis no longer can generate an abnormal profit, leaving the use of insider information the only way to earn a higher profit than a simple buy-and-hold strategy.

In the strong form efficiency all information public as well as private information is incorporated in the current prices. This implicate that it is not possible by any means, not even insider information, to systematically generate higher profit.

Note that the information set is gradually increasing throughout the three forms. This means that if the market is efficient in the strong form it is of course also efficient in the weak and semi strong form. On the other hand, if the market is efficient in its weak form, it is not necessarily efficient in the semi and strong form. As implicated earlier, the market cannot be efficient in its weak form, if technical analysis works and the market cannot be semi-strong or strong if it is not efficient in the weak form. Therefore, if evidence is found in the empirical part that technical analysis outperforms a simple buy-and-hold strategy, it must be synonymous with a rejection of the weak form efficiency and hereby a rejection of the EMH at any levels.

The discussion regarding the EMH and the degree of efficiency has been a hot subject among academics through the last 30 years and has provided breeding ground for a number of studies. Most studies agree upon the notion that the market is not efficient in the strong form, due to the numerous scandals such as e.g. the Enron scandal. Regarding the weak and semi-strong form, not all studies have reached the same conclusion, which has made the debate more interesting.

3.4 Challenges to the EMH

The fact that the EMH only is an estimate of how the real world behaves has of course led a lot of people to try to prove that the theory is insufficient or downright wrong. In this section, the main challenges will be described in a chronological order starting out with financial market anomalies that began to appear in the 1970's.

3.4.1 Anomalies

Soon after Fama published his famous article: *'Efficient Capital Markets: A Review of Theory and Empirical Work'*, reports of anomalies began to pop up in a variety of academic journals. Anomalies can be defined as the systematic behavior of investors, which is not in accordance with the EMH *(Stracca, 2004)*. The anomalies could be seen as an attack on the EMH. All though the anomalies did not present significant evidence against the EMH, they still worked as a thorn in the side of EMH believers. Fama had already, in his article, reported some anomalies, like slight serial dependencies in the stock market returns, but optimistically pointed out how small the anomalies were *(Shiller, 2003)*. The purpose of this section is to form a general view and discussion of the major anomalies existing in the market. The anomalies discussed in this thesis are:

- The calendar effects
- The small firm effect
- The Value Premium puzzle
- Winner's curse

3.4.1.1 The Calendar Effects

There are numerous different calendar effects but only the two most famous, the weekend and the January effect, will be described subsequently. The weekend effect refers to an apparently systematic drop in stock prices from Friday to Monday.

According to the EMH, the price on Mondays should be higher than every other day, because it should contain the return from three days instead of only one. A possible explanation is that companies release positive information throughout the week, while waiting to release the bad news until late Friday when the market has closed. The idea behind this is that the investors perhaps will not react as strongly once they have been giving the time to think the new piece of information through. Obviously, this cannot be united with the EMH, because investors will instantly pick this profit opportunity up and immediately eliminate it *(French, 1980)*.

The second calendar effect, the January effect, concerns the fact that returns in January are significantly higher than the return in the remaining eleven months of the year. Rozeff & Kiney *(1976)* were the first to recognize the January effect. Using stocks from The New York Stock Exchange (NYSE) from the period 1904-1974, they found that stocks returns averaged 3.5 percent in January, while the following 11 months only generated a return of 0.5 percent per month. Later studies document the effect persists in more recent years: Bhardwaj & Brooks *(1992)* for the period from 1977-1986 and Eleswarapu & Reinganum *(1993)* for 1961-1990. Furthermore, the effect has also been found in other countries as well as in bonds.

A possible explanation could be to look at it in a tax perspective. Investors have an incentive to sell out poor performing stocks to a gain a tax deduction of there loses. Reinganum *(1983)* argues that this cannot explain the entire effect because the degree of the effect should correlate with the tax rate, which is not the case. Furthermore, the January effect has also been found in countries, where the tax year does not end December 31st. Alternatively, the January effect could just be a simple feature of the human behavior. Similar to a New Years resolution, people wish to make a fresh start at beginning of a new year. Like a bad habit, investors want to get rid of a poor performing portfolio and purchase a new portfolio in January. Supporting this argument, the effect is found strongest in the first five trading days of January. Finally, Keim *(1983)* shows that the small firm effect and the January effect might be two sides of the same coin. The January effect only appeared in tests, where the sample gave equal weight to small and large firms *(LeRoy, 1989)*.

3.4.1.2 The Small Firm Effect

The small firm effect states that stocks from smaller firms give a higher return than stocks from larger firms *(Banz, 1981) (Reinganum, 1983).* According to the EMH, this can only be the case if the higher return is a consequence of taking part of a higher risk. Reinganum *(1983)* rejects this. Another possible explanation is that small firms stocks do not get adequate attention, causing the price not to fully reflect all information. Obviously, this is not in accordance with the EMH.

3.4.1.3 The Value Premium Puzzle

Studies have shown that value stocks generate a higher return than growth stocks and this is known as the value premium puzzle. The most common methods of identifying values stocks are to look at the earnings-to-price (E/P) and book-to-market (B/M) ratios. Normally, the value premium puzzle value is split up in two anomalies, the E/P-effect and the B/M-effect respectively. However, due to the purpose of this thesis, it seems reasonable to treat them together. Other measures, such as cash flow-to-price and past growth in sales, can also be used to classify stocks but these will not be dealt with specifically in this thesis. The difference between value and growth stocks will be described and discussed in greater detail in chapter 4.

Nicholson *(1960)* was the first to recognize, that Stocks with high E/P (value stocks) systematically outperform those with low E/P (growth stocks). The finding seems to be consistent with the behaviorist view that investors tend to be overconfident with their ability to project high earnings growth and thus, overpay for growth stocks *(Malkiel, 2003)*.

The B/M-ratio has also been found to be a useful predictor of future return. Again, the overconfidence of the investors can be seen as an explanation. Investors tend to overpay for growth stocks, which subsequently fail to live up to expectations.

Of course, giving these two key figures predicting power cannot be consistent with EMH. Nevertheless, Fama & French *(1993)* argue that these findings do not necessarily imply inefficiency, but simply imply that the CAPM fail to capture all dimensions of risk.

3.4.1.4 Winner's Curse

De Bondt & Thaler *(1985)* were the first to recognize the Winner's curse. They discovered that stocks that had experienced a large drop in price were generating a higher return than stocks having experienced a large increase in price. A large price decrease was followed by an increase and vice versa. The effect showed to be more significant after a decrease in prices compared to an increase - a so-called asymmetric mean reversion. An explanation of this phenomenon, which was confirmed by De Bondt and Thaler *(1990)*, could be that the market overreacts on new information and perhaps the overreaction is largest on bad news. Normally, the market is considered to consist of a sufficient amount of rational agents to make the irrational agents irrelevant. De Bondt & Thaler *(1990)* concluded that this was not the case. This issue has been captured in the noise-trading theory. Furthermore, the systematic overreaction may be related to the excess volatility represented in variance-bounds literature. Both noise-trading and excess volatility will be discussed later in this chapter.

3.4.1.5 Implications of the Anomalies

Even though the anomalies are an attack on the idea of the EMH, there is still great disagreement among academics, how serious the attacks should be considered. Some state that the anomalies just are exceptions confirming the rule; others think they are much more devastating. It is very tricky to summarize the literature. On the one hand, the fact that the anomalies have existed for a long period of time shows that the market is inefficient. On the other hand, the fact that many of them has disappeared after they were discovered, support the EMH.

Merton *(1987)* noted that there was a problem regarding selection bias. He believed that because it was headline-creating finding prove for anomalies, these studies were more likely to be published than the "boring" papers just confirming the EMH. Furthermore, the problem regarding datasnooping should not be underestimated. If you search long enough, something incriminating will eventually be found. A related problem is that anomalies are typically tested on the same data, on which they are discovered, so analysts can construct their classification so as to maximize the findings *(Leroy, 1989)*.

The anomalies discovered might be considered at worst small departures from the EMH. While the weekend and January effect are perhaps the most famous, they are also the less troubling for efficient market theory. On the contrary the volatility anomaly seems much more crucial. The evidence regarding excess volatility seems, to some observers at least, to imply that changes in prices occur for no fundamental reason at all *(Shiller, 2003)*. The volatility anomaly and especially the volatility test will be discussed next.

3.4.2 Volatility Test

Maybe the greatest stir in academic circles has been created by the results of volatility tests – also known as variance bounds tests. These tests were designed to test for rationality of market behavior by examining the volatility of share prices relative to volatility of the fundamental variables that effect share prices. Shiller *(1981)* and LeRoy & Porter *(1981)* were some of the first to introduce these tests. Shiller tested a model in which the stock prices were the present value of future dividends, whereas Leroy & Porter made a similar analysis for the bond market. Below a brief presentation of the general procedure of Shiller's volatility test will be given. The starting point of the volatility test is the expression for the stock price derived earlier:

(3-20) $$P_t = \sum_{k=1}^{\infty} \delta^k E\left(\frac{U^{/}(c_{t+k})}{U^{/}(c_t)} \times D_{t+k}\right)$$

The formula above takes the rational valuation formula as the model of the determination of stock price. The stock price P_t is determined as the present value of the expected future dividends D_{t+k}, discounted with the discount factor δ^k. The $U^{/}(c_{t+k})/U^{/}(c_{t+k})$ part is the marginal substitute relationship and can be seen as a time varying weight, which relates to future dividends and thereby works as a time varying discount rate.

Shiller simplified his volatility test by making an assumption of constant marginal utility, thus expression (20) can be reduced to:

(3-21) $$P_t = \sum_{k=1}^{\infty} \delta^k D_{t+k}^e$$

By comparing the variance of actually stock price with the variance of the estimated stock price P^* determined from (3-21), Shiller could now test for market efficiency. The first step is to compute (3-21). As estimation always is combined with some level of uncertainty, P^* can now be written as the perfect foresight stock price P_t and a residual term u_t, representing the forecast error:

(3-22) $$P_t^* = P_t + u_t$$

Due to the assumptions about rationale expectation P_t and u_t are independent thus, the $Cov(P_t, u_t)$ is zero. The variance of P^* can now be written as:

(3-23) $$Var(P_t^*) = Var(P_t) + Var(u_t) \Rightarrow Var(P_t) = Var(P_t^*) - Var(u_t)$$

As variances cannot be negative it can be seen from (3-23) that:

(3-24) $$Var(P_t) \leq Var(P_t^*)$$

The entire concept of volatility test is to test whether (3-24) holds. If $Var(P_t)$ exceeds $Var(P_t^*)$ the EMH cannot be accepted. Both Shiller's and LeRoy & Porter's tests revealed significant volatility. They found that $Var(P_t)$ was between 5.5 to 12.5 times larger than $Var(P_t^*)$. The security prices were much more volatile than is consistent with the efficient market model. Put in another way, fluctuations in actual prices were greater than the changes implied by the changes in fundamentals (i.e. dividends). Shiller suggested that the excess volatility was a result of fads or waves of optimistic or pessimistic market psychology.

Since the first volatility tests many studies has later confirmed the excess volatility, among them, Cochrane *(1991)* and West *(1988a).* Also criticism has been raised. Flavin *(1983)* argued that the apparent excess volatility was entirely a consequence of imperfect econometric methods. He demonstrated that small-sample problems led to bias against the acceptance of efficiency and Kleidon *(1986)* showed that if the dividends had unit roots it led to similar problem as those Flavin described regardless of the sample size. Later criticism has focused on the assumption behind the test and especially the subject regarding a constant real discount rate has been attacked. However, the criticism did not stand unanswered for very long and West *(1988a)* constructed a test, which was not only independent of the time series stationary ability, but also took hand of the early tests strict assumption about a constant discount rate. The conclusion was indisputable; the market was still influenced by excess volatility *(LeRoy, 1989)*.

Despite all the criticism it is broadly agreed that the excess volatility is present and cannot be properly explained by any variant of the efficient market model. After all the efforts to defend the efficient market theory, it is reasonable to think that, even though the market is not completely crazy, there is still substantial noise to influence stock price fluctuations. The efficient market model has never persuasively linked the stock market movements with subsequent fundamentals *(Shiller, 2003)*. Acknowledging this by the end of the 1980s, the restless minds of academics had to turn towards other theories.

3.4.3 Bubble Theory

Trying to explain the excess volatility, the academics developed two interesting theoretical frameworks, the bubble theory and the noise trading theory. This section will deal with the first mentioned.

The theoretical foundation for the bubble theory was already built in the early 1980's, but it was not until Diba & Grossman *(1988a)* linked the theory to stock market, it started to gain attention. The theory is represented here:
Recall equation (3-17):

(3-25) $$P_t = \sum_{k=1}^{\infty} \delta^k E\left(\frac{U^{/}(c_{t+k})}{U^{/}(c_t)} \times D_{t+k}\right) + \delta^n E\left(\frac{U^{/}(c_{t+n})}{U^{/}(c_t)} \times P_{t+n}\right)$$

The difference between (3-19) and bubble theory is expressed by the terminal condition, which before was omitted due to the transversality condition. Where the first term of (3-25) represent a fundamental part while the last term represents the bubble part. It is now possible to rewrite (3-25) to:

(3-26) $$P_t = F_t + B_t$$

where B_t is the solution to the homogeneous expectational difference equation:

(3-27) $EB_{t+1} - \delta^{-1}B_t = 0$

The actually market price P_t deviates from its fundamental value F_t by the amount of the bubble B_t. The bubble part contains non-fundamental information's such as self-fulfilling expectations. Expectation of an increase in price will lead to a price increase, which again will build up expectation and so on. Despite of this, bubbles are still compatible with the assumption of rational expectation and an information efficient market. Thus, these types of bubbles are labeled rational bubbles. Furthermore, these kinds of explosive expectations imply that negative bubbles cannot exist. The existence of negative bubbles implies that the price of stocks at some time will be negative. Given free disposal, stockholders cannot rationally expect this, because they always can get rid of stocks at no costs.

Under the assumption of rational expectation, it can be extracted from (3-27) that:

(3-28) $B_{t+1} = E(B_{t+1}) + z_{t+1} = (1+\chi)B_t + z_{t+1}$

The random variable z_{t+1}, with $E(z_{t+1}) = 0$, contains new information at date $t+1$. This information can be completely irrelevant (unrelated to F_{t+1}) or it can be related to truly relevant variables, such as D_{t+1}, through parameters that are not present in F_{t+1}. According to Diba & Grossman a bubble can only exist if the bubble was already present at the first trading date. Hence, prior to the first trading date investors would anticipate the initial price of the stock to be overvalued relative to market fundamentals. Due to the nonnegative condition, it is known that $B_0 \geq 0$. Now, suppose that it is assumed that $B_0 = 0$, so that $B_1 = z_1$. As $E(z_1) = 0$, then z_1 must equal zero with probability one, thus B_1 must also equals zero. Diba & Grossman also showed that if a bubble burst it cannot restart. To show this, it is assumed that z_{t+1} from (3-28) can be written as:

(3-29) $z_{t+1} = (\theta_{t+1} - \delta^{-1})B_t + \varepsilon_{t+1}$

By substituting (3-29) in (3-28):

(3-30) $B_{t+1} = \theta_{t+1}B_t + \varepsilon_{t+1}$

Here θ_{t+1} and ε_{t+1} are mutually and serially independent random variables with a mean of δ^{-1} and zero respectively. Now suppose that $\theta_{t+1} = 0$, the bubble will burst in next period unless $\varepsilon_{t+1} > 0$. As it is known that when $E(\varepsilon_{t+1}) = 0$, $B_{t+1} = 0$ with a probability of one, it shows that once a bubble has burst it cannot restart.

Facing the fact that a bubble cannot be negative and cannot restart once it has burst what is the rationality behind a positive bubble? In principle a positive bubble is possible since there is no upper limit on stock prices. However, imagine that the bubble part becomes relative larger than the fundamental part, investors might think that the bubble will burst soon. If investors believe the bubble will burst some time in the future, it will undoubtedly burst. Suppose that an investor thinks that the bubble will burst in the year 2010, the investor must realize that the market price in the year 2009 will consist only of a fundamental part. But if the price in the year 2009 only consists of a fundamental part, the price today must also only reflect fundamentals, because of the non-possibility of a restarted bubble. Thus, it seems as if rational bubbles only can really exist if the markets horizon is shorter than the time period when the bubble is expected to burst. The analogy is that one will only pay a price above the fundamental value if it is believed, that someone else will pay an even greater price in the future *(Cuthbertson, 2004)*.

3.4.3.1 Test of Rational Bubbles

Diba & Grossman *(1988b)* tested for the presence of rational bubbles by examining the stationarity characteristics of stock and dividend series in the United States in the period 1871-1986. If stock prices and dividends were found to be stationary in first-difference or co-integrated, explosive bubbles cannot exist. Diba & Grossman *(1988b)* concluded that both series were indeed stationary in first-difference but not in level. Furthermore, a co-integration test concluded that the series were co-integrated. West *(1987 & 1988b)* took a different approach. By estimating the discount rates in a Bubble model and in a simple present value model West found evidence for the discount rates were significantly different and, in light of that, concluded the existence of bubbles could not be excluded. The problem with West's test was that the difference in discount rates could also be a result of a misspecification of the model, so–called noise. West *(1988b)* realized this problem and has later been much more critical towards the relevance of bubbles in stock prices and bubble theory's ability to explain the rejection of the EMH.

Not being able to reveal the presence of rational bubbles, academics had to turn elsewhere in the attempt to explain the excess volatility. The next research area became the theory of Noise-Trading.

3.4.4 Noise-Trading

As mentioned earlier, the EMH does not require all participants in the market to be rational but do set limit on the proportion between the rational and irrational investors. This gives room for irrational investors and the study of the effect of their presence is the concept behind the noise-trading theory. Black *(1986)* was the first to introduce this idea. While rationale investors (smart moneys) are fully informed and build expectations on fundamental information, irrational investors (noise-trader) build their expectations on a less adequate information set or even on heuristics. The consequence is that noise-traders can drive the stock price away from its fundamental value by buying too expensive and selling too cheap. The smart money exploits this opportunity and thereby pushes the price back to the fundamental value. Clearly, the noise-trader will loose money in the long run and slowly be eliminated from the market. If this is the case, the entry of new noise-traders must take place in a continuous flow to maintain a market of both smart moneys and noise-traders. This continuous regulation between smart money and noise-traders could be one of the explanations of the mean-reversion, discussed in section 3.5.1.4.

3.4.4.1 An Alternative Noise-Trading Model

The insights of the early and original literature of noise-trading are introduced above, but alternative aspects was soon developed and a model proposed by De Long, Shleifer, Summers & Waldmann *(1990)* was one of the most sensational. The model differs from other noise-trading theories by questioning the traditional understanding of noise-traders possibility to survive. In the model both smart money and noise-traders maximize expected lifetime utility. They are both risk averse and both have a finite horizon, which makes arbitrage risky. The model is constructed in such a way that there is no fundamental risk (i.e. dividends are known with certainty) but only noise-trader risk. This means that smart money develop the optimal forecast, because they form their expectations from fundamentals, which per definition are known with certainty. Noise-traders, on the other hand, develop biased forecast. The market consists of two assets: a risky asset and a safe asset. Because both smart moneys and noise-traders are risk averse their demand for the risky asset depends positively on expected return and inversely on the noise-trader risk. Furthermore, the noise-traders demand also depends on whether they feel bullish or bearish about the stock market. The stock price in the model can be determined as followed.

(3-31) $$P_t = 1 + \frac{\mu}{r_f} \times \rho^* + \frac{\mu}{(1+r_f)} \times (\rho_t - \rho^*) - \frac{2\mu^2 \gamma \sigma^2}{r_f (1+r_f)^2}$$

Here μ represent the proportion of investors who are noise-traders, r_f is the risk free real rate of interest and γ represent the absolute risk aversion. ρ_t is a random variable, normally distributed with mean ρ^* and variance σ^2 ($\rho_t \sim N(\rho^*, \sigma^2)$). This means that ρ_t represents the difference between the noise-trader forecast and optimal forecast, whereas σ^2 is the variance of the noise-traders misperceptions.

The first part of (3-31) ($P_t = 1$) reflects the fundamental value, and the other three terms are caused by the existence of noise-traders. The stock price will differ from its fundamental value due to the existence of noise-traders. This is easy to see because if $\mu = 0$, meaning no noise-trader, (3-31) will be limited to $P_t = 1$. The second term is present because noise-traders misperceptions on average differ from zero. The noise-traders will push the price above the fundamental value if they believe that the market is bullish ($\rho^* > 0$). This will lead to an increase of the noise-traders stock proportion ($\mu \uparrow$) and they will thereby take on a greater part of the risk.

Correspondingly, the smart money will take a smaller part of the risk and therefore be willing to pay a higher stock price. The third term reflects the short-term expectation of the noise-traders. It takes into account that in a given short term period a generation of noise-traders can have dissimilar expectations compared to the average expectation of all generations of noise-traders (either bullish or bearish). The last term states that the more risk averse and the greater the variance of misperceptions of the noise-traders, the lower the stock price will be. The interpretation is clear. The smart money want compensation in form of a lower stock price and a higher return to take on a more risky stock. Using this model De Long et al. showed that noise-traders are able to survive even though they buy high and sell low. The reason for this is that noise-traders are taking on a greater part of the risk and therefore can generate a higher profit. This is true under the assumptions that noise-traders are neither to bearish nor to bullish and that noise-traders have the same expectations regarding the volatility as smart money do. Furthermore, the model assumes that investors are myopic, which means they are acting from a short-term perspective. Critics have attacked these assumptions. Bhushan, Brown & Mello *(1997)* show that if the noise-traders also make a misperception of the volatility, it cannot be ruled out that the stock price is only reflected from fundamentals. This will at the same time question the noise-traders ability to survive.

Anyway, the idea that noise-traders can coexist with smart money is a new and important theoretical innovation. This theory can in principle explain sharp movements in stock prices and therefore contribute to the explanation of the excess volatility in the stock market. The model shows how the stock market may be subject to quite violent changes in mood completely unrelated to fundamentals. Thus, these changes in moods are not based on rational behavior. However, the noise-trading theory does also not give any explanation for the reason of these changes. A help to understand these mood swings could be to turn the focus towards behavioral finance and especially the theory surrounding mass psychology and herd behavior *(Cuthbertson, 2004)*.

3.5 Recapitulation

Since the introduction of security markets the development and determination of security prices have been of great interest among the world's academics - from the early beginning with Bachelier's random walk hypothesis to the theory of noise-trading. Fama introduced the EMH in 1970, and since then, the theory has served as starting point for almost every paper regarding this subject. Many attempts have been made to prove that the EMH is wrong but so far no one has been able to do so convincingly. It is still the best alternative to describe how security prices behave. However, some traits of the security markets are still a puzzle. One of these is the value premium puzzle as described in section 3.4.1.3. This puzzle will be described in detail in the next chapter, as it is an important part of the empirical analysis.

4 Growth and Value Stocks

Portfolio managers often follow an overall investment philosophy. They will have to decide what kind of stocks they want to invest in and most methods to do that follow one of the two most used approaches to equity investing. Either they can decide to invest in value stocks and hence follow a value investment approach or they can decide to use a growth stock investment approach by investing in growth stocks. Of course, you can also have a mixed portfolio but most investment funds have preferences for one of the two philosophies.

4.1 Value Stocks

The general idea in the value investment approach is to identify securities that are temporarily undervalued or unpopular for various reasons. Value investors are, so to speak, looking out for bargains where the price of a security has been beaten down unfairly. They focus on whether the market price is below the estimated economic value of the tangible and intangible assets of the company. To measure the economic value investors look at easily measurable tangible assets such as plants, equipment, real estate and common stock or financial holdings in subsidiaries etc. When value investors find a stock where the current market price is below a conservative estimate of the tangible assets a real bargain can be made and the larger the gap between the market price of a stock and the market of its tangible assets the more attractive the investment is *(Hirschey & Nofsinger, 2005).*

Value investors look at certain measures when judging whether a stock is selling at a discount. The most common used measures are P/E and P/B ratios and dividend yields. They search for ratios below the historical level of the company and market average or stocks with an above-average dividend yield. This often leads to value investors having a preference for industrial stocks or companies in the financial service or utilities sector. However, one must be aware that a bargain is not always the low price stocks. The fact that a stock is cheap does not automatically mean that it is a good deal. The company behind must be a quality firm selling at a low price compared with the above-mentioned criteria, not a bad company selling at a low price.

Instead of comparing to other market measures value investors can compare the price of the stock to the fundamental value of the company. If the stock price is thought to be below the fundamental value the stock is undervalued and a good deal can be made. The price can go below the fundamental value if an entire industry falls into disfavor. The companies that only experience this temporarily can become undervalued. As before it is important to identify those companies that are cheaply priced compared to their fundamental value and be aware of the fact that some companies are simply bad companies on the brink of bankruptcy or with a poor business model and hence priced correctly at a low level *(Hirschey & Nofsinger, 2005)*.

Generally, when identifying value stocks investors look for the following characteristics:

- Ample cash reserves (cash > 10% of market cap).
- Ample free cash flow to fund necessary investment (EBITDA > capital spending).
- Conservative dividend payout policy (dividend < 75% of EPS).
- Conservative financial structure (debt < 50% of market cap).
- Conservative issuance of common stock to managers and other employees (constant or falling number of shares outstanding).
- Low P/B ratio relative to the market and the history of the company (P/B < 75% of S&P 500 average).
- Low P/CF ratio relative to the market and the history of the company (P/CF < 75% of S&P 500 average).
- Low P/E ratio relative to the market and the history of the company (P/E < 75 % of S&P 500 average).
- Negative investor sentiment as reflected in poor financial ratings (S&P rating of B- or worse).

(Hirschey & Nofsinger, 2005)

It is very rare to find a stock with all these characteristics. Investors will, however, still invest in the stock as long as some of the criteria are fulfilled and the company behind is a sound business. To identify these healthy businesses some value investors make use of an investment rule of thumb called the value of ROE or just VRE. To find the VRE, ROE% is divided by the P/E ratio. If VRE ≥ 1 the stock may be worthy of further investigation. If VRE ≥ 2 the stock may represent a very attractive investment. Finally, if VRE ≥ 3 the investment is extraordinarily attractive.

Following a value investment strategy can be a tough psychological challenge. The strategy involves buying stocks currently out of favor and selling stocks that are popular. To master this, value investors must be in full control and avoid being influenced by psychological biases.

4.2 Growth Stocks

Whereas value investors focus on the present situation and price of the stock compared to the market, growth stock investors analyze the future growth potential of a firm. There are numerous ways to identify growth stocks, and different investors look at different indicators. Some look for above-average growth in earnings per share and revenues while others look for growth rates at at least twice the average of the standard company. In general however, growth stock investors look at whether a company has sufficient internal financial slack and thereby is able to finance future growth without borrowing additional funds. Investors also look at the business environment of the company. Idealistically, the company is situated in a fast-growing sector where all companies are growing rapidly. If not so, the investment target could also be in some kind of a niche in a saturated market.

Growth stocks also have some distinct characteristics just as value stocks have. These characteristics are:

- Markets expectations of future growth.
- Low book-to-market ratio.
- Low cash flow-to-price ratio.
- Low earnings-to-price ratio.
- High past growth rates in sales.

(Lakonishok, Shleifer and Vishny, 1994).

These characteristics must however, be carefully studied before using them as criteria for dividing stocks into certain categories. A low book-to-market ratio can simply describe a company with a lot of intangible assets that are not reflected in the book value. Another problem with the book-to-market measure is that it can reflect a company with high temporary profits but without high growth opportunities. A current example on this is oil-producing companies. They earn high profits due to the exceptional high oil price and thus have a low book-to-market ratio. Also, one should be aware of looking at past growth rates since these measures often are imperfect and does not always have implications for future growth.

Besides looking at stock specific measures, growth stock investors also look at the business environment in which the company operates. To find out whether a growth stock is an attractive investment analysts often look for the following characteristics:

- No sharp competition.
- Highly talented and well-paid employees. Low overall labor costs.
- Leading within product development and ability to spot new markets and/or market segments.
- Non-sensitive to changes in regulation.
- Conservative capital structure and steadily growing earnings per share. ROA should also be attractive.

(Hirschey & Nofsinger, 2005).

It is clear that to sustain a high growth rate competition must be minimized and to do that companies must have a competitive advantage over other companies in the business sector. This competitive advantage can come from the sources mentioned above. You must have the best employees to develop the best products and spot new potential markets but at the same time also keep your costs down. The reason why growth stock companies should have a conservative financial structure is that during hard times the company will still be able to sustain high growth without facing financial distress. If the company is making use of heavy debt financing lenders tend to be inflexible during hard times and this may cause growth to slow down.

4.3 Value vs. Growth Stocks

Since Graham and Dodd in 1934 came up with the idea of dividing stocks into categories based on the above-mentioned measures in their famous book "Security Analysis", researches have investigated whether one of the strategies is superior to the other. Most have come up with the result that a value strategy outperforms a growth strategy. A famous study by Fama & French *(1992)* showed that the ratio of book value to market value of equity and company size were the main explanatory variables for cross-sectional stock returns. Their empirical tests, which used data from NYSE, AMEX and NASDAQ, showed β[3] had no effect on average stock returns but returns were more a result of size and book-to-market ratio. When sorted by book-to-market ratio growth stocks yielded an average monthly return on .30% while value stocks had a return on 1.83%. Fama and French also tested on stocks sorted by earnings-to-price ratio and came up with the same result. Growth stocks yielded a monthly average of 1.04% and value stocks yielded 1.72%. The fact that the beta's of the portfolios was merely the same led to the conclusion that other variables explained the difference in return better than the capital asset pricing model[4] (CAPM) did. Another famous study conducted by Lakonishok, Shleifer & Vishny *(1994)* came to the same conclusion as Fama & French. They tested four different strategies, dividing stocks into the growth or value category based on book-to-market ratio, cash flow-to-price, earnings-to-price or growth in sales. The test was based on yearly returns and for all the four categories value stocks clearly outperformed growth stocks. The difference in the average annual five-year return per year was 10.5%, 11%, 7.6% and 6.8% respectively.

One might argue that testing on the same data and period can lead to the problem of datasnooping. To test whether the value premium is only an American phenomenon Fama & French *(1998)* tested on thirteen major markets. They found that in twelve of the thirteen markets value stocks outperformed growth stocks. Italy stands out as the only country where growth stocks outperform value stocks. Fama & French also tested whether there was a value premium in emerging markets and came to the

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[3] β states the risk of a single stock compared to the total market risk and is calculated on the basis of historical observations *(Christensen & Pedersen, 2003).*

[4] The CAPM describes the relationship between risk and expected return.

conclusion that this was indeed the case. All this suggests that the value premium is real and not a case of datasnooping.

While almost all researches agree that value stocks earn higher return than growth stocks there are divergent opinions about why this is the case. As fathers of the EMH Fama & French *(1996)* argue that the higher return must be the result of increased risk compared to growth stocks. The increased risk is due to stocks with high book-to-market value are more likely to experience financial distress than stocks with low book-to-market value. Thus, according to Fama and French value stocks are fundamentally riskier than growth stocks and the value premium is compensation for bearing more risk.

The competing explanation considers behavioral finance as the important reason for the higher return on value stocks. Lakonishok, Shleifer & Vishny *(1994)* argue that investors tend to get overly exited with stocks that have performed well in the past and thus the stocks become overpriced. On the other hand investors overreact to stocks that have performed poorly in the past and thus oversell them resulting in these stocks to become under priced. The reason for these overreactions can be numerous. Maybe investors extrapolate past earnings growth to far into the future. Lakonishok et al. found evidence of a systematical pattern of expectation errors among investors. The expectations of future growth appear to be tied on past growth rates only despite the fact that future growth rates are highly mean reverting. To put excessive weight on recent past history instead of a rational prior is a common psychological error not just in stock markets but in everyday life as well. Another reason for the over- and under pricing problem can be that investors assume a trend in the stock price or that they simply overreact to good or bad news. It is not only individual investors who tend to have a bias toward stocks with high historical growth. Also institutional investors seem to prefer “good” companies with steady earnings and dividend growth. The reason for this can be that it is easier to justify investments in stocks that have a good track record and hence a better story. Sponsors may wrongly believe that growth stocks are a safer investment than value stocks because of the perceived lower risk of running into financial distress problems. Also career concerns of money managers may tilt them towards investing in growth stocks. While a value strategy can take 3 to 5 years to pay off, growth stocks can earn a high abnormal profit within few months, which is something that many individuals look for. To make their lives easier, money managers may tilt towards growth stocks even though they know this is not the optimal strategy but simply to please sponsors and keep their job.

It can be concluded that there is relatively large agreement about value stocks outperform growth stocks when measured in returns. When the discussion is turned towards the explanation of the value premium the agreement stops.
Having the theoretical background in place the thesis will now shift focus. In the second part it will be tested whether it is possible to earn a better return with the use of technical trading rules, which in this case is moving average trading rules.

Part Two: Empirical Analysis

5 Earlier Studies of Technical Analysis

Many studies have been conducted to test for the profitability of technical trading rules. Some have concluded that it is possible to earn an abnormal profit through the use of these strategies, while others have come to the opposite conclusion. This chapter will introduce four main articles in a chronological order starting out with Alexander *(1961)* and Fama & Blume *(1966)*. The two last articles are of a newer date, namely Sweeney *(1988)* and Brock, Lakonishok & LeBaron *(1992)*.

5.1 Alexander, 1961

The starting point for Alexander's study was to investigate the profitability of filter rules compared to a simple buy-and-hold strategy. The filters tested varied in size from 5 to 50 percent. The data were obtained from the DJIA and the S&P Industrials index and covers the period from 1897-1929 and 1929-1959 respectively.

Alexander reached the conclusion that trends could be found in stock prices and the use of filter rules would lead to a higher return compared to the buy-and-hold return in general. Alexander noted that the best-performing rules were those with smaller filters.

There are, however, many objections to the results. Alexander does not test for significance of the return difference and thus, the higher return may just be a chance of luck. Furthermore, the indices are not adjusted for dividends, which bias the result in favor of the filter rules.

Also, the fact that the analysis is based on stock indices means that there is a risk of non-synchronous trading, which may cause first order serial correlation. Alexander does also fail to include transaction costs in the analysis. By neglecting these, the result does not tell whether or not a real profit can be made through the filter rules.

The conclusion that the smaller filter rules generate the highest profit is also insignificant since these are also the ones with most transactions and hence, the profit will fall most for these rules. Finally, the return for the filter rules has been calculated on the basis of non-observed prices. It has been assumed that it has been possible to trade at the exact price from which the signal was generated.

These objections make it difficult to judge whether the use of filter rules is a superior strategy or the higher profits are simply results of coincidences.

5.2 Fama & Blume, 1966

Fama & Blume also investigates filter rules. They do not however, test the rules on an index but instead they test the rules on each of the 30 stocks included in the DJIA. Results from each rule and each stock plus an average return from all stocks and rules are reported. Furthermore, the influence from transaction costs, only taking long positions and taking the opposite position as the rule suggest is also investigated.

Fama & Blume came to the opposite conclusion as Alexander. They found that filter rules did not yield a higher return than a buy-and-hold strategy. Even before transaction costs were introduced the conclusion was the same. None of the other adjustments to the strategy changed the conclusion.

As with Alexander's analysis there are some pitfalls in the analysis. First of all, there is no test of significance. Instead, an average from the filter rules and stocks are used to compare the return with the buy-and-hold strategy. This procedure helps screen out results that are mere coincidences but unfortunately, there is also the risk that it might screen out trading rules that are really able to generate an abnormal profit.

5.3 Sweeney, 1988

Sweeney was inspired by Fama & Blume and picked out those stocks that had generated a return that was better through the use of the 5% filter rule than the buy-and-hold strategy. Sweeney thus, tested whether the stocks that had generated a higher return in the previous test period also would generate a higher return in the following period.

The filter rule strategy as used in Sweeney consists of periods in and out of the market. Following a buy signal a long position in the stock is taken whereas a sell signal causes the investor to move out of the market and invest in a risk free asset. Sweeney argues that during sell periods the return is poor and the strategy also reduce transaction costs, thus, this strategy. The last part of the article considers the effect of transaction costs and discusses these. The results are tested through a t-test.

The use of a statistical test for significance of the mean difference is the main difference compared to the two earlier articles mentioned above. The t-test, however, assumes that the stock returns are normally distributed and independent of time. These assumptions are not fulfilled and thus, the value of the test is limited.

5.4 Brock, Lakonishok & LeBaron, 1992

BLL investigated ten, with their own words, very popular moving average trading rules and six trading range breakout rules for the DJIA. The test period was very long and covered the period from 1897 to 1986. To increase the validity of the results the test period was divided in four sub-periods where the same trading rules were tested. BLL emphasized the significance test of the results and combined the bootstrap procedure with technical analysis testing four popular null models: Random Walk with Drift, AR (1), GARCH-M and EGARCH. The bootstrap procedure will be explained in detail in chapter 7. BLL reported the results on the basis of risk and return measures in buy and sell periods, and they also tested whether the returns in buy and sell periods were different.

The conclusion was very clear. The results showed that the simple technical trading rules all outperformed the buy-and-hold strategy. Furthermore, the bootstrap results conclude that the returns obtained from buy and sell signals are not likely to be generated by the four null models and thus, support the traditional tests that technical trading rules have predictive power.

Even though the analysis of the DJIA conducted by BLL is very thorough there are still objections to be made. First of all, the trading rule strategy is not clearly defined. The fact that the number of observations for the trading rules without band does not tally with the number of observations for the entire return series minus the length of the long moving average causes that it is muddled how the trading rules are used. Secondly, a mean return for each trading rule is not calculated. This makes it difficult to compare the return directly with the buy-and-hold return. Instead, BLL uses a measure defined as the mean buy return minus the minus the mean sell return. This measure can, however, only be regarded as a total return if the number of buy and sell days are the same. Thirdly, as was the case with Alexander's analysis there may be problems with using the DJIA index due to the risk of non-synchronous trading. BLL argues that this is not a problem for the analysis since the DJIA consists of very liquid stocks. The fact that there is no correction of dividends in the composition of the DJIA also favors technical analysis. Finally, BLL do not take transaction costs into account. This might be the most important objection to the analysis and causes that nothing can be concluded about the profitability of the trading strategies for investors, and hence, nothing can be concluded about the EMH.

The above articles give an impression of the changes the analysis of technical trading rules have undergone through time. In the following part, the four articles will serve as inspiration for the empirical analysis. The main inspiration comes from the BLL *(1992)* article but the approach of the three other articles will also be used in part.

6 Data

There are surprisingly many issues to consider when constructing portfolios and unfortunately there are no clear guidelines. However, by picking up good practice from earlier studies and adding a few criteria it should be possible to find a feasible method. Still, it leaves a lot of choices to the researcher and raises the question how much the empirical results are affected by the researchers choices. This section does not only aim at describing how the portfolios of this thesis are constructed but also at discussing and justifying the authors' choices. The section will discuss the issues that have to be dealt with when constructing the portfolios, such as the source of data, when to form the portfolio, biases etc. Furthermore, there will be a description of how return and risk are calculated.

6.1 Data Source

For most researchers the Center for Research in Security Prices (CRSP) has been the main source for data extraction mainly because of the wide range of data and its high reliability. However, this thesis uses Thomson DataStream (TDS) especially because of the high degree of user friendliness and easy access. Well aware that user friendliness and easy access must not overrule the reliability of the data, TDS has been recognized as an excellent provider of equity data, although researchers might experience screening problems *(Ince & Porter, 2004)*. Some of these screening limitations have been experienced in the data colleting phase of this thesis. As an example, proper screening between stocks from NYSE and AMEX is not possible because they appear with same ticker identifier[5]. Similar, all dead stocks in US are allocated a six-digit number regardless of origin (NYSE, AMEX or NASDAQ). Furthermore, TDS does not provide a screening criterion for common stock and it is not possible to identify stocks with fiscal year in December. While rummaging through the NYSE homepage has solved the three first problems, Compustat has been used to identify companies with fiscal year in December.

6.2 Portfolio construction

In order to test a buy-and-hold vs. a technical analysis approach when using different investment strategies two portfolios are formed each of the 19 years studied. The

[5] Both stocks from NYSE and AMEX is identified by an U whereas NASDAQ is identified by an @.

first portfolios are formed at the end of April 1986 based on earnings and book value information from fiscal year 1985 and held to end of April 1987. The portfolios are rebalanced each year. The holding period is a trade-off between having the purest value and growth portfolio and being able to perform an meaningful analysis on the technical trading rules. By rebalancing more often the length of the moving average rules would be to short while it would make the value and growth portfolios more pure. Thus, a one year holding period has been found optimal. The last portfolio is formed at the end of April 2004 and held to end of April 2005.

The portfolios are made up of common stocks listed on NYSE during the period mentioned. Preferred stocks, ADR's, REIT's and closed-end-funds are excluded. Furthermore, only stocks with fiscal year in December are included in the sample. The investment strategies that are of interest in this thesis are a value and a growth strategy accordingly. To make the purest value and growth portfolios the stocks have been divided into quintiles based on earnings-to-price ratios. Using the description of value and growth stocks in chapter 4 the quintile containing stocks with the highest E/P-ratios are classified as value stocks and the quintile containing the stocks with the lowest E/P-ratios are classified as growth stocks. To make the two selected portfolios more pure value or growth portfolios, they are further divided into triples based on book-to-market value. As before, the stocks with highest book-to-market ratio are assigned to the value portfolio and the stocks with lowest book-to-market ratio are assigned to the growth portfolio. This results in the size of portfolios ranging from 52 to 83 stocks. The range fulfills the requirements of a diversified portfolio, which states that the number of stocks in the portfolio must be at least 30-40 *(Statman, 1987)*. In Statman's article the traditional case is described where the optimal number of stocks in a portfolio is a tradeoff between the benefits of risk reduction and transaction costs. In this study the tradeoff does not concern this issue but instead between diversification and the pureness of the growth and value portfolios.

The yearly earnings-to-price measure is calculated based on the earnings from the end of the trailing fiscal year and the price on the 30th of April current year. In order to get the earnings from the end of the last fiscal year the earnings are retrieved on the

30th of March the current year. This date have been found optimal due to the fact that almost all companies have made earnings announcements for the trailing fiscal year but still have not made the first quarterly earnings announcement for the current year. By the end of February 90% of all NYSE-listed companies have made earnings announcements and by the end of April the number is 99% *(Bartholdy, 2001)*. This suggests that end of April would have been a more optimal point of time to retrieve earnings information. However, when using end of April as fix point, it has been found that too many stocks in TDS have announced their first quarterly earnings for the current year, and hence a tradeoff has been made. The ticker for all stocks can be seen in appendix 1.

6.3 Data Bias

It has been of high priority to construct the portfolios as unbiased as possible. Several data biases, such as forward-looking bias, survivorship bias etc., are associated with the forming of portfolios. In the following there will be a short description of the biases and how these are corrected for.

6.3.1 Forward-looking Bias

During the construction of the portfolio it has been attempted to minimize the forward-looking bias i.e. information that is available ex-post should not be used. If data that are not available to the investor at the time he/she forms expectations the estimates provided by the model are not valid *(Vaihekoski, 2004)*. By forming the portfolios based on the earnings from the previous year the forward-looking bias is avoided in this thesis.

6.3.2 Survivorship Bias

Survivorship bias arises when the portfolio is constructed on the basis of the companies that have survived the time period of the test and are available for portfolio construction. If survivorship bias is not corrected for there is a risk that the study will skew higher because only companies successful enough to survive the entire period are included in the sample *(Schoenfeld, 2004)*. To avoid this problem, all common stocks that were removed in the investigated period has been identified and added to the sample. The stocks were identified through a list of removed common stocks from NYSE. However, correcting for survivorship bias results in a new possible bias, the delisting bias.

6.3.3 Delisting Bias

When including dead stocks in the portfolio, the situation where a stock is getting delisted during a period emerges. This creates a problem of how to deal with the delisting return. TDS does not report delisting returns but simply lock the last trading price to infinite, and thereby fails to distinguish between delisting reasons. There can be several different reasons for delisting e.g. bankruptcy, merger and acquisition, liquidation or migration to another exchange. Of course the delisting reason has great influence on which price should be used as a fair proxy for the remaining part of the period. While mergers, acquisitions, and migration might be more or less neutral, bankruptcy and liquidation will certainly result in a lower price. Due to the fact that it is often difficult to track down the reason many researchers have chosen to simply remove the stock price from the sample and thereby ignoring the delisting bias. Fortunately, the delisting reasons in the portfolios are relative easy to track down in TDS. The portfolios involve 90 stocks for which delisting reasons have to be tracked down. 68 of those are delisted due to mergers, 3 due to acquisition and for the remaining 19 stocks no details can be found. These stocks are all from the period 1986-1989, which indicates that TDS does not provide this kind of information prior to 1990. It is therefore found reasonable to assume that these stocks also have been merged or acquired.

After determining the delisting reason the price to fill in through out the period has to be decided. Typically, the merged or acquired stock is getting cashed in at the price quoted at the last trading day. This of course release new funds to the investors and the question arises what is the appropriate way to deal with those without affecting the portfolios overall return or risk. The easiest way is to invest the released funds in a risk free asset. A reasonable estimate for the risk free rate is the use of government securities such as Treasury bills or Treasury bonds. The choice between e.g. Treasury bills and Treasury bonds depends on the cash flow involved, meaning the security, has to match the cash flows duration *(Copeland, Koller & Murrin, 2000)*. Therefore the most appropriated security for calculating delisting returns is the 6 months Treasury bill.

6.4 Return and Risk

The portfolio consists of one of each stock selected on the basis of the criteria described above. A mean price of the portfolio is calculated by calculating the equal weighted geometric mean of all the stock prices. By using geometric mean instead of arithmetic mean equal weight is given to price changes irrespective of the relative price. If arithmetic mean were used there would have been a problem in the years where the Berkshire Hathaway "A" is included in the portfolio[6]. The price level of this particular stock is extremely high compared to the rest of the stocks and would thus have too much influence on the return and give a wrong picture of the average return. Using a value-weighted portfolio could of course minimize the problem but an equal weighted portfolio has been chosen well aware that there may be a problem with overemphasizing the importance of relative price changes for small companies for the average investor.

Roughly, there are two ways of measuring return: percentage return and logarithmic return (continuously compounded return). While percentage return is frequently used in practice, continuously compounded return (i.e. logarithmic relative of the price) has become *de facto* standard in financial research *(Vaihekoski, 2004)*. In this thesis the continuously compounded return will be used and is defined as:

(6-1) $$r_t = \ln \frac{P_t}{P_{t-1}}$$

where P_t is the current price and P_{t-1} is the price at the end of the previous time period.

The continuously compounded return has been chosen due to several advantages of the method. First, multi period return is just the sum of the returns of the period. Second, this type of return typically demonstrates higher degree of normality due to its symmetry. Finally, heteroscedasticity is a smaller problem for continuously compounded returns compared to percentage returns *(Vaihekoski, 2004)*.

[6] The Berkshire Company is run by the famous value investor Warren Buffet who has been able to increase the share price from $12 in 1965 to more than $90.000.

During sell periods it has been decided to move out of the market and invest in a risk free asset instead of selling short. The risk free data are based on the six-month US T-Bill obtained from TDS. The annualized rates are converted into daily rates using the formula as used in Sullivan, Timmerman & White *(1999)*:

(6-2) $$r_f = \frac{\ln(1 + r_{ann})}{261}$$

Where r_f is the daily interest rate, r_{ann} is the reported annualized rate and 261 are the average number of trading days in a year in this study.

The return (r) for each trading rule is then given by the following formula defined by Allen & Karjalainen *(1999)*:

(6-3) $$r = \sum_{t=1}^{T} r_t I_b(t) + \sum_{t=1}^{T} r_f(t) I_s(t) + n \ln \frac{1 - c}{1 + c}$$

Where T is the number of trading days, r_t is the daily continuously compounded return, $I_b(t)$ is an indicator variable equal to one if the day is a buy day and zero if the rule indicates a sell day, $r_f(t)$ denotes the risk free rate on day t and $I_s(t)$ is the indicator variable with value of one on sell days and zero on buy days. In the empirical analysis it will initially be investigated whether the technical trading rules are able to outperform the buy-and-hold strategy without correcting for transaction costs. If the returns generated by the trading rules are indeed significantly better than the buy-and-hold strategy without transaction costs, the effect of introducing transaction costs will be analyzed. These costs are calculated in the last part of the formula where n is the number of roundtrip transactions made by the rule i.e. a buy and a sell signal, and c is the one-way transaction cost. Notice that this last part is only included in the formula if the moving average returns ex-ante transaction costs are higher than the buy-and-hold return. The level of transactions costs is very hard to define since it differs from investor to investor. As mentioned in section 5.3, Sweeney *(1988)* discusses this issue and comes to the conclusion that money managers can achieve transactions at around 1/10 to 1/5 of 1 percent whereas floor traders can trade at for around 1/20 of 1 percent in one-way transactions costs. Finally, he estimates that private transactors pay 4/10 of 1 percent in one-way transaction costs. On the basis of this it has been chosen to set the one-way transaction costs to 0.25% which is also the rate set by Allen & Karjalainen *(1999)*.

The buy-and-hold return is given by:

(6-4) $$r_{bh} = \sum_{t=1}^{T} r_t + \ln \frac{1-c}{1+c}$$

Notice that the last part of the formula refers to transaction costs and is only included in the return calculation if the technical trading rule strategy outperforms the buy-and-hold strategy ex-ante transaction costs.

An important aspect in the analysis is how the actual deal is made when a signal occurs. As the price on which the analysis is based is the daily closing price the signal can only be registered after the market has closed. The order is therefore placed on the following morning and it is assumed that the opening price is the same as the closing price the day before. It is assumed that it is possible to trade at this price. When rebalancing the portfolio, the position is ended. This happens on the 29th of April if possible and if not, on the last trading day before that day and to that day's closing price. The rebalanced portfolio is then bought on the following morning, either the 30th of April or the first coming trading day if the market is closed on that date.

The risk is calculated as the standard deviation of the returns. Since the technical trading strategy results in the investor being out of the market in certain periods the standard deviation differs from the buy-and-hold strategy. As already mentioned, there is invested in a risk free asset during sell periods. However, seen over the 19-year period the investment in sell periods is not totally risk free. Thus, the standard deviation on the technical trading strategy includes the standard deviation from sell periods. To risk adjust the returns and make them comparable the Sharp Ratio is used[7].

6.5 Technical Trading Rules

The empirical analysis is based on eight moving averages. The time span of the moving averages has been chosen in accordance with the rebalancing of the portfolio. Due to the fact the rebalancing takes place after one year the long averages used in BLL *(1992)* have been found to long. Instead, shorter "long

[7] Sharp Ratio: $Sharp = \frac{r_p - r_f}{\sigma_p}$, where r_p is the return on the portfolio, r_f is the risk free rate of return and σ_p is the standard deviation on the portfolio.

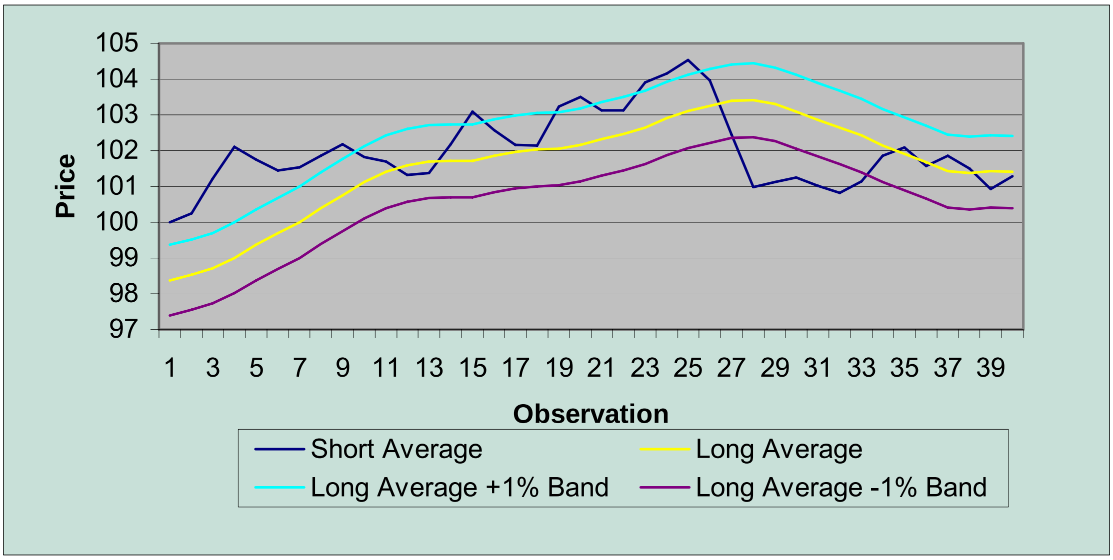
averages" has been used with the shortest being a 10-days moving average. An argument for using shorter averages is that it is more in accordance with the time horizon for real investors. Investors usually measure their performance over a one-year period and thus, try to maximize their profits in this period. A shorter moving average also captures the direction of the trend at an earlier stage. This, however, also increases the signals generated by the trading rule, which is the major disadvantage of these. To minimize the amount of false signals, a band is put around the moving average as described in section 2.2.3.1.4. All the trading rules are displayed below. Notice that all the rules use a short moving average of only one day. Thus, the trading rule can be described as a simple one moving average rule also described in section 2.2.3.1.4.

Table 6.1 Technical Trading rules

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Short Average	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Long Average	**10**	**10**	**20**	**20**	**30**	**30**	**50**	**50**
Band in Percentage	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**

To decide what position to take at the beginning of the period, price information is retrieved from 1st of February the same year as the portfolio is formed. The trading rules are then used as follows: After defining the long average, all days are divided into either buy or sell days. If the short moving average is above the long and the band is zero the day is classified as a buy day and if it is below it is a sell day. When using bands the short average in this thesis, the actual price has to cross either the upper or lower band to generate a signal. This means that in the case of the short average crossing the long from above no sell signal is generated, but instead it has to cross the long average minus 1% before selling the portfolio. The position is changed when the short average crosses the long moving average plus 1%. The strategy is illustrated in figure 6.1.

Figure 6.1 Moving Average



In the figure above you start out by taking a long position since the short average is above the long. Without a band you will go out of the market on the 12th day and invest in the risk free asset. This, however, seems to be a false signal since the position is changed again on the 14th day. With a 1% band this signal is avoided. The band ensures that you stay in the long position until the 28th day and hence, you avoid acting on a false signal. The risk free asset is then held for the rest of the period shown since the upper line is not crossed again. By introducing a band around the long moving average the number of signals is approximately halved.

7 Empirical Results

In this chapter the empirical results are presented. The data on which the analysis based upon is enclosed in appendix 2. The first section presents the results from traditional tests when no transaction costs are assumed. Furthermore, the differences between the growth and value portfolios are discussed. Due to the fact that some of the assumptions behind the traditional approach are not fulfilled the second part concerns the bootstrap methodology as used in BBL. The last part of the chapter looks at the significance of introducing transaction costs and how this alters the conclusion.

7.1 Traditional Tests

The main question in this thesis is whether or not a strategy based on technical trading rules, in this case moving average trading rules, is able to outperform a buy-and-hold strategy as proved by BLL *(1992)*. To test this many academic articles make use of a standard *t-test* which tests for equality of two means. Formally, the hypothesis tested is written as:

(7-1)
$$H_0 : \mu = \mu_0$$
$$H_1 : \mu \neq \mu_0$$

where μ_0 is the population mean, in this case the buy-and-hold mean return, and μ is the sample mean, the mean return generated by the moving average trading rule. A significance level must be decided which in most cases is set to 5%. As the test is two-tailed this means that there is 2.5% in each tail of the test. If H_0 is accepted it cannot be concluded that there is inequality of the two means. If, however, H_0 is rejected there is a statistical significant difference between the two means. If the return generated from the technical trading rules is above the return from the buy-and-hold strategy, such a rejection will mean that the moving average trading rule is able to outperform the buy-and-hold strategy.

Firstly, the results from the growth portfolio are presented. Secondly, the value portfolio is analyzed. Thirdly, a short discussion of the differences of the two portfolios is conducted and finally, the assumptions of the traditional test are questioned and examined.

7.1.1 Growth Portfolio

In table 7.1 the results of the trading strategies are presented. The first column refers to the length of the trading rule and whether a band is used. The second column reports the total number of trading days, and in the two following columns this number is divided into either buy days or sell days. On buy days the investor is in the market whereas on sell days a position in a risk free asset is taken. The number in brackets is the fraction in percent of correct signals, meaning positive returns during buy-periods and negative returns during sell-periods, produced buy the trading rule. The last two columns report the returns during buy and sell periods respectively. The figures listed in italic are the standard deviation.

Table 7.1 Results for Growth Portfolio

	Observations	N(Buy)	N(Sell)	Mean Buy Return	Mean Sell Return
MA (1-10-0)	4958	2763	2195	0.05285	-0.05165
		(56.5)	(47.3)	*0.81232*	*1.24875*
MA (1-10-1)	4958	2768	2190	0.02671	-0.01815
		(55.0)	(45.4)	*0.82384*	*1.24203*
MA (1-10-2)	4958	2685	2273	0.03059	-0.02176
		(54.9)	(45.3)	*0.81534*	*1.23576*
MA (1-20-0)	4958	2801	2157	0.06109	-0.06418
		(56.8)	(47.8)	*0.79287*	*1.27008*
MA (1-20-1)	4958	2830	2128	0.01974	-0.01090
		(54.8)	(45.3)	*0.79194*	*1.27944*
MA (1-30-0)	4958	2891	2067	0.05557	-0.06193
		(56.5)	(47.7)	*0.77751*	*1.30037*
MA (1-30-1)	4958	2888	2070	0.02435	-0.01819
		(55.1)	(45.6)	*0.78944*	*1.29239*
MA (1-50-0)	4958	2972	1986	0.03407	-0.03453
		(55.4)	(46.1)	*0.78378*	*1.31385*
MA (1-50-1)	4958	2979	1979	0.01673	-0.00867
		(54.3)	(44.4)	*0.79938*	*1.30207*

From the table it is clear that the signals produced by the trading rules are able to identify positive and negative returns. During “buy-periods” all the moving average rules produce a positive daily mean return while the “sell-periods” are characterized by negative daily mean returns. For all trading rules, the number of “buy-days” exceeds the number of ”sell-days”, which is consistent with an upward-sloping trend in the market and indicates that the rules are appropriate. It can also be seen that “buy-signals” are more accurate than “sell-signals”. Approximately 55% of the returns following a “buy-signal” are positive while for the returns following a “sell-signal” only 44% to 48% are negative. Notice also that the volatility is higher during “sell-periods”. This is consistent with a well-known characteristic of asset returns named the leverage effect, which states that volatility associated with negative returns is greater than for volatility associated with positive returns. This will be discussed more detailed in a later section.

Table 7.1 reports daily mean returns on “buy” and “sell” days only. As the purpose of this thesis is to investigate whether moving average trading rules can outperform a buy-and-hold strategy, the mean return of the entire period is of interest, since this can be compared to the mean return of the buy-and-hold strategy. Recall from section 6.5 that when the trading rule produces a sell signal the long position is ended and a risk-free asset is bought. Thus, the sell-return will not be dealt with in the further analysis.

In table 7.2 the daily mean return for the moving average rules is reported with the corresponding t-statistics written below. This tests if the return obtained by using technical trading rules is significantly different from the return obtained by a buy-and-hold strategy. The t-statistics are computed in the following way:

(7-2) $$t = \frac{\mu_{TR} - \mu_{BH}}{\sqrt{\frac{s_{TR}^2}{n} + \frac{s_{BH}^2}{n}}}$$

where μ_{TR} is the mean return obtained from the technical trading rule and s_{TR} is the standard deviation for the technical trading rule strategy. μ_{BH} and s_{BH} is the mean return from the buy-and-hold strategy and standard deviation respectively. n is the total number of observations. The standard deviation and Sharpe Ratio is reported in column 3 and 4, while the total number of roundtrip signals is reported in the last column.

Table 7.2 Traditional Test Results for the Trading Rules for the Growth Portfolio

	Daily Mean Return	Standard Deviation	Sharpe Ratio	Signals
MA (1-10-0)	0.0374 *1.8177*	0.60663	0.03174	317
MA (1-10-1)	0.0226 *0.9369*	0.61554	0.00709	149
MA (1-20-0)	0.0423 *2.1136*	0.59630	0.04045	194
MA (1-20-1)	0.0190 *0.7338*	0.59829	0.00136	113
MA (1-30-0)	0.0399 *1.9754*	0.59397	0.03662	148
MA (1-30-1)	0.0217 *0.8943*	0.60250	0.00590	88
MA (1-50-0)	0.0277 *1.2429*	0.60685	0.01566	142
MA (1-50-1)	0.0174 *0.6318*	0.61961	-0.00131	76
Buy-and-Hold	0.0066	1.02984	-0.01126	19

The results from using moving average as trading rule are remarkable. First of all they all generate a return that is above the buy-and-hold strategy. What is most striking, however, is that three of the eight trading rules produce an average daily return that is above and statistically significantly different from the buy-and-hold return at the 5% significance level using a two-tailed test[8]. The best performing trading rule is the 1-20-0 rule. The average daily return from this strategy is 0.0423% which in annual terms amounts 11.04%[9]. This compares to the annual average return for the buy-and-hold strategy of only 1.7%. It is noteworthy that the three trading rules generating significantly different returns all are rules with no bands. Only the 1-50-0 rule does not generate a return which is significantly higher than the buy-and-hold strategy. If a band is used around the moving average none of the

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[8] 5% significance level: $t = 1.645$

[9] The annual average return is calculated by multiplying the daily mean return with 261, which is the average number of trading days in a year.

tested strategies are able to significantly outperform the buy-and-hold strategy at the 5% significance level even before transaction costs are accounted for.

The standard deviation is much lower for the technical trading rules than for the buy-and-hold strategy. This is due to the nature of the investment strategy of the technical trading rules where one moves out of the market and invests in a risk free asset during sell periods. When following the buy-and-hold strategy the investor is obviously in the market at all times and hence, carries more risk. The fact that the risk differs from each investment strategy causes it to make good sense to compare the returns on a risk-adjusted basis. Calculating the Sharpe Ratio does this[10]. When adjusting for risk all technical trading rules also outperform the buy-and-hold strategy. Only the 1-50-1 rule is difficult to interpret since the Sharpe Ratio of this is negative but when decomposing the numerator and denominator, it is clear that this trading rule also outperforms the buy-and-hold strategy in economical terms since the return is higher and standard deviation lower.

Finally, the number of trades decreases, as it was expected, as the long moving average increase in days because trading rules are less sensitive to variation in the price. The introduction of a band around the moving average further lowers the number of signals. As mentioned in chapter 2 using a band help to avoid signals when the two averages used bounces up and down close to each other.

7.1.2 Value Portfolio

The results for the value portfolio are very similar to the results obtained in the growth portfolio. Again, the number of “buy-days” exceeds “sell-days” which is consistent with an upward-sloping trend in the market. The trend seems however to be more upward sloping for the value portfolio than for the growth portfolio. The number of “buy-days” is consistently greater than was the case for the growth portfolio. For the value portfolio “buy-days” exceeds “sell-days” with approximately 50%, whereas the same ratio was only approximately 35% for the growth portfolio. Notice also that the fraction of correct signals following a “buy-signal” is higher and lies at around 59% while for “sell-days” the fraction is about the same. The steeper

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[10] The Sharpe Ratio is calculated as: $SR = \frac{r_{portfolio} - r_{rf}}{\sigma_{portfolio}}$

trend can also be seen on the size of the "buy" return, which is consistently higher than the "buy" return on the growth portfolio. It is important to mention that the higher return is not the result of greater risk. The volatility of the value portfolio is much lower than was the case for the growth portfolio indicating that the value premium discussed in chapter 4 is also evident in this thesis.

Table 7.3 Results for Value Portfolio

	Observations	**N(Buy)**	**N(Sell)**	**Mean Buy Return**	**Mean Sell Return**
MA (1-10-0)	4958	2998	1960	0.11646	-0.05453
		(58.8)	(47.3)	*0.61982*	*0.93848*
MA (1-10-1)	4958	3027	1931	0.10092	-0.03233
		(58.7)	(47.1)	*0.62523*	*0.94020*
MA (1-10-2)	4958	2754	2204	0.08220	0.00757
		(57.6)	(44.6)	*0.65265*	*0.88628*
MA (1-20-0)	4958	3088	1870	0.11156	-0.05425
		(59.2)	(48.2)	*0.60862*	*0.96333*
MA (1-20-1)	4958	3134	1824	0.09849	-0.03598
		(58.8)	(47.6)	*0.62146*	*0.95971*
MA (1-30-0)	4958	3154	1804	0.10824	-0.05451
		(59.3)	(48.6)	*0.61616*	*0.96600*
MA (1-30-1)	4958	3159	1799	0.10169	-0.04346
		(59.1)	(48.1)	*0.61911*	*0.96528*
MA (1-50-0)	4958	3206	1752	0.10506	-0.05352
		(59.4)	(48.7)	*0.62071*	*0.96973*
MA (1-50-1)	4958	3123	1835	0.09411	-0.02772
		(58.7)	(47.2)	*0.63173*	*0.94760*

In table 7.4 the figures that are comparable to the buy-and-hold strategy are presented.

Table 7.4 Traditional Test Results for the Trading Rules for the Value Portfolio

	Daily Mean Return	Standard Deviation	Sharpe Ratio	Signals
MA (1-10-0)	0.0776 *2.2220*	0.48430	0.12273	284
MA (1-10-1)	0.0689 *1.5415*	0.49016	0.10353	101
MA (1-20-0)	0.0767 *2.1542*	0.48239	0.12134	175
MA (1-20-1)	0.0693 *1.5648*	0.49556	0.10314	74
MA (1-30-0)	0.0759 *2.0733*	0.49330	0.11690	128
MA (1-30-1)	0.0719 *1.7618*	0.49576	0.10826	56
MA (1-50-0)	0.0748 *1.9855*	0.50080	0.11311	91
MA (1-50-1)	0.0665 *1.3416*	0.50266	0.09608	47
Buy-and-Hold	0.0490	0.76618	0.04025	19

If the results of the growth portfolio were remarkable, the results for the value portfolio are even more striking. 5 of the 8 technical trading strategies generate a significantly higher return than the buy-and-hold return. In the value portfolio the highest return is generated by the 1-10-0 trading rule. The average daily return generated by this rule is 0.0776% or 20.25% at an average annual rate. This compares to the buy-and-hold average daily return of 0.049%, which equals 12.79% at an annual rate. As was the case with the growth portfolio, the trading rules that do not make use of bands are the best performing. All of them generate a return that is above and statistically significantly different from the buy-and-hold strategy. However, one of the trading rules with band also generates a return that is significantly different from the return generated by the buy-and-hold strategy, which was not the case for the growth portfolio.

The volatility is again, not surprisingly, much lower for the trading strategies than for the buy-and-hold strategy. It is also noteworthy lower for the value portfolio than for the growth portfolio. Thus, having a higher return and lower risk the trading rules all outperform the buy-and-hold strategy on a risk-adjusted basis. It is interesting, however, that the Sharp Ratio for the buy-and-hold strategy in the value portfolio is higher than the Sharp Ratio for 9 out of 10 technical trading rules in the growth portfolio. Only the 1-20-0 rule in the growth portfolio produces a better risk-adjusted return. This issue will be addressed further in the next section. The lower volatility can also be detected in the number of signals. All of the trading rules generate fewer signals when they are used on the value portfolio compared to the growth portfolio. Most signals are of course generated by the 1-10-0 rule with a total of 284 roundtrip signals or 14.9 signals per year. The 1-50-1 rule with a total of 47 signals generates the fewest signals. On a yearly basis this amounts to 2.5 signals per year.

7.1.2.1 The Value Premium

The results presented in this section confirm the value premium discussed in chapter 4. In this thesis the difference between the two portfolios is outspoken. The value portfolio generates a yearly mean return of 12.79% while the growth portfolio only earns 1.7% on a yearly basis. Furthermore, the standard deviation is lower on the value portfolio, so the higher return cannot be explained by an increase in risk. Consequently, it seems as if the value premium is present in the data examined. When testing for differences of the mean return the result is as follows:

(7-3) $$t = \frac{0.049021203 - 0.00658795}{\sqrt{\frac{0.76618^2}{4958} + \frac{1.029832^2}{4958}}} = 2.329$$

At the 5% significance level, the value portfolio return is above and significantly different from the return generated by the growth portfolio. However, some of the premium may be caused by the fact that the period in question entails the year of the Internet bubble, which must be assumed to have a greater impact on growth stocks than value stocks according to the classification of the two in section 4.1 and 4.2. Examining the returns for the period April 2000 to April 2001 indeed confirm this. The return for the growth portfolio in year 2000 is -22.06% while the value portfolio generates a return of 29.26%. In appendix 3 the yearly return of the portfolios are presented. Studying these it can further be seen that the growth portfolio suffers most from negative shocks such as the crash of 1987. However, the fact that the impact of different shocks differentiates between the two portfolios does not change the conclusion of a value premium in the data.

With an average yearly buy-and-hold return of only 1.7% on the growth portfolio the return is lower than what can be earned if investing in the risk free rate[11]. The fact that three of the trading rules generate a return that is above and significantly different from the buy-and-hold strategy may be relevant from a technical trading perspective, but for an investor it is irrelevant. No rational investor would consider applying technical trading rules in a portfolio generating a significantly poorer return since it would require the trading rules to have extremely good forecasting power to generate a return that is as good as or better than the benchmark. Therefore, it will make no sense to further analyze the growth portfolio and hence, the further analysis only concerns the value portfolio.

7.2 Further Analysis

The results presented above are indeed striking. The trading rules, especially the rules without bands, are able to earn an abnormal return, when they are compared to a buy-and-hold strategy. However, the scenarios under which the investments are made and tested are not truly realistic. First of all, the test statistics used to determine the significance of the differences might have caused the conclusion to be biased in favor of technical analysis. It is commonly known that stock returns are characterized by certain properties that are not in accordance with the assumptions behind the t-test. This leaves the question open whether the seemingly better performance of the trading rules is simply caused by the use of a test that does not capture the effect of the specific properties of the data. To check for this the bootstrap method is used.

Another important deviation from the real world is the omission of transaction costs. As discussed in section 5.3 investors face costs when buying and selling stocks. Not accounting for these costs will bias the results in favor of technical analysis since this kind of investment analysis causes many transactions and hence, higher transaction costs. As commented on in the previous sections the number of signals is higher the shorter the long moving average is. This means that the 1-10-0 trading rule suffers

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[11] The average yearly risk free rate of return is 4.75% in the corresponding period.

most from transaction costs. If introducing transaction costs, it is not certain that the use of technical trading rules will result in abnormal profits for investors. This must of course be investigated. The problems regarding statistical inference and transaction costs will be addressed in the next parts of the chapter.

7.2.1 Properties of Stock Returns

The assumptions behind the t-test are that the stock returns are normal, stationary and independently distributed. These assumptions can normally not be fulfilled when testing on stock returns, since these deviate from this distribution in many ways. Among these deviations are kurtosis, autocorrelation, conditional heteroscedasticity and changing conditional means. Thus, if the data suffers from these deviations the t-statistics will not be t-distributed under the null hypothesis and hence, inappropriate. To check for this the properties of the data is described.

7.2.1.1 Preliminary Analysis

Perhaps the most important faulty of the return series is the lack of normality in the unconditional distribution. If the conditional distribution of the returns is n.i.i.d. (normal, identical and independently distributed), the unconditional distribution is expected to be normal distributed as well. Departures from the conditional normality in the sample must then come from either the data not being i.i.d. or not being conditionally normal. One way of testing for normality is to compute the skewness and kurtosis of the unconditional returns. Skewness is a measure of asymmetry in the distribution, where a normal distribution has a skewness of zero (symmetric). Large negative skewness indicates long left tails and vice versa. Kurtosis measures the thickness of tails. A Normal distribution has a kurtosis of 3. A kurtosis higher than this implies fat tails and a high peak. A distribution dominated by kurtosis is said to be leptokurtic and many empirical studies have stated that this in fact is typical for stock returns.

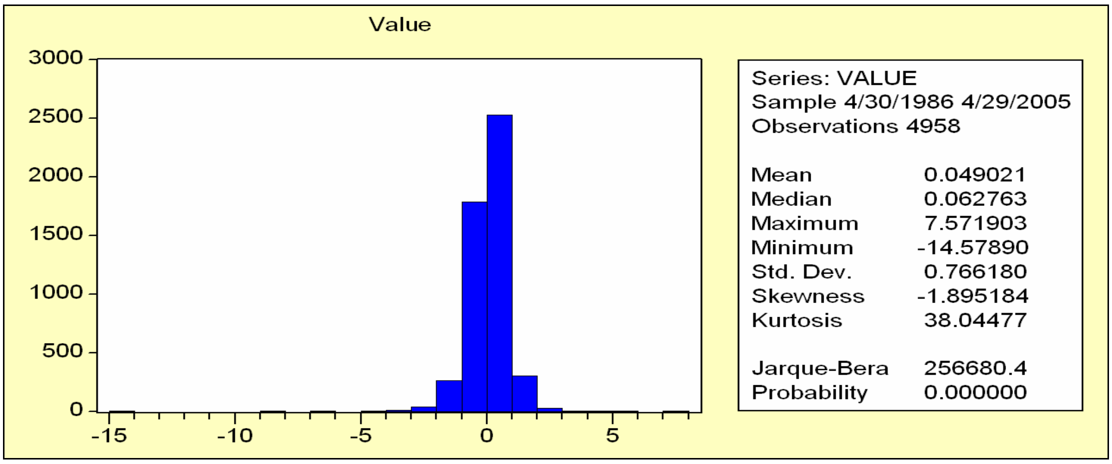
An approach for testing for normality is to use the Jarque-Bera test. The test measures the difference of skewness and kurtosis in the series compared to the normal distribution and is given by:

(7-4) $$Jarque - Bera = \frac{N-k}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

where S is the skewness, K is the kurtosis and k is the number of estimated coefficients. Under the null hypothesis of normal distribution, the Jarque-Bera statistic is distributed as χ^2 with two degrees of freedom. Small probability values lead to rejection of the null hypothesis *(Eviews 5 User's Guide).*

Figure 7.1 displays the histogram and the related descriptive statistics for the value portfolio.

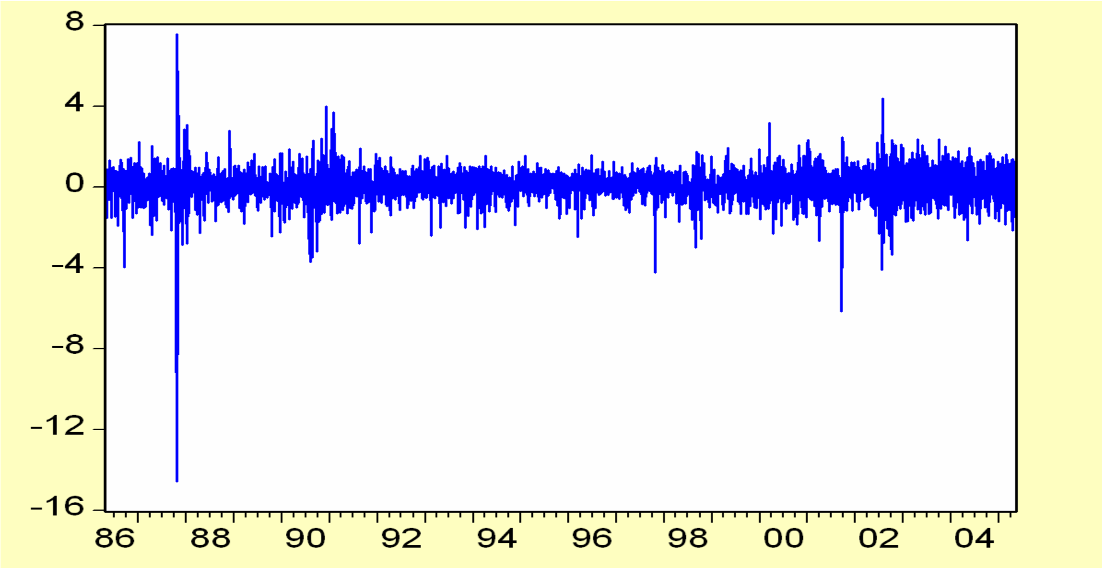
Figure 7.1 Descriptive Statistics



From the histogram it is obvious that the return series cannot be said to follow a normal distribution. The Jarque-Bera test for normality furthermore, rejects the null hypothesis of normality. Splitting up the Jarque-Bera test, the series face negative skewness and high kurtosis. While the skewness does not create a serious problem the extremely high kurtosis must be the main reason for non-normality. The high kurtosis in stock returns typically comes from crashes and especially one event has had a great impact on the return series in the covered period. The 19th of October 1987 the stock market experienced the largest one-day decline in recorded stock market history – known as Black Monday. The high kurtosis implies that the distribution is heavier tailed and higher peaked compared to a normal distribution. Thus, the series is leptokurtic distributed, which is typical for stock returns *(Watsham & Parramore, 2002)*.

Like Black Monday, other major events are captured in the stock returns. The return series is displayed in figure 7.2.

Figure 7.2 Daily Continuously Compounded Return



While Black Monday clearly dominates the picture, other events, like the terror attack on September 11th 2001, stand out too. Comparing the effects 9/11, which are fresh in mind, with the effects of Black Monday, certainly puts the impact of the latter in perspective

From Figure 7.2 it is clear that the series variance is not constant, hence, it suffers from heteroscedasticity. The observed variance seems to behave in a pattern well-known from stock price, known as volatility clustering; shifting from periods of high volatility to periods of low volatility. However, despite the time-varying variance it appears that the series is stationary in mean, but to be sure a unit root test for stationarity is necessary.

Table 7.5 Unit Root Test for Stationarity

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.943.358	0.0001
Test critical values:	1% level	-3.431.487	
	5% level	-2.861.928	
	10% level	-2.567.019	

By examining table 7.5 the conclusion is clear. The null hypothesis of a unit root is strongly rejected meaning that the series is indeed stationary.

Another important property of return series is the assumption of independency. Dependency comes in many forms but in this context it is found sufficient only to test for linear dependency. This can be obtained by investigating the autocorrelation and partial autocorrelation.[12]

Table 7.6 Test for Linear Dependency

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.168	0.168	140.63	0.000
		2	0.050	0.022	152.92	0.000
		3	0.041	0.030	161.28	0.000
		4	0.036	0.024	167.54	0.000
		5	0.068	0.058	190.21	0.000
		6	0.025	0.002	193.30	0.000
		7	0.021	0.011	195.39	0.000
		8	0.010	-0.000	195.85	0.000
		9	-0.001	-0.007	195.86	0.000
		10	0.015	0.012	197.04	0.000

Which can be seen in table 7.6 the first order autocorrelation is positive and significant, while the correlations at higher lags are considerably closer to zero. This indicates that there is linear dependency in the return series. The autocorrelation can however, be a result of nonsynchronous trading. It is a fact that different stocks have different trading frequencies. For daily price series, the price of a stock is its closing price which is the last transaction price quoted that trading day. The actual time of

[12] The concept of independency, autocorrelation and partial autocorrelation will be further elaborated in section 7.3.2.1.1.1.2

the last transaction varies however, from day to day and thus, it is wrong to assume that daily returns are an equal-spaced time series with a 24-hour interval. This may lead to a conclusion of serial correlation at lag 1 even though the true return series is serially independent *(Tsay, 2002)*. However, the noise of nonsynchronous trading of a single asset is minimized when it is a part of a portfolio *(Vaihekoski, 2004)*.

The intensive investigation of the return series above has confirmed the misgivings. The series faces high kurtosis, skewness and linear dependency, besides suffering from heteroscedasticity. These findings are not reconcilable with the normal distribution assumption. The assumptions behind the t-test are violated which means that the results from the previous section may be unreliable. Fortunately, when the traditional approaches for statistical inference fails alternative methods for statistical inference can be applied.

7.3 Bootstrapping

Efron introduced the bootstrap procedure in 1979. The term “bootstrapping” is derived from the phrase ‘pulling oneself up by one’s bootstraps’[13]. Initially, the bootstrap was presented as a computer-based resampling method to estimate the standard error of a parameter estimate. Nowadays, the bootstrapping has found relevance in numerous statistical procedures and has become a widely accepted alternative to traditional statistical inference. Bootstrap can be classified as parametric or nonparametric, however only the nonparametric method will be described in this thesis.

7.3.1 The Bootstrap Concept

Suppose drawing a simple random sample $S = \{X_1, X_2 ..., X_n\}$ from a population $P = \{x_1, x_2 ....., x_N\}$, where the intention is to obtain a statistic $T = t(s)$ as an estimate of the corresponding population parameter $\theta = t(P)$. The traditional approach to statistical inference is to make an assumption about the structure of the population (e.g. assumption of normality), and use this assumption to derive the sampling distribution of T. However, if the assumption about the population is wrong, the

[13] The term ‘bootstrap’ in this context comes from an analogy with the fictional character Baron Münchhausen, who got out from the bottom of a lake by pulling himself up by his bootstraps.

corresponding sampling distribution of the statistic may be inaccurate and hence, make the statistic invalid *(Fox, 2002).*

The non-parametric bootstrap, on the other hand, makes it possible to estimate the sampling distribution of the statistic empirically without making assumptions about the distribution of population and without deriving the sampling distribution explicitly. The basic concept is to draw a sample of size n with replacement from the observations in S and obtain $S_1^* = \{X_{11}^*, X_{12}^* ..., X_{1n}^*\}$. The sampling with replacement is necessary because the bootstrap sample otherwise just becomes a replication of the original sample S. The sample S is treated as an estimate of the population P, so that each observation X_i of S is selected for the bootstrap sample with probability $1/n$. This procedure is repeated a large number of times R, which results in R bootstrapped samples $S_b^* = \{X_{b1}^*, X_{b2}^* ..., X_{bn}^*\}$. Thus, the underlying idea of bootstrapping is that:

'The population is to the sample as the sample is to the bootstrap samples'

Source: Fox (2002).

A statistic T_b^* obtained from a bootstrap sample is called a *bootstrap replication of* $\hat{\theta}$. For instance, the average of the bootstrapped statistic estimates the expectation of the bootstrap statistics and is given by.

(7-5) $$\overline{T}^* = \hat{E}^*(T^*) = \frac{\sum_{b=1}^{R} T_b^*}{R}$$

And the estimated bootstrap variance of T^* is given by.

(7-6) $$\hat{V}^*(T^*) = \frac{\sum_{b=1}^{R}(T_b^* - \overline{T}^*)}{R-1}$$

Besides the variance, the bootstrap methodology can also be applied on confidence intervals and hypothesis testing. However, note that the number of bootstrap replicates needed is reliant on which statistical instrument is going to be used. For example, $R = 50$ is often sufficient to give a good estimate of $\hat{V}^*(T^*)$ and very rarely are more $R = 200$ needed. However, much larger numbers of R is needed when bootstrapping confidence intervals and hypothesis test *(Efron, 1993).*

7.3.1.1 The Bootstrap Methodology of BLL

The bootstrap algorithm can be used in many different contexts and thus, also be applied on time series models. Even under time series a number of different types of bootstrap approaches have been used like the Block Bootstrap, Sieve Bootstrap and Estimation-Based Bootstrap. The Estimation-Based Bootstrap was inspired by Efron *(1982)* and Freedman *(1984)* and is basically a computer simulation of time series, which aims at capturing the properties and the distribution of the conditional moments under various null models. BLL combined the Estimation-Based Bootstrap technique with test based on technical trading rules. As the BLL method will be used in this thesis a description of this procedure will be given.

The first step of the procedure is to fit a given model to the original series and obtain the estimated parameters and residuals. The residuals are then standardized using estimated standard deviation for the error process. Hereafter, the residuals are randomly drawn with replacement to construct a scrambled residuals series. The scrambled residuals are used together with the estimated parameters to form a new representative return/price series for the given null model[14]. Then the technical trading rules are applied on the simulated series and the average return and standard deviation are obtained for the buy and sell periods. Each simulation is based on 500 replication of the null model, which should provide a good approximation of the return distribution under the null model. The decision rule is to reject null hypothesis at the α percent level if the returns obtained from original series are greater than α percent cutoff of the simulated returns under the null model *(BLL, 1992).*

7.3.2 Hypothesis Formulation

Before a thorough presentation of the bootstrap procedure the exact objective of the bootstrap approach needs to be declared. In other words, what is in fact tested? The objective of the test is formulated in the following hypotheses:

[14] Note that no assumptions of the distribution of the residuals are necessary.

H_0 : The null models are able to explain the returns observed in the original series. Thus, the results obtained from applying the technical trading rules on the value portfolio is simply due to omission of the well-known features of stock returns such as non-normality, autocorrelation or time-varying variance.

H_1 : The various null models cannot explain the returns obtained in the original series. Hence, the results obtained from applying technical trading rules on the value portfolio is not due to omission of the well-known features of stock returns such as non-normality, autocorrelation or heteroscedasticity.

However, the hypothesis above cannot be tested by a single decision rule. Instead, two sub hypotheses have to be applied: one for the mean return and one for the standard deviation. If both these null hypotheses are rejected the main null hypothesis above is also rejected.

The decision rule for the mean return hypothesis:

(7-8) $$H_0 : \frac{N(R^* > R)}{500} > 0.95, \qquad H_1 : \frac{N(R^* > R)}{500} \leq 0.95$$

where $N(R^* > R)$ denotes the count of how many of the returns from the simulated series R^* exceeds the return from the value portfolio R. The number is divided by 500 to obtain the fraction. If the fraction exceeds 0.95 it means that over 95% of the simulations from the given null model generates a mean return higher than the original series, thus, the null hypothesis cannot be rejected. The fraction can be interpreted as a 'reversed p-value'[15]. The significance level is set to 5 %.

The decision rule for the standard deviation:

(7-9) $$H_0 : \frac{N(S^* > S)}{500} < 0.05, \qquad H_1 : \frac{N(S^* > S)}{500} \geq 0.05$$

---

[15] Normally low p-values result in a rejection of the null hypothesis. Here it is turned around

where $N(S^* > S)$ denotes the count of how many of the standard deviations from the simulated series S^* exceeds the return from the value portfolio S. The number is again divided by 500 to obtain the fraction. If the fraction is below the significance level the null hypothesis cannot be rejected. Hence, less than 5% of the simulations generate a standard deviation larger than the one obtained from the original series. Thus, the fraction can here be interpreted as a normal p-value.

7.3.3 The Bootstrap Procedure

With the theoretical foundation for the bootstrap approach in place this section will clarify the practical approach to the method. It can more or less be seen as a guide to help one through the almost 20 GB of data contained in the various spreadsheets of appendix 4.

In general, the bootstrap procedure can be separated into six steps:

1. Specify the null models that suite the characteristics of the data and obtain their parameters and the residual series.
2. Resample the residuals/standardized residuals.
3. Create return series.
4. Create price series and moving average price series.
5. Carry out technical analysis.
6. Calculating average mean, standard deviation and fraction.

These six steps will be elaborated on in the following subsections. Most space is used on the first step since this step requires that the theory of time series is clarified.

7.3.3.1 Specification and Estimation of Null Models

This section is divided in two parts. First the theory of time series is described, and second this theory is used to find suitable null model. This part is by far the largest of section 7.3.3 due to the fact that the theoretical foundation for the null models has to be explained.

7.3.3.1.1 Time Series Theory

The following subsection introduces the most common time series models. The models described in this section are those that will be examined further in the next section of the chapter, where the purpose is to find those models that describe the stock return series most appropriate. The theory below is by no means exhaustive but will cover the parts found relevant for the further analysis.

7.3.3.1.1.1 Basic Concepts

Roughly, time series models can be divided into two categories: linear time series models and conditional heteroscedastic models. Before presenting the different models a few important concepts need to be discussed.

7.3.3.1.1.1.1 Stationarity

The foundation of time series analysis is the concept of stationarity. A time series is said to be strictly stationary if its properties are unaffected by changes in time. In other words, strict stationarity requires that the joint distribution is invariant under time shift. This is a very strong condition and very hard to verify empirically. Instead, a weaker form is imposed. Weak stationarity or covariance stationarity only impose that the mean and variance are constant and the correlation between values Y_t and Y_{t-j} only depends on the time difference j. Hence, only the mean, variance and correlation are independent of time rather than entire distribution *(Verbeek, 2000)*.

7.3.3.1.1.1.2 Correlation, ACF and PACF

The correlation coefficient between two variables X and Y is defined as

(7-10) $$\rho_{x,y} = \frac{Cov(X,Y)}{\sqrt{Var(X)VAR(Y)}} = \frac{E\lfloor (X-\mu_x)(Y-\mu_y)\rfloor}{\sqrt{E(X-\mu_x)^2 E(Y-\mu_y)^2}}$$

where μ_x and μ_y are the mean of X and Y, respectively. The coefficient $\rho_{x,y}$ measures the linear dependency between X and Y and lies within $[-1;1]$. The two random variables are uncorrelated if $\rho_{x,y} = 0$ and hence, if both X and Y are normal random variables then $\rho_{x,y} = 0$ if and only if X and Y are independent. In a time series framework correlation is known as autocorrelation. Autocorrelation ρ_l measure the linear dependency or correlation between for instance r_t and past values r_{t-i}. The autocorrelation function (ACF) is given by:

(7-11) $$\rho_l = \frac{Cov(r_t, r_{t-l})}{\sqrt{Var(r_t)VAR(r_{t-l})}} = \frac{Cov(r_t, r_{t-l})}{Var(r_t)} = \frac{\gamma_l}{\gamma_0}$$

Here the property for a weakly stationary series is used $Var(r_t) = Var(r_{t-l})$. By definition lag zero (ρ_0) is one and ρ_l lies within $[-1;1]$. For $l > 0$ the weakly stationary series r_t is not serially correlated if, and only if, $\rho_l = 0$. If ACF dies out slowly this indicates that the process is non-stationary. If, on the other hand, all ACF's are close to zero the series should be considered white noise.

The correlation between r_t and r_{t-i} after removing the linear relationship of all observations between r_t and r_{t-i} is called the partial autocorrelation function (PACF). Thus, the PACF shows the added contribution of r_{t-i} to predicting r_t.

Independency in time series has often been thought to be identical with the autocorrelation, however, this is not exactly the truth. Autocorrelation only gives information about the first moments and only measures the linear dependence. Anyway, it is quite common in the preliminary analysis to estimate autocorrelation and partial autocorrelation coefficients directly from the data. Often this indicates which model might be appropriate. One way of testing for correlation is the Ljung-Box independence test and the Q statistic is given by:

(7-12) $$Q_{LB} = T(T+2)\sum_{J=1}^{p}\left(\frac{r_j^2}{T-j}\right)$$

where r_j is j-th autocorrelation and T is the number of observations. The Q statistic at lag k is a test statistic for the null-hypothesis of no autocorrelation up to order k. Typically it is said that autocorrelation of stock return series have small positive values and rarely above first order *(Tsay, 2002).*

7.3.3.1.1.1.3 Heteroscedasticity

The condition of homoscedasticity refers to constant variance and is one of the crucial assumptions in the classic linear regression model. If this assumption is not satisfied the data suffers from heteroscedasticity. There are a numerous ways of testing for heteroscedasticity. The test used in this thesis is the Lagrange multiplier test for autoregressive conditional heteroscedasticity in the residuals (ARCH LM test). The ARCH LM test was proposed by Engle *(1982)* and its specification of the heteroscedasticity was originally motivated by the observed behavior of the residuals in financial time series. The magnitude of the residuals seems to be related to the magnitude of the recent residuals. The ARCH LM statistics are computed from an auxiliary regression and tests the null hypothesis of no ARCH effects up to order q in residuals.

7.3.3.1.1.2 Linear Time Series Models

In the following both stationary as well as non-stationary linear time series will be presented.

7.3.3.1.1.2.1 Autoregressive models

A regression model in which r_t is predicted using past values, r_{t-1}, r_{t-2} …is called an Autoregressive model (AR). This model has been shown to be useful in modeling return series and have the following appearance:

(7-13) $AR(p)$ $$r_t = \phi_0 + \phi_1 r_{t-1} + ... + \phi_p r_{t-p} + a_t ,$$

(7-14) $AR(1)$ $$r_t = \phi_0 + \phi_1 r_{t-1} + a_t$$

where a_t is a white noise series with zero mean and constant variance. Weak stationary is a sufficient but also necessary condition of an AR model and is obtained if all the characteristic roots are less than one. For an AR (1) model it means that $|\phi_1| < 1$.

A method for identifying an AR process and its given order is to observe the autocorrelation (ACF) and the partial autocorrelation (PACF). For an AR (1) process the ACF should exponentially decay with the rate ϕ_1 and starting value $\rho_0 = 1$. Even though, the ACF of an AR process has the characteristic exponentially declining shape it is often of little use in distinguishing AR processes of different orders. The PACF, on the other hand, is more helpful. It can easily be shown that for an AR (1) the PACF cuts off after lag one and for an AR (2) the PACF will cut off after lag two etc. *(Tsay, 2002)*.

7.3.3.1.1.2.2 Moving Average model

Another suitable model for modeling return series is the moving average model (MA)[16]. The model can be represented in two ways: either the model can be treated as a simple extension of white noise series or it can be treated as an infinitive order AR model. The last approach is adopted. Recall the $AR(\infty)$:

(7-15) $$r_t = \phi_0 + \phi_1 r_{t-1} + ... + \phi_p r_{t-p} + a_t$$

This model consists of an infinite numbers of parameters and therefore it is not realistic. However, by adopting some constraints on the parameters the model can be determined by a finite number of parameters. A special case of this idea is:

(7-16) $$r_t = \phi_0 - \theta_1 r_{t-1} - \theta_1^2 r_{t-2} - \theta_1^3 r_{t-3} ..... + a_t$$

Note the coefficients depend on a single parameter θ_1. Through some simple mathematical operations the above expression can be transformed to the general form of the MA process:

(7-17) $MA(q)$ $$r_t = c_0 + a_t - \theta_1 a_{t-1} - ..... \phi_q a_{t-q} \qquad q > 0,$$

(7-18) $MA(1)$ $$r_t = c_0 + a_t - \theta_1 a_{t-1}$$

where c_0 is a constant and a_t is a white noise series. The MA model is always weakly stationary since it consists of infinite linear combinations of a white noise sequence for which the two first moments are time-invariant *(Tsay, 2002).*

Examining the ACF and PACF can also identify MA processes. In fact the correlation patterns compared to the AR process is reversed. Hence, it is now the PACF that damps out and the ACF's cut off that determines the order.

7.3.3.1.1.2.3 ARMA Models

In some applications, the orders of the AR and MA may have to be high to capture the dynamic structure of the data. Thus, many parameters have to be estimated

[16] The Moving Average model in this section does not have any connection to the moving average trading rules described in chapter 2 and section 6.5.

which may lead to perplexity and increase the risk for over fitting. To overcome these problems the autoregressive moving average model (ARMA) was introduced. Basically, the ARMA model combines the features of the AR and MA models so that the numbers of parameters used is kept small. A time series follows an ARMA process if it satisfies:

(7-19) $$ARMA(p,q)\ \ r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i}$$

(7-20) $$ARMA(1,1)\ \ \ r_r = \phi_0 + \phi_1 r_{t-1} - \theta_1 a_{t-1} + a_t$$

The series r_t is a function of past values plus current and past values of the error term (noise). Again a_t is a white noise series. The parameter ϕ_0 is the constant and $\phi_1 r_{t-1}$ and $\theta_1 a_{t-1}$ represent the AR and MA term, respectively. For the model to be meaningful, $\phi_1 \neq \theta_1$; Otherwise, they cancel out each other, reducing the process to a white noise series. The properties of the ARMA (1,1) are very similar to those of the AR (1) model with only some minor modifications. Thus, the condition of stationarity is still $|\phi_1| < 1$. The fact that the ARMA model is a combination of the AR and MA model is clearly visualized in the ACF and PACF structure. While the ACF structure in the ARMA (1,1) model is very similar to the ACF in the AR (1) model, whereas the PACF structure is very similar to the PACF in the MA (1) model. However, in both cases the correlations exponentially decay starting at lag 2 instead of lag 1. *(Tsay, 2002).*

7.3.3.1.1.2.4 Random Walk Models

As indicated above, stationarity in time series is an important concept. However, in some applications like interest rates, foreign exchange rates or price series the process tend to be non-stationary. A non-stationary series is in the time series literature known as a unit root non-stationary series and the best-known example is the random walk model. A process follows a random walk if:

(7-21) *Random Walk* $$p_t = p_{t-1} + a_t$$

or:

(7-22) *Random Walk with Drift* $$p_t = \mu + p_{t-1} + a_t,$$

where p_0 denotes the starting value and a_t is a white noise series. The μ term is the drift and is sometimes referred to as the time trend. A positive drift is called a sub-martingale, whereas a negative drift is named a super-martingale. If the drift is zero you have a normal random walk like (7-21).

Recall that for the AR (1) model $|\phi_1| < 1$satisfies the weak stationary condition. However, if $|\phi_1| = 1$ then the AR (1) becomes a random walk, hence the name unit root. The non-stationarity of the random walk model implies that the series has a strong memory because it remembers all past shocks. Hence, past shocks do not decay over time and therefore have a permanent effect on the series. Non-stationarity is therefore also observable in the ACF and PACF, however a much more plausible method for detecting a random walk model can be applied. Dickey & Fuller derived the unit-root test in 1979, which in all its simplicity involves testing the null hypothesis H_0: $|\phi_1| = 1$ against the alternative hypothesis H_1: $|\phi_1| < 1$. By maintaining H_0 it cannot be rejected that the process has a unit root and hence, it cannot be rejected that it follows a random walk. *(Tsay, 2002).*

7.3.3.1.1.2.5 ARIMA models

When an ARMA model is allowed to have a unit root then the model becomes an autoregressive integrated moving-average (ARIMA). Like the random walk, the ARIMA model has strong memory because the coefficient in its MA representation does not decay towards zero. Hence, it is implying that past shocks a_{t-i} has a permanent effect on the series *(Tsay, 2002)*.

7.3.3.1.1.2.6 Information Criteria and Model Checking

Often, it can be difficult to determine the exact model by just observing the ACF and PACF patterns. Sometimes there exist no clear cut off and neither the ACF nor the PACF damps out. In such cases an alternative approach, based on Bayesian theory can be adopted. The basic idea behind a Bayesian approach is to acknowledge that there are many possible models to explain any time series. The data series is treated as one particular realization of a random process and the models are treated as random variables. The concept is then to seek the answer to the question of which model has most likely generated the data. In other words: Given the data, which model has the highest probability of having generated the data? In practice, this is done by calculating the information criteria from a number of estimated models and picking the model with the lowest value. There are several well-known information criteria. Perhaps the two most famous are Schwartz's Bayesian Information Criterion (SC, BIC or SBC) and Akaike's Information Criterion (AIC). Both criteria are likelihood based and represent different types of trade-off between 'fit', as measured by the log likelihood value, and 'parsimony', as measured by the number of free parameters ($p+q$). In this thesis the SBC is preferred because it has superior ability to select the right model for low numbers of p and q of the true ARMA model and empirically stock returns are considered to only have lag in first order *(Verbeek, 2000)*.

Even though the SBC enables one to pick the best alternative of different models, the SBC does not guarantee that the model is adequate. For a fitted model to be adequate the residual series should behave as white noise. The ACF and Ljung-box statistic can be used to check the closeness of $\hat{a}_t$ to white noise. If the model is correctly specified then $Q(m)$ follows an asymptotically chi-squared distribution with $m-g$ degrees of freedom, where g denotes the number of parameters used in the model. If the residual series of the fitted model does not behave as white noise then the model has to be refined.

7.3.3.1.1.3 Conditional Heteroscedastic Models

As stated earlier, autocorrelation is not synonymous with dependency. The autocorrelation only gives information about the linear dependency and only involve the first moments. The fact is that in financial time series it is often observed what is referred to as volatility clustering, where big shocks are followed by big shocks and small shocks are followed by small shocks. The stock market is typically characterized by periods of high volatility and more quit periods of low volatility. One way of handling this behavior is to allow the variance of ε_t to depend upon its history. One of the first to do so was Engle *(1982)* by proposing the concept of autoregressive conditional heteroscedasticity (ARCH). The ARCH model allows the variance of the error term at time t to depend upon the squared error terms from previous periods. The ARCH (q) can be written as follows:

(7-23) $$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad ,$$

where the unconditional variance is given by:

(7-24) $$\sigma = \frac{\omega}{1 - \sum_{i=1}^{q} \alpha_i}$$

To ensure that the conditional variance, $\sigma_t^2 \geq 0$, both ω and α_i must be non-negative. Furthermore, it is required that α_i is less than one for the process to be stationary. By imposing non-negativity, large volatility at time $t-i$ will lead to large variance at time t and thereby increase the probability for large volatility at time t. Hence, the volatility clustering characterizing the stock market is taken into account. However, critics of the ARCH (q) model states that the number of lags q often needs to be very large to catch the dynamic of the conditional variance, thus many parameters have to be estimated. To overcome this, a generalized ARCH model was proposed.

7.3.3.1.1.3.1 GARCH Model

The generalized ARCH or GARCH (q, p) model was proposed by Bollerslev *(1986)* and can be written as:

(7-25) $$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j \sigma_{t-j}^2$$

The advantage compared to the ARCH (q) is the need for fewer lags. Often a GARCH (1,1) is sufficient and actually a GARCH (1,1) can be written as an ARCH (∞):

(7-26) $$\sigma_t^2 = \frac{\omega}{1-\beta} + \sum_{i=1}^{\infty} \alpha\beta^{i-1} \varepsilon_{t-1}^2$$

Thus, the GARCH specification may provide a parsimonious alternative to a higher order ARCH process. Here, only three parameters need to be estimated ω, α and β. For non-negative in σ_t^2 all parameters have to be ≥ 0. The unconditional variance for the GARCH (1,1) can be written as:

(7-27) $$\sigma^2 = \frac{\omega}{1 - \alpha - \beta}$$

Stationarity requires that $\alpha + \beta \leq 1$. Values close to one imply high persistence in the volatility and a value of one means that σ^2 cannot be defined and the model can be considered as an IGARCH (1,1) model. The fine properties of the GARCH model makes is possible to catch volatility clustering characterized in the stock market. The volatility clustering has the same characteristics as the winner's curse anomaly discussed earlier in this thesis. Recall, that the winner's curse describes a mean reversion in the stock market. A large increase in stock price was followed by a decrease and vice versa. Although winner's curse does not specifically mention volatility there is an obvious link. Recall that mean reversion additionally was identified as being asymmetrical where large drops followed by an increase were considerably more significant than the opposite case due to overreaction on bad news. The GARCH model does not capture the asymmetric feature, but it shows that other models have this ability.

7.3.3.1.1.3.2 Exponential GARCH

Empirical observation has stated that changes in volatility are negatively correlated with return. This is known as the leverage effect *(Black, 1976)*. Bad news (drop in prices) has a larger impact on future volatility compared to the effect of good news. Asymmetric models like the threshold ARCH/GARCH (TARCH), the GJR model and the Exponential GARCH (EGARCH) capture behavior like this. Next, the EGARCH model will be introduced while the TARCH and GJR model will not be elaborated. The EGARCH model is given by:

(7-28) $$\log \sigma_t^2 = \omega + \beta \log \sigma_{t-1}^2 + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}, \quad |\beta| < 1$$

Notice that the logarithmic transformation has two implications: Firstly, no restrictions on the parameters are required to ensure the conditional variance to be non-negative and secondly, the leverage effect is exponential rather than quadratic. Stationarity is ensured as long as $|\beta| < 1$. This is furthermore, a sufficient condition for the QMLE to be consistent and asymptotic normal *(Shephard, 1996)*. The parameters α and γ represent the size and sign effect of the conditional shocks, respectively, on the conditional variance. The EGARCH model is asymmetric as long as $\gamma \neq 0$ and the leverage effect is present if $\gamma < 0$.

7.3.3.1.1.3.3 Estimation of GARCH process

Before leaving the GARCH subject, a short description of the estimation procedures will be in order. A GARCH (1,1) will be used as an example:

(7-29) $$y_t = \mu + \sigma_t z_t = \mu + \varepsilon_t$$

(7-30) $$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Because σ_t^2 is not observable it is not possible to use linear regression, instead it is necessary to use maximum likelihood estimation (MLE). MLE assume $z_t \sim N(0,1)$ and it is well known in linear regression that for normality OLS = MLE and that OLS is unbiased and consistent despite that MLE's assumptions of the distribution are wrong. For the GARCH model it can be shown that MLE for the parameters μ, ω, α and β are consistent even though z_t is not normally distributed, however, this does require that the conditional variance σ_t^2 is correctly specified. This type of estimation is called quasi MLE (QMLE). In general, when estimating GARCH model z_t is assumed to be normally distributed, but no rule without exception. Often the distribution of z_t is not gaussian but suffers from excess kurtosis, which indicate that a student-t distribution is more suitable. The advantage of a student t distribution is that it captures the fat tail of the residuals caused by excess kurtosis. The disadvantage is that if the residuals do not follow a student-t distribution MLE becomes inconsistent.

7.3.3.1.1.3.4 Information Criteria and Model Checking

The SBC can also be applied on the conditional heteroscedastic models above. However, to control whether the fitted model is adequate the ARCH LM test is preferred.

7.3.3.1.2 Model Estimation and Selection of Linear Models

From the unit root test performed in the preliminary analysis it was stated that the series did not have a unit root and hence, it can be concluded that the series does not follow a random walk. Thus, to find a suitable model the ACF and PACF must be examined again.

Table 7.7 Autocorrelation and Partial Autocorrelation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.168	0.168	140.63	0.000
		2	0.050	0.022	152.92	0.000
		3	0.041	0.030	161.28	0.000
		4	0.036	0.024	167.54	0.000
		5	0.068	0.058	190.21	0.000
		6	0.025	0.002	193.30	0.000
		7	0.021	0.011	195.39	0.000
		8	0.010	-0.000	195.85	0.000
		9	-0.001	-0.007	195.86	0.000
		10	0.015	0.012	197.04	0.000

Clearly both ACF and PACF cut off after lag 1 indicating that a first order series is appropriate. However, neither ACF nor PACF clearly damps out so it is difficult to distinguish between an AR (1) and MA (1) model. One trend though seems to be consistent: The first order serial correlation coefficient is positive and significant, while the correlations at higher lags are considerably closer to zero. It is therefore decided to estimate an AR (1), MA (1) and ARMA (1,1) model and compare the fit of these through the Schwartz's Bayesian Information Criterion. Furthermore, the ARMA (2,2) will be included in the table below just for comparison.

Table 7.8 Schwartz Bayesian Information Criterion for ARMA Models[17]

	AR (1)	MA (1)	ARMA (1,1)	ARMA (2,2)
Value Portfolio	2.2792*	2.2815*	2.2801*	2.2798

** Indicates that all parameters in the model are significant at the 5% level.*

In table 7.8 it can be seen that the AR (1) generates the lowest SBC score and thereby indicates that this is the model with the best fit. Not surprisingly the ARMA (2,2) has insignificant parameters confirming what the correlation patterns previously indicated. The fitted AR (1) model has the following appearance:

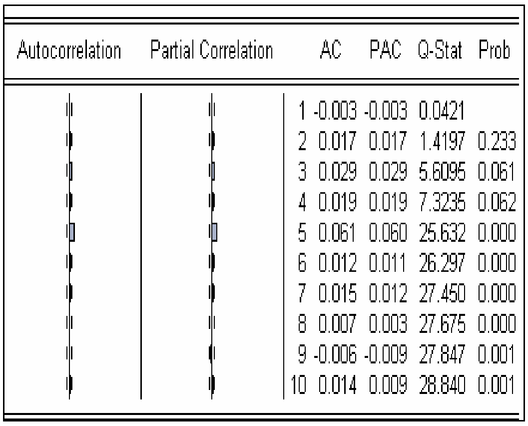
(7-31) $$R_t = 0.04946 + 0.1678 R_{t-1}$$

[17] The estimation output for all the relevant linear time series models are enclosed in appendix 5.

The unconditional mean of the fitted AR (1) model equals $\frac{0.04946}{(1-0.1678)} = 0.05943$, which is a bit larger than sample mean of 0.049021, indicating that the model might be misspecified. By modeling the first order serial correlation the linear dependency in the data is taken into account, but perhaps some kind of non-linear effect is present in the residuals. To check whether the model is adequate an intensive investigation of the residuals will be conformed.

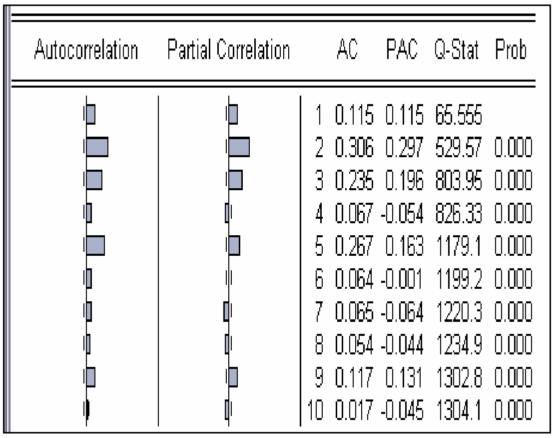
Figure 7.3 Residual Investigations

Panel A: Correlogram Residuals



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.003	-0.003	0.0421	
		2	0.017	0.017	1.4197	0.233
		3	0.029	0.029	5.6095	0.061
		4	0.019	0.019	7.3235	0.062
		5	0.061	0.060	25.632	0.000
		6	0.012	0.011	26.297	0.000
		7	0.015	0.012	27.450	0.000
		8	0.007	0.003	27.675	0.000
		9	-0.006	-0.009	27.847	0.001
		10	0.014	0.009	28.840	0.001

Panel B: Correlogram Squared Residuals



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.115	0.115	65.555	
		2	0.306	0.297	529.57	0.000
		3	0.235	0.196	803.95	0.000
		4	0.067	-0.054	826.33	0.000
		5	0.267	0.163	1179.1	0.000
		6	0.064	-0.001	1199.2	0.000
		7	0.065	-0.064	1220.3	0.000
		8	0.054	-0.044	1234.9	0.000
		9	0.117	0.131	1302.8	0.000
		10	0.017	-0.045	1304.1	0.000

Panel E: ARCH LM Test

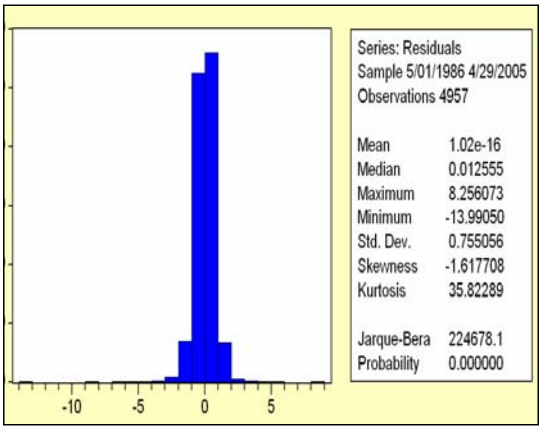
ARCH Test:

F-statistic	156.9983	Probability	0.000000
Obs*R-squared	792.3545	Probability	0.000000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/05/06 Time: 14:41
Sample (adjusted): 5/09/1986 4/29/2005
Included observations: 4951 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.252369	0.045755	5.515677	0.0000
RESID^2(-1)	0.042264	0.014222	2.971698	0.0030
RESID^2(-2)	0.263622	0.014045	18.76995	0.0000
RESID^2(-3)	0.149096	0.014513	10.27350	0.0000
RESID^2(-4)	-0.058987	0.014513	-4.064510	0.0000
RESID^2(-5)	0.163136	0.014045	11.61504	0.0000
RESID^2(-6)	-0.000919	0.014223	-0.064597	0.9485

Panel D: Descriptive Statistics



Panel A displays the autocorrelation function for the residuals from the estimated AR (1) model. From the panel it appears that the residuals are white noise, suggesting that the right linear model has been found. However, the fifth lag is slightly positive and significant, but because of the small magnitude no further action will be taken[18]. Panel B displays the autocorrelation for the squared residuals. Notice that no serial correlation is rejected and especially the first five lags seem important. This is additionally confirmed by the ARCH LM test shown in panel C, where the null hypothesis of no ARCH effects of the first five lags is rejected. It is obvious that the AR (1) model only captures the linear dependency so a conditional heteroscedastic model of some order is needed. Finally, it can be seen in panel D that the residuals are still not normally distributed but instead they suffer from excess kurtosis.

7.3.3.1.3 Model Estimation and Selection of GARCH Models

In the previous section it was concluded, that the AR (1) model did not have the sufficient complexity to capture the volatility behavior of the return series. However, this does not come as a surprise having figure 7.2 in mind. Figure 7.2 clearly indicated heteroscedasticity as well as volatility clustering in the return series. A model fit for this kind of behavior is the GARCH model. Before determining which order of the ARCH or GARCH model that fits the data best a few estimation issues have to be addressed. Recall that the residuals from before suffer from excess kurtosis and hence, are not normal distributed. On that behalf it seems reasonable to discuss whether the conditional heteroscedastic models should be estimated under the assumptions that the standardized residuals z_t are student-t distributed rather than normally distributed. However, the safe choice is to assume normality and adjust for non-normality by using Bollerslev and Wooldridge Robust standard errors[19]. In this way, the parameter estimates will still be consistent even though the residuals are not conditionally normal distributed. However, it requires that the model is correctly specified. The safe choice is chosen.

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[18] Heteroscedasticity in the data can cause minor disturbances in the correlation patterns.

[19] EViews only allows too compute the robust Bollerslev-Wooldridge standard errors if the error-term is assumed normal distributed.

To capture the first order autocorrelation all GARCH models will be estimated simultaneously with the AR (1) model. The models are estimated using maximum likelihood and again the SBC will be used as selection criteria.

Table 7.9 Schwarz Bayesian Information Criteria for GARCH Models[20]

	ARCH (6)	GARCH (1,1)	GARCH (1,2)	GARCH (2,1)
Value Portfolio	2.04127*	2.02673*	2.02637	2.02542

** Indicates that all parameters in the model is significant at the 5% level*

From table 7.9 it is worth noticing that the GARCH (1,2) and the GARCH (2,1) contains insignificant parameters in the variance specification. Thus, the actual choice is only between the ARCH and the GARCH (1,1) models. The optimal ARCH model has the order of 6 but as mentioned earlier a GARCH (1,1) reconcile with an ARCH (∞). Hence, not surprisingly, the GARCH (1,1) describe the data best. The joint estimation of the AR (1)-GARCH (1,1) from table 7.9 gives the following specification:

(7-32) $$r_t = 0.078107 + 0.159934 r_{t-1} + \varepsilon_t$$

(7-33) $$\sigma_t^2 = 0.021004 + 0.8584546\sigma_{t-1}^2 + 0.104571\varepsilon_{t-1}^2$$

Note, that all parameters are non-negative ensuring that the conditional variance $\sigma_t^2 > 0$. From the fitted model above the sum of the ARCH and GARCH coefficients $(\hat{\alpha} + \hat{\beta})$ (0.104571+0.858454 = 0.963025), is very close to one, indicating that the volatility shocks are very persistent. This leads to imposing the constraint $\hat{\alpha} + \hat{\beta} = 1$. This is known as an integrated GARCH model (IGARCH) *(Tsay, 2002)*. But before considering any variant of the GARCH model, it should be investigated whether the obtained AR (1)-GARCH (1,1) model is adequate. This is obtained by checking whether there are any ARCH effects left in the residuals (standardized residuals).

[20] The estimation output for all relevant GARCH models can be seen in appendix 6.

Table 7.10 ARCH LM Test for AR (1)-GARCH (1,1)

F-statistic	0.778024	Probability	0.565393
Obs*R-squared	3.891.777	Probability	0.565100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.962631	0.051401	1.872.795	0.0000
STD_RESID^2(-1)	0.023188	0.014219	1.630.758	0.1030
STD_RESID^2(-2)	0.005678	0.014223	0.399230	0.6897
STD_RESID^2(-3)	0.013780	0.014221	0.968978	0.3326
STD_RESID^2(-4)	-0.003926	0.014222	-0.276017	0.7825
STD_RESID^2(-5)	-0.001430	0.014218	-0.100544	0.9199

Above the ARCH LM Test output is displayed. The table shows that the null hypothesis of no remaining ARCH effects cannot be rejected, indicating that the model is adequate. It seems that the properties of the GARCH model have captured the volatility clustering. However, the GARCH model does not have asymmetric properties and hence, the model is not able to capture the leverage effect. For this reason, it must be examined whether there are variants of the GARCH model that have a better fit.

7.3.3.1.3.1 The EGARCH Model

Although many special additions of the GARCH model, like the IGARCH and GARCH-in-mean, could be of interest it is chosen to omit these models due to the limitation of this thesis. Instead, the focus will be put on the EGARCH model, due to its asymmetric attributes. Alternative asymmetric models like the TARCH and GRJ model will also be omitted.

As before, the optimal order of the EGARCH model has to be found and once more the models will be estimated simultaneously with the AR (1) model and SBC will still be used as selection criteria. The distribution of the residuals is assumed normal distributed rather than student-t or GED.

Table 7.11 Schwarz Bayesian Information Criteria for EGARCH Models[21]

	EGARCH (1,1)	EGARCH (1,2)	EGARCH (2,1)	EGARCH (2,2)
Value Portfolio	2.01094*	2.01075	2.01220	2.01237

** Indicates that all parameters in the model are significant at the 5% level*

From the table above it seems that the EGARCH (1,2) model has the best fit. However, the t-ratio of the parameters in the variance equation suggests that the second order ARCH term is insignificant. The only model significant in all parameters is the EGARCH (1,1) model, and thus, the choice is clear. The estimated AR (1)-EGARCH (1,1) model is:

(7-34) $$r_t = 0.05943 + 0.169448 r_{t-1} + \varepsilon_t$$

(7-35) $$Log(\sigma_t^2) = -0.159636 + 0.167274 \times \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| \right) - 0.0918578 \times \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) + 0.95789 \times \left(\log(\sigma_{t-1}^2) \right)$$

[21] The estimation output for all relevant EGARCH models can be seen in appendix 7.

The left hand side of the variance equation is the logarithmic value of the conditional variance and implies that the leverage effect is exponential rather than quadratic and at the same time provides that the conditional variance becomes non-negative. Note, that from the fitted model above the parameter $\gamma = -0.0918578 < 0$ stating that the leverage effect is present. As expected, the size effect, $\alpha = 0.167274$, has a positive impact on the conditional variance and notice that $|\alpha| > |\gamma|$ indicating that the sign effect has larger impact than the size effect. Finally, the parameter $\beta = 0.95789 < 1$ fulfills the condition of stationarity indicating that it is likely that the QMLE is consistent and asymptotic normal. However, before settling the ARCH LM test is conformed.

Table 7.12 ARCH LM Test for AR (1)-EGARCH (1,1)

F-statistic	0.803952	Probability	0.546634
Obs*R-squared	4.021.368	Probability	0.546344

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.947438	0.050191	1.887.671	0.0000
STD_RESID^2(-1)	0.020320	0.028017	0.725271	0.4683
STD_RESID^2(-2)	0.008402	0.010655	0.788530	0.4304
STD_RESID^2(-3)	0.016155	0.011695	1.381.303	0.1672
STD_RESID^2(-4)	0.001329	0.008770	0.151510	0.8796
STD_RESID^2(-5)	0.006354	0.011054	0.574801	0.5655

In the upper part of table 7.12 the probability for ARCH effects up to lag 5 is presented. The conclusion is clear; the presence of ARCH effects in the residuals is rejected and the model seems adequate.

7.3.3.1.4 Selecting Null Models

After estimation and comparing of various models with different properties it is now time to pick which models that will serve as null models. Four models have been selected. The first model is surprisingly the Random Walk with Drift. Obviously, it is not because it fits the data but due its unpredictable element. The second is the best of the linear model, the AR (1) model. Although it did not pass the residual investigation it still qualifies as a null model due to the first order serial correlation observed in the return. The two last models are the AR (1)-GARCH (1,1) model and the AR (1)-EGARCH model, which differentiate themselves from besides being adequate also being able to capture the volatility clustering and leverage effect respectively. All four models have previously in the financial literature been linked to the behavior of stock returns. The estimated parameters for all the null models are summarized in the table below.

Table 7.13 Estimation results

Panel A:	Random Walk with Drift		
μ : 0.049021			
Panel B:	AR (1)		
ϕ_0 : 0.049457	ϕ_1 : 0.167809		
Panel C:	AR (1)-GARCH(1,1)		
ϕ_0 : 0.078107	ϕ_1 : 0.159934		
ω : 0.021003	α : 0.104571	β : 0.858454	
Panel D:	AR (1)-EGARCH(1,1)		
ϕ_0 : 0.059430	ϕ_1 : 0.169448		
ω : -0.159636	α : 0.167274	γ : -0.091858	β : 0.957894

The parameters in table 7.13 will together with the scrambled residuals be the only input variables for creation of the return series. Next section will elaborate on how the resampled residual series is obtained.

7.3.3.2 Resampling of Residuals/Standardized Residuals

The residual series from the null models are obtained from EViews. Each residual series, the ordinary residuals from the AR model and the standardized residuals from the GARCH and EGARCH models, are resampled with replacement to obtain a new scrambled series. This procedure is repeated 500 times with the use of the Excel add-in version 3.2 program from Resampling Stats Inc[22]. The number of bootstrap simulations are set to 500 as has been found sufficient in earlier studies *(see e.g. BLL, 1992)*.

7.3.3.3 Creation of Return Series

The first model to be considered is the Random Walk with Drift and is by far the simplest model to bootstrap. It is simply done by randomly drawing with replacement the returns from the original portfolio and through this procedure new return series are created. The new simulated series will then have the same drift, volatility and unconditional distribution as the original does.

The second specification considered is the AR (1) model:

(7-36) $$r_t = \phi_0 + \phi_1 r_{t-1} + \varepsilon_t\,, \qquad |\phi_t| < 1$$

The basic bootstrap procedure is to resample the residuals ε_t with replacement and recursive create new return series. However, to get the bootstrap process started, it is necessary to find an initial value for r_t which is done by finding initial values for $a_1 r_{t-1}$ and ε_t. The initial values are set to the unconditional values which for the $a_1 r_{t-1}$ is $\frac{\phi_0}{(1-\phi_1)} = \frac{0.049457}{1-0.167809} = 0.05943$ and for the ε_t is zero. After this, it is easy to create the new return series by using the scrambled residuals and recursive create one return after another until an entire return series of 4958 observations is made. The procedure can be written as:

(7-37) $$r_1 = 0.049457 + 0.167809 \times 0.05943 + 0$$

$$r_2 = 0.049457 + 0.167809 \times r_1 + \varepsilon_2^*$$

[22] The resample add-in program can be downloaded at Resamplestats Inc.'s homepage www.resample.com

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$$r_{4958} = 0.049457 + 0.167809 \times r_{4957} + \varepsilon^{*}_{4958}$$

This procedure is carried through 500 times with a different residuals series each time.

The third model in question is the AR (1)-GARCH (1,1) model. The model can be divided into two equations: a mean equation and a variance equation:

(7-38) *Mean equation:* $r_t = \phi_0 + \phi_1 r_{t-1} + \varepsilon_t, \quad |\phi_t| < 1$

(7-39) *Variance equation* $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ *where,* $\varepsilon_t = \sigma_t^{½} Z_t$

The bootstrap procedure is slightly different compared to the AR (1) model. Firstly, it requires calculation of the variance equation, before dealing with the mean equation. The results from the variance series are used in the mean equation and the same recursive procedure as in (7-37) are then applied to finally arrive at the return series. Secondly, the resampling algorithm is now applied to the standardized residuals. This is done to maintain the heteroscedastic structure in the simulations. The unconditional mean and unconditional variance will be used as initial values to start the process.

The last model up for bootstrapping is the AR (1)-EGARCH model:

(7-40) *Mean equation:* $r_t = \phi_0 + \phi_1 r_{t-1} + \varepsilon_t, \quad |\phi_t| < 1$

(7-41) *Variance equation:* $Log(\sigma_t^2) = \omega_0 + \alpha_1 \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| \right) + \alpha_2 \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) + \beta_1 \left(\log(\sigma_{t-1}^2) \right)$

where $z_t = \varepsilon_t / \sigma_t$

Once again, the standardized residuals z_t are resampled and together with the estimated parameters used to generate simulated EGARCH series.

7.3.3.4 Creation of Price and Moving Average Series

After the return series are constructed the next step is to convert the return series into an artificial price index. This is necessary because technical analysis is applied on prices and not returns. Using the following formula the transformation from a return series to a price index is performed:

(7-42) $$P_t = \exp(r_t / 100) \times P_{t-1}$$

where P_t is the price index at time t and r_t is the simulated return at time t (log return). Because it is converted to an index, P_0 is set to 100. Recall, that in the original price series the portfolios were rebalanced every year. This cannot be done in the artificial price series. Thus, a small and insignificant difference between the original portfolio and the artificial price series must be accepted. After the price series are obtained it is now possible to compute the moving averages. Again, a small bias compared to original portfolio occurs. In the original portfolio the moving averages are already available at time P_0 because the price series are available prior to the day of rebalancing. This is not the case with the bootstrapped series and the consequence is that at the beginning of every moving average series the moving average is 'not available'. Hence, for a 20 day moving average the first 19 observation is 'not available' (N/A). The missing observation is replaced with 10.000 to be sure that the technical trading rule formula (how the formula works will be elaborated in next step) generates the risk free rate of interest.

7.3.3.5 Technical Analysis

Now all is set to perform the technical analysis. When conducting technical analysis on 8 trading rules containing 500 series each it is necessary to find a formula that can easily be repeated/copied through various spreadsheets. The essence of the formula for the trading rules without band is straight forward and looks as follows:

(7-43) $$(P_{t-1} > MA_{t-1}) \Rightarrow r_t$$

(7-44) $$(P_{t-1} \leq MA_{t-1}) \Rightarrow rf_t$$

The concept is: If the price yesterday exceeds the moving average yesterday then the return today is generated (buy day). If not, the risk free rate of today is generated (sell day). In contrast the trading rules with band are more complex:

(7-45) $$(P_{t-1} > MA^{+}_{t-1}) \Rightarrow r_t$$

(7-46) $$(P_{t-1} \leq MA^{-}_{t-1}) \Rightarrow rf_t$$

(7-47) $(TA_{t-1} = r_{t-1}) \Rightarrow r_t$

(7-48) $(TA_{t-1} \neq r_{t-1}) \Rightarrow rf_t$

If the price yesterday exceeds yesterday's moving average upper band then the return today is generated. However, if yesterday's price was below the moving average lower band then the risk free rate is generated. This leaves a gap between the two bands and is handled by the last two constraints. Hence, the last two constraints (7-47 and 7-48) are only valid if the first two constrains are false. If yesterday was identified as a buy day then today should also be identified as a buy day and vice versa. Hence, a buy day can only be followed by a sell day if constraint 2 is fulfilled and a sell day can only be followed by a buy day if constraint 1 is fulfilled.

7.3.3.6 Calculation of Mean, Standard Deviation and Fraction

Last step in the bootstrap procedure is to calculate the mean return and standard deviation for each simulation. These results are then calculated as the fraction of how many of the 500 simulated series exceed the results obtained from the original series[23]. The fraction can be interpreted as p-values. The mean fraction have to exceed 0.95 before it statistically can be concluded that the null model can generate a higher mean return than the original series. The standard deviation fraction is, however, turned around. Thus, the fraction has to be below 0.05 before it can be concluded that the null model can generate a standard deviation lower than the original series. The results are presented in table 7.14 in next section.

7.3.4 Bootstrap Results

The results from the bootstrap simulation are presented in table 7.14. The first column indicates the trading rule in question. The second states which null model is used and finally, the last two columns report the results for the mean return and standard deviation respectively.

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[23] In appendix 4 the fraction is calculated from the cumulative return instead of average mean return. This of course provides the same results, as the number of observations is the same in the simulated series and in the original series.

Table 7.14 Bootstrap Results

Trading Rule	Null Model	Mean	Std. Dev
1-10-0	Random Walk	0.000	1.000
	AR(1)	0.184	1.000
	AR(1)-GARCH(1,1)	0.158	0.990
	AR(1)-EGARCH(1,1)	0.296	0.954
1-20-0	Random Walk	0.000	1.000
	AR(1)	0.084	1.000
	AR(1)-GARCH(1,1)	0.094	0.992
	AR(1)-EGARCH(1,1)	0.148	0.980
1-30-0	Random Walk	0.000	1.000
	AR(1)	0.072	1.000
	AR(1)-GARCH(1,1)	0.088	0.990
	AR(1)-EGARCH(1,1)	0.130	0.984
1-50-0	Random Walk	0.000	1.000
	AR(1)	0.060	1.000
	AR(1)-GARCH(1,1)	0.078	0.990
	AR(1)-EGARCH(1,1)	0.124	0.980
1-10-1	Random Walk	0.000	1.000
	AR(1)	0.142	1.000
	AR(1)-GARCH(1,1)	0.180	0.994
	AR(1)-EGARCH(1,1)	0.234	0.992
1-20-1	Random Walk	0.000	1.000
	AR(1)	0.086	1.000
	AR(1)-GARCH(1,1)	0.096	0.990
	AR(1)-EGARCH(1,1)	0.154	0.992
1-30-1	Random Walk	0.000	1.000
	AR(1)	0.048	1.000
	AR(1)-GARCH(1,1)	0.060	0.984
	AR(1)-EGARCH(1,1)	0.098	0.986
1-50-1	Random Walk	0.000	1.000
	AR(1)	0.124	1.000
	AR(1)-GARCH(1,1)	0.144	0.992
	AR(1)-EGARCH(1,1)	0.218	0.984

In the first line the results for the 1-10-0 trading rule with the Random Walk with Drift as null model is displayed. From the mean column it can be seen that 0% of the simulations generated by the Random Walk with Drift yields an average return higher than the average return of the original series. This implies that the results from the original series cannot be explained by the fact that the series follow a random walk. In the Std. Dev column it can be seen that 100 % of the standard deviations generated by the Random Walk with Drift are greater than the standard deviation for the original series. Hence, the Random Walk with Drift model cannot explain the low level of volatility observed in the original series. The same picture repeats itself through out the rest of the trading rules. Again, the Random Walk with Drift can neither explain the level of the mean or the standard deviation of returns observed in the original series.

By taking into account the first order serial correlation in the AR (1) model the bootstrap simulations actually generate a higher level of means compared to the Random Walk with Drift, but not surprisingly the results for the standard deviation stay unchanged. Still, the conclusion is the same; the AR (1) model can neither explain the level of mean or standard deviation of returns in the original series.

The GARCH model generates a slightly higher mean than the AR model, but it is noticeable that the GARCH model can actually generate standard deviations that are lower than the original series, even though it is only a few. This suggests that the GARCH model's ability to capture the volatility clustering has an impact on both the mean and standard deviation.

Turning to the EGARCH model it is clear that it is superior regarding both the average mean and standard deviation. It suggests that the leverage effect is present which means that negative shocks are more effective. Despite its superiority the EGARCH model is not even close to generate high enough values to be statistically significant at any level.

In general there is a clear trend in bootstrap results. The shorter moving average used and the more complex the model is, the closer the simulations come to the original series. Therefore it can also be noted that the EGARCH model applied to the1-10-0 trading rule gives the best result with an average mean exceeding the original series 29.6 % of the times and a standard deviation exceeding 95.4 % of the times. Furthermore, the trading rules without bands are superior to those with band, with the exception of the 1-50-1 rule. This could indicate that the bands are not able to capture false signals but it is more likely that it is caused by the fact that the bootstrap results are without transaction costs which, ceteris paribus, is an disadvantage for the trading rules with bands due to a greater number of transactions. The outlier, the 1-50-1 rule, is properly just a result of a coincidence in the original series[24]. Thus, for all the simulated null models the null hypothesis specified in section 7.3.2 is rejected. The predictability and profits obtained by applying the trading rules on the original value portfolio are not the result of the omission of one of the well-known features of asset returns as non-normality, autocorrelation, or time-varying mean or variance.

7.4 Effects of Transaction Costs

In the first part of this chapter it was proved that a majority of the technical trading rules were able to earn a return above and significantly different from the buy-and-hold strategy. It was, however, also noted that the assumptions made about the investment environment might have played an important role for the conclusions reached. A very important missing in the first tests was the omission of transaction costs, which cannot be allowed if the conclusions reached are to be realistic and a violation of the EMH. As the technical trading rules involve many transactions the costs of using this strategy are higher than they are for a simple buy-and-hold strategy. Thus, omitting transaction costs have without doubt tilted the results in favor of technical trading rules. It must therefore be investigated whether the introduction of these costs alter the results in a such way that the conclusions change. A conclusion for all kind of investors can however, never be reached since different investors face different transaction costs. The costs have here been determined to be 0.25% per transaction, meaning a buy or a sell. In the table below the total transaction costs for each trading rule is presented.

Table 7.15 Total Transaction Costs in Percentages

MA (1-10-0)	**MA (1-20-0)**	**MA (1-30-0)**	**MA (1-50-0)**
-145.07448	*-89.394484*	*-65.38568*	*-46.485132*
MA (1-10-1)	**MA (1-20-1)**	**MA (1-30-1)**	**MA (1-50-1)**
-51.593388	*-37.801096*	*-28.606235*	*-24.008804*

[24] The 1-50-1 rule applied on the original series generates an average return much lower than the rest of the trading rules.

As can be seen, the costs of trading are quite substantial. The trading rule that suffers most from these costs is the 1-10-0 rule, which is also what could be expected since this is the rule that is most sensitive to price movements in the index. Actually, almost 4/10 of the total return generated by this trading rule is shaved off when accounting for transaction costs. When the long moving average increases the transaction costs drop dramatically. The largest drop is observed when going from a 10 to a 20-day average. This increase causes the costs to drop with 56% whereas a further increase from 20 to 30 days only results in a lowering of the costs of about 25%. The introduction of a 1 percentage band also causes a dramatical drop in transaction costs. The use of bands is in fact more effective than increasing the long moving average in terms of minimizing transaction costs. For all the rules a band reduce the costs of trading with about 1/3 to1/2. Recall that the best performing trading rules were the rules without bands when no transaction costs were assumed. This might change since these are also the rules with the highest transaction costs. In table 7.16 the results are presented on an after transaction costs basis.

Table 7.16 Results after Transaction Costs

	Daily Mean Return	**Standard Deviation**	**Sharpe Ratio**	**Signals**
MA (1-10-0)	0.0484 *0.1010*	0.48430	0.06231	284
MA (1-10-1)	0.0585 *0.8874*	0.49016	0.08230	101
MA (1-20-0)	0.0587 *0.9042*	0.48239	0.08397	175
MA (1-20-1)	0.0617 *1.1275*	0.49556	0.08776	74
MA (1-30-0)	0.0627 *1.2055*	0.49330	0.09017	128
MA (1-30-1)	0.0661 *1.4676*	0.49576	0.09662	56
MA (1-50-0)	0.0655 *1.4149*	0.50080	0.09439	91
MA (1-50-1)	0.0616 *1.1200*	0.50266	0.08645	47
Buy-and-Hold	0.0471	0.76618	0.03769	19

The effect of transaction costs can clearly be seen in the table above. Still, all the moving average trading rules generate a return that is higher than the return generated by the buy-and-hold strategy. The volatility is also lower for all trading rules so the return is also better when it is adjusted for risk. However, it cannot be concluded that the returns are statistically significantly different from the buy-and-hold return. Thus, the inclusion of transaction costs changes the conclusion about the rules that outperformed the buy-and-hold strategy. Under the assumptions made about transaction costs the best performing trading rule is now the 1-30-1 rule which generates a daily average return of 0.0661% or 17.25% at an annual rate. The buy-and-hold strategy yields a daily mean return of 0.0471% corresponding to 12.29% yearly. The 5% excess return generated by the trading rule cannot be rejected as being a result of pure luck and it cannot be concluded that the trading rule outperforms the buy-and-hold strategy. Since the 1-30-1 rule is the best performing compared to the buy-and-hold strategy this conclusion is valid for the rest of the trading rules.

The introduction of transaction costs causes that the trading rules with bands generally performs better than those without band. The only exception is the 1-50-1 rule which generates a return slightly lower than the 1-50-0. This is what was expected when examining the transaction costs. Thus, the use of bands seems to help avoiding false signals and hence, lower the transaction costs that lead to improved returns. Another result that appears from the table is that the shorter long moving average rules perform poorer than the longer long moving average rules. However, the volatility also seems to increase along with the higher return. The reason for this can be found in table 7.3. As can be seen in this table the number of buy days increase along with the length of the moving average. Thus, with more days in the market the volatility increases since the volatility of the stock returns is higher than the volatility of the risk free asset. The higher volatility does not, however, offset the fact that the longer long moving average trading rules perform better. The Sharpe Ratio generally increases proportionally with the moving average indicating that the return is better even after adjusting for risk.

The results presented above can of course be discussed. First of all, the level of the fees for trading varies from investor to investor. Large, institutional investors trade at much lower costs than private investors and hence, the level set above is in fact not the true level for all investors. As mentioned earlier, some investors can trade for as low as 0.05% per transaction whereas private investors must pay around 0.4% per transaction. It could therefore be argued that institutional investors might be able to profit from using the technical trading rules due to low transaction costs whereas the level of transaction costs for private investors offsets the potential profit that could be earned by following the signals generated by the simple technical trading rules. A sensitivity analysis of the level of transaction costs can decide at which level the trading rules are able to statistically significant outperform the buy-and-hold strategy. This will however not be done since it is out of the scope of this thesis. The second objection to the results above is that some of the trading rules are close to being above and significantly different from the buy-and-hold strategy. If the alpha level were set to 10% instead of 5% the 1-30-0 and 1-30-1 rule would generate a return above and significantly different from the buy-and-hold strategy. However, the two objections do not change the fact that under the assumptions made earlier, none of the trading rules are able to outperform the buy-and-hold strategy.

8 Implications of Findings

The results reached in chapter 7 are much in line with earlier studies. First of all they confirm what was concluded by BLL supporting the use of simple technical trading rules by generating a return above and significantly different return from the buy-and-hold strategy. However, one thing is that the results showed to be statistically significant, another issue is whether the trading rules enable investors to realize excess returns. The introduction of transaction costs indeed questioned this, as was the case with Alexander *(1964)* and Fama & Blume *(1966)*. This chapter will put the empirical findings in perspective.

Previously it was stated that the return series did not follow a random walk. However, in the EMH the random walk is initially applied on stock prices. If stock prices follow a random walk then price changes are white noise. Therefore, testing whether returns are white noise is equivalent to testing for random walk in the stock prices. The autocorrelation in table 7.7 confirms that the return series does not follows a white noise series and hence confirms that stock prices do not follow a random walk. The serial correlation found indicate that it might be possible, at least to some extend, to predict future returns, which of course is not in accordance with the EMH. However, before rejecting the EMH it must be declared whether the predictability can be exploited to earn excess return. One-way of exploiting serial correlation in return series is the use of technical analysis.

In section 3.3 it was argued that market efficiency could be divided into three levels, weak, semi-strong and strong form efficiency. It was also argued that if the empirical tests proved that the technical trading rules were able to outperform a buy-and-hold strategy, this would be a rejection of the weak form efficiency and hence, market efficiency at all levels. The main inspiration for this thesis, the article of BLL *(1992)*, did not deal with the question of market efficiency directly, but instead focused on the distributional properties of the return series. It has however, been chosen to extend the analysis in this thesis to also cover the economical profitability of the trading rules by introducing transaction costs. By including these it is possible to make a conclusion about the implications for the EMH.

The first tests in chapter 7 challenged the EMH. Five of the eight trading rules outperformed the buy-and-hold strategy to such a degree that they were significantly better. The better return could not be explained by the statistical properties of the return series. Thus, there are signs of stock returns being more predictable than suggested by the EMH. This contradiction of the EMH is, however, only present in the absence of trading costs. When the profits are corrected for transaction costs none of the trading rules generate an abnormal profit and hence, the EMH in its weak form cannot be rejected. This conclusion goes hand in hand with some of the earlier studies of technical analysis. Despite the fact that Alexander *(1961, 1964)* concluded that the trading rules he tested would have made a profit prior to transaction costs, he also concluded that: *"In fact, at this point I should advise any reader who is interested only in practical results, and who is not a floor trader and so must pay commissions, to turn to other sources on how to beat buy and hold." (Alexander, 1964 (p. 351))*. Fama & Blume *(1966)* share the same view that the market neglected any information from past prices in setting current prices. Fama *(1976)* comments upon this and states that: *"Strictly speaking, then, the filters uncover evidence of market inefficiency, but the departures from efficiency do not seem sufficient for any trader to reject the hypothesis that the market is efficient so far as his own activities are concerned." (Fama, 1976 (p. 142))*.

Another finding that is more troublesome for the EMH is the confirmation of the value premium puzzle. It was concluded in section 7.1.2.1 that the return generated by the value portfolio was higher and statistically different from the return generated by the growth portfolio. The better return could not be explained by increased risk as measured in terms of volatility. If one accepts the CAPM, the finding violates the EMH. The behavioral explanation is that investors are overconfident in their ability to project high earnings growth and hence, overpay for growth stocks. Advocates of the EMH, however, have another explanation. As discussed in section 3.4.3.1, Fama & French *(1993)* argue that the value premium is the result of the CAPM fails to capture a risk factor that is priced into the market. This argument is quite normal in the EMH debate and is often referred to as a joint hypothesis problem. The hypothesis states that a test for market efficiency must be based on an asset pricing model. If the findings are against the efficient market it can be because of two things: either the market is indeed inefficient or the asset pricing model underlying is incorrect.

The size of the value premium in the portfolios, however, leads the authors to believe that a puzzle is indeed present and cannot be explained by increased risk. The value portfolio generates a yearly extra return of more than 11% compared to the growth portfolio and furthermore, it is less risky measured in terms of volatility. It is not likely that an unknown dimension of risk causes this value premium, but instead the behavioral explanation is supported. It is simply believed that investors overestimate future growth rates of growth stocks relative to value stocks. Thus, the fact that valuation parameters seemingly have predictive power of returns is a violation of the EMH.

However, at the end of the day it must be argued that even though the financial markets might be inefficient to some degree it is very difficult to exploit this. If it indeed is possible to earn abnormal profit through some rather simple techniques these will self-destruct in the future. History shows that once an anomaly has been discovered it is quickly arbitraged away.

9 Conclusion

Since the formulation of the Efficient Market Hypothesis many attempts have been made to dismiss it. A popular test of market efficiency has been to test whether the use of technical trading rules enables investors to systematically earn excess return. If this indeed is the case the market can be considered as inefficient. The use of technical trading rules to test for market efficiency is relevant due to the fact that the approach is widely used in practice.

One of the most famous studies of technical trading rules was conducted by Brock, Lakonishok & LeBaron and published in 1992. This study proved that it was possible to generate a return that was above and significantly different from the buy-and-hold return through the use of simple trading rules. BLL were the first to combine the bootstrap procedure with test of technical trading rules. The use of this procedure helps to overcome the problems connected with the assumptions behind traditional t-tests when testing on return series.

This thesis investigates the profitability of eight simple technical trading rules applied on growth and value stocks. The trading rules are based on simple moving averages. The short moving average is for all rules the actual price whereas a 10, 20, 30 and 50 days period has been used for the long moving average. All rules are tested with a 0% and 1% band. Following a buy signal a long position is taken while a sell signal results in the portfolio is sold and a position in a risk free asset is taken. The trading rules are tested on data from the New York Stock Exchange. All common stocks in the period 1986-2004 have been divided into quintiles based on Earnings-to-Price ratio and further into triples based on Book-to-Market ratio. The portfolio with lowest E/P and B/M-ratio is classified as the growth portfolio while the portfolio containing stocks with highest E/P and B/M-ratio is classified as the value portfolio. The portfolios are rebalanced each year.

The results show that the trading rules are able to identify periods with positive and negative returns. For both portfolios the mean return following buy signals is positive for all trading rules while it is negative following a sell signal. Furthermore, sell periods are characterized by higher volatility than buy periods. This is consistent with the leverage effect. More important is it that the use of simple technical trading gives a better return compared to a buy-and-hold strategy also when adjusting for risk. This is valid for all trading rules and on both portfolios. For the growth portfolio, three of the eight trading rules generate a return that is above and statistically significantly different from the buy-and-hold at the five percent significance level using a two-tailed test. These three rules are all without band. For the value portfolio five of the trading rules generate a return that is above and statistically significantly different from the buy-and-hold strategy. Again, the rules without band are superior.

The value premium is evident in the portfolios. The return generated by the value portfolio is above and significantly different from the return generated by the growth portfolio. In fact, the return of the growth portfolio is lower than what can be earned by investing in the risk free rate. It can therefore be concluded that the use of technical trading rules might help improve returns compared to a buy-and-hold strategy but compared to what can be earned on other portfolios the use of technical trading rules helps only little. This makes it irrelevant to further discuss the application of technical trading rules on this portfolio. The fact that the value portfolio clearly outperforms is a violation of the EMH. It has been argued that an anomaly is present but it must be questioned whether it is possible to exploit this systematically. The only person that comes to mind who has done so is the famous value investor Warren Buffet.

As it is well known that asset returns present a certain number of features that violates the assumptions behind the t-test, bootstrap simulations, as applied in BLL, are performed to check whether the previous results are due to these features. This is strongly rejected for all the four null models tested, even though features such as autocorrelation, volatility clustering and the leverage effect are present in the return series. Thus, the results are in general consistent with those reported by BLL for the DJIA, confirming that simple technical trading rules have predictability power for value stocks.

The seemingly superiority of the technical trading rules must, however, be seen in the light of the fact that the assumptions made about the investment environment are not realistic. Most important is the omission of transaction costs. However, these are introduced in the last part of the analysis. The level of the transaction costs is set to 0.25% per transaction. The introduction of transaction costs has greatest impact on the trading rules with the shortest long moving average without band, simply, due to the fact that they generate more signals. Following this argument, it can be concluded that the trading rules using a band are now better than those not using a band. The central finding, however, is that the introduction of transaction costs causes that none of the trading rules generate a return that is statistically significantly different from the buy-and-hold return. This implies that investors cannot expect to earn an abnormal return by using the tested trading rules on stocks classified as value stocks. The abnormal return generated by the trading rules may simply be due to pure luck.

The findings of this thesis have several implications for the EMH. The fact that at least some forecasting power is documented, need not to be a violation of the EMH. The introduction of transaction costs causes that equality, between the return generated by the trading rules and the return obtained through a buy-and-hold strategy, cannot be rejected. Thus, the weak form efficiency cannot be rejected for value stocks.

Thus, it can be concluded that the use of simple technical trading rules does not enable investors to systematically earn abnormal profits when applied on value and growth stocks.

The results are much in line with a well-known story of a finance professor and a student who comes across a $100 bill lying on the floor. As the student of course stops to pick it up the professor says:

'Don't bother - if it were indeed a $100 bill it wouldn't be lying there'.

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List of Appendices

Appendix 1 Tickers

Growth stocks	Value stocks
1986	
519839	515423
702121	701649
702577	702638
905423	902173
905453	902245
906224	902304
906699	902322
906883	902323
906899	905169
907692	905761
912223	905767
916070	906177
916926	906184
921758	907527
921916	912369
922442	916025
944100	916466
944813	916964
945563	921332
945593	921513
945644	923464
951028	933183
951606	951064
952172	U:AWR
981720	U:CHG
992224	U:CLF
U:BBN	U:CNP
U:BW	U:CV
U:CHD	U:CVX
U:CTG	U:DTE
U:DLX	U:ETR

U:DP	U:EXC
U:HNH	U:FE
U:JH	U:FQE
U:JNJ	U:GXP
U:LIZ	U:ISH
U:LSI	U:LUK
U:MNR	U:MDR
U:OXE	U:MEL
U:PHM	U:NI
U:PRX	U:NMK
U:RBD	U:NSC
U:SBA	U:OXY
U:SBL	U:PCG
U:SNV	U:PGN
U:STJ	U:PNW
U:SYK	U:SO
U:TRC	U:SUN
U:TRR	U:TXU
U:TSS	U:UCM
U:TW	U:UIL
U:UNC	U:WFC

Growth stocks	**Value stocks**
1987	
@ALW	515423
@XQ	516657
702121	701649
702577	702125
741080	702616
741277	702638
904272	740838
905270	749321
905791	902245
906899	902322
907692	902339
916085	903706

916926
921258
923414
930516
944084
944187
944305
944636
944813
945593
951028
951606
981720
U:APC
U:APR
U:AZA
U:BBN
U:BW
U:CCN
U:CHD
U:CHE
U:CY
U:DCN
U:DOW
U:DP
U:EK
U:GCI
U:HMT
U:KII
U:LIZ
U:MIL
U:MRK
U:MZ
U:OHM
U:PRX
U:RBD
U:RHI
904381
905136
905169
905449
905761
905845
912369
916029
916466
916805
923024
923460
923464
923670
951064
951964
982772
U:ANL
U:AOS
U:BPL
U:CBU
U:CI
U:DSL
U:DTE
U:ETR
U:FAC
U:IFC
U:JPM
U:KEY
U:LNC
U:MDC
U:MTB
U:MTZ
U:NDE
U:NSC
U:ORI
U:PCG

U:SBA	U:PNW
U:SVM	U:SO
U:SYK	U:STC
U:TR	U:TXT
U:TRC	U:TXU
U:TSS	U:UCM
U:TXN	U:UIL
U:WON	U:WFC
U:YND	U:ZMX

Growth stocks	**Value stocks**
1988	
@ALW	@ALPC
741080	516657
741277	517170
741713	518937
756249	701649
902267	702125
905043	729679
905126	740838
905252	741210
905684	749321
905791	771756
906899	903706
906991	904381
912176	904803
916085	905845
916926	905892
921190	912734
921778	916029
923119	916805
923461	921016
944813	922497
945762	923091
981720	923700
992224	933183

998260
U:ALX
U:APC
U:APR
U:AXP
U:AZA
U:BRKA
U:CCC
U:CCN
U:CCU
U:CD
U:CKP
U:CL
U:CLF
U:CUZ
U:CY
U:CZM
U:DP
U:DS
U:GEN
U:HNH
U:KGM
U:LLY
U:MEG
U:MIL
U:MNR
U:MRK
U:MTZ
U:NBL
U:PVA
U:RHI
U:SBO
U:SYK
U:TRC
U:TRN
U:TSS
U:VHI

944881
982772
992947
U:ACP
U:BVC
U:CBU
U:CES
U:CI
U:CMS
U:DSL
U:DTE
U:DW
U:ETR
U:EXC
U:FBP
U:FMT
U:GDW
U:GM
U:IEC
U:LMS
U:MBI
U:MER
U:NBR
U:NDE
U:NFB
U:ORI
U:PD
U:PHM
U:PNM
U:PS
U:PXT
U:RLI
U:SCRB
U:SOV
U:TXU
U:UCM
U:UIL

U:WMX	U:WBS
U:WON	U:WHI
U:YND	U:Y

Growth stocks	Value stocks
1989	
@ALW	@ALPC
@XQ	@OV
510331	516657
702956	518937
741080	519345
741277	701649
741839	702125
759694	729679
905279	740838
905366	741210
905423	741387
905606	902173
906060	902322
906864	904803
916085	905892
916262	912909
916685	916309
916926	916805
921316	921697
923461	923435
923768	923700
930365	933183
930516	951020
933399	982772
938978	998355
945762	U:ACP
981720	U:AMR
992752	U:ANL
998260	U:ARW
998683	U:BNK

U:APC	U:BPL
U:APR	U:BVC
U:AZA	U:CBH
U:BHI	U:CHG
U:CRDB	U:CMO
U:CTL	U:CNP
U:CUZ	U:DSL
U:ELK	U:DX
U:HL	U:ETR
U:HLT	U:FAC
U:HNH	U:FBP
U:MEG	U:IEC
U:MNR	U:IFC
U:MNT	U:IOM
U:MRK	U:JPM
U:MTZ	U:KEY
U:MZ	U:MER
U:NBL	U:MTH
U:OHM	U:NDE
U:PKC	U:NMK
U:RBD	U:PSG
U:S	U:PTA
U:SBA	U:PXT
U:SGP	U:RF
U:SLB	U:RLI
U:STJ	U:SOV
U:SYK	U:TCB
U:TRC	U:TXU
U:TSS	U:UB
U:WMX	U:UIL
U:WRE	U:WHI
U:WWY	U:WM

Growth stocks	**Value stocks**
1990	
@ALW	@ALPC

@BTR
@XQ
510331
702457
702577
702956
741080
755753
759710
905366
905671
905814
906699
916926
921385
923768
938978
945762
981720
998260
998683
U:APC
U:APR
U:AZA
U:BHI
U:BMY
U:BRKA
U:CCC
U:CCU
U:CHD
U:CKP
U:CRDB
U:CTL
U:DP
U:EFX
U:FQE
U:HNI

@DEP
@EIC
@OV
516657
702616
740838
755679
771756
905845
905892
912369
912789
912909
916029
921018
921113
921232
921697
921923
923483
944100
951020
951064
951510
U:ACP
U:ANL
U:ASO
U:BNK
U:BOW
U:BVC
U:CBU
U:CFC
U:CI
U:DRL
U:EGP
U:FDB
U:FJ

U:IVC	U:FMT
U:KII	U:GR
U:KO	U:HVT
U:MEG	U:IFC
U:MHP	U:IMD
U:MNT	U:KEY
U:MTZ	U:MEL
U:NBL	U:MTH
U:NEM	U:NDE
U:RBD	U:NFB
U:S	U:ORI
U:SBA	U:PHM
U:SGP	U:PNM
U:SLB	U:PNW
U:STJ	U:SOV
U:SYK	U:SUB
U:TRC	U:TCB
U:TSS	U:TXT
U:VRCZ	U:UB
U:WMX	U:WB
U:WRI	U:WHI

Growth stocks	**Value stocks**
1991	
@BTL	@DEP
@BTR	@EIC
@XQ	@MGR
510110	@NYB
741080	@OV
755753	516657
905814	702125
906699	740838
912401	749321

930516
938978
945762
951028
981567
981720
U:AZA
U:BCR
U:BHI
U:BRKA
U:CCC
U:CHD
U:COG
U:CRDB
U:CTL
U:DJ
U:DP
U:EFX
U:ELJ
U:HMT
U:HRH
U:IVC
U:JNJ
U:KO
U:KOL
U:MIL
U:MNR
U:MNT
U:MRK
U:PEP
U:PLAA
U:RBD
U:SBA
U:SFS
U:SIE
U:SII
U:SLB

755679
759807
771756
902301
904381
905781
905845
912369
912789
916309
921697
951020
992447
992947
U:ACP
U:ANL
U:BK
U:CMO
U:DFG
U:DRL
U:DW
U:DX
U:EGP
U:FMT
U:FNB
U:GR
U:HVT
U:IFC
U:ISH
U:JPM
U:KEY
U:KT
U:LUK
U:NDE
U:ORI
U:PSA
U:RF

U:SON	U:SFE
U:STJ	U:SFI
U:SWY	U:SOV
U:SYK	U:SQAB
U:TRB	U:SQAA
U:TRC	U:UB
U:TSS	U:USB
U:TTI	U:WB
U:UNH	U:WHI
U:WMX	U:WSO
U:WRI	U:Y

Growth stocks	**Value stocks**
1992	
@DNKG	511131
@VTK	516657
@XQ	545759
510110	701649
544791	702616
545442	771756
702956	902266
771982	904381
902221	905121
905062	905845
905364	905892
905366	912789
905814	916029
906699	916693
906783	921601
921258	921697
945762	923091
981720	923700
992224	929813
U:AES	932927
U:AIN	981743
U:BOL	982772

U:BRKA	999679
U:BTV	U:ACP
U:BWI	U:AYD
U:CCU	U:BBT
U:CD	U:BXS
U:CIA	U:CI
U:CL	U:CT
U:CRDB	U:DFG
U:CTL	U:DRL
U:DJ	U:DSL
U:ETN	U:EGP
U:FOE	U:FBP
U:GT	U:FMT
U:JNJ	U:FNB
U:KII	U:GMT
U:KO	U:HU
U:OSI	U:HVTA
U:PFE	U:IEC
U:PLA	U:IHC
U:PLAA	U:ISH
U:RBD	U:LUK
U:SHX	U:NDE
U:SMF	U:ORI
U:SSP	U:OSG
U:SY	U:PSA
U:SYK	U:PTA
U:TGX	U:SFE
U:TRC	U:SJW
U:TSS	U:TUR
U:UNH	U:UB
U:UST	U:UCI
U:VTR	U:UHS
U:WMX	U:WHI
U:YND	U:WM

Growth stocks | **Value stocks**

1993	
@BSN	@ALPC
@DNKG	326837
325075	327366
327328	511131
510110	543628
544104	544371
545442	545759
545524	702441
702457	740838
755753	755679
759694	771756
759710	777010
771982	902173
905062	902198
916262	904849
930516	905845
U:ANV	912236
U:ATI	912734
U:AZA	912764
U:BRKA	916070
U:BRO	916693
U:CCU	923490
U:CD	981743
U:CEM	992447
U:COG	993432
U:CR	U:ACP
U:CTB	U:AYD
U:DD	U:BBT
U:ELK	U:BOW
U:EMC	U:C
U:EOG	U:CCN
U:FDC	U:DFG
U:FUS	U:DRE
U:HET	U:DRL
U:HMT	U:DSL
U:KAI	U:EDO

U:KCS	U:FAF
U:LUV	U:FBP
U:MDR	U:FED
U:MZ	U:FMT
U:NEM	U:FST
U:ODP	U:JPM
U:OSI	U:LFG
U:PLA	U:MDD
U:PLAA	U:ORI
U:RBD	U:PTA
U:SHX	U:PTC
U:SUP	U:RYL
U:SY	U:SCRB
U:SYK	U:SF
U:TBL	U:STC
U:TEN	U:TCB
U:TGX	U:TG
U:TRB	U:UB
U:TRC	U:UHS
U:TSS	U:UNC
U:UNH	U:WBS
U:VVI	U:WHI
U:WAK	U:WM
U:WNC	U:WYL

Growth stocks	**Value stocks**
1994	
@BSN	@ALPC
@TEJ	@DEP
312466	@TH
326025	324950
327318	325527
542347	357051
545442	511131
545524	544131
756249	544530

771982
905364
906188
916262
921050
921258
922351
U:ANV
U:APC
U:APH
U:AZA
U:BID
U:BYD
U:CCC
U:CCU
U:CD
U:CHB
U:CVH
U:DD
U:EC
U:EFX
U:ELY
U:EMC
U:ENQ
U:EOG
U:FDC
U:FMC
U:FUS
U:GGC
U:HDI
U:HET
U:HRB
U:IAC
U:IDC
U:KAI
U:KOL
U:LAW

702441
729679
740838
741210
771809
902173
902198
902239
902245
904505
905845
906018
906899
923490
944881
981743
U:ACP
U:AFG
U:AP
U:ASO
U:BED
U:BVC
U:BXS
U:C
U:CCN
U:CHG
U:CPF
U:CTP
U:CZC
U:DFG
U:DSL
U:EGP
U:FAF
U:FMT
U:HVTA
U:IHC
U:JPM

U:LUV	U:LFG
U:LYO	U:LTR
U:LZ	U:MMI
U:MAT	U:NMK
U:MHP	U:NSS
U:MIL	U:ORI
U:NBL	U:PHM
U:NEM	U:PNW
U:ODP	U:PRA
U:OSI	U:PSD
U:PFE	U:PTA
U:SHX	U:PXT
U:SPG	U:RF
U:SY	U:RLI
U:SYK	U:SCRA
U:TGX	U:SCRB
U:TRC	U:SF
U:TSS	U:STC
U:VH	U:WBS
U:WAK	U:WM
U:WNC	U:WTM
U:WWY	U:Y

Growth stocks	**Value stocks**
1995	
@BSN	@CRP
132032	@TH
325083	312410
325684	325527
326106	327284
328732	357051
357699	357779
510110	360583
544869	510057
545442	511131
545524	544131

702457
702577
756249
771982
777515
902170
904821
905005
916262
921050
921923
944100
945762
U:APH
U:ATI
U:AZA
U:BID
U:BSX
U:BYD
U:CBR
U:CCU
U:CD
U:CHK
U:DP
U:EC
U:EK
U:GGI
U:GLW
U:HET
U:HLT
U:IAC
U:IFF
U:IMD
U:IO
U:ITT
U:KAI
U:KO

544530
545643
702441
729679
740838
741889
771756
902301
904381
905845
906899
916466
923464
981743
992947
U:ACP
U:AF
U:AN
U:ANL
U:APN
U:BNK
U:C
U:CBU
U:CI
U:CV
U:DFG
U:DRL
U:EAS
U:FG
U:FHT
U:FMT
U:FQE
U:HLO
U:HVT
U:HVTA
U:IHC
U:ISH

U:KOL	U:JPM
U:LSI	U:MDC
U:MAN	U:MHO
U:MFE	U:MMI
U:MIL	U:NYB
U:MOT	U:OLP
U:NBL	U:ORI
U:NEM	U:PHM
U:ODP	U:PNM
U:OMI	U:PRE
U:OSI	U:PTA
U:PPP	U:PVA
U:RHI	U:PXT
U:SGA	U:RS
U:SLB	U:SCRA
U:SPG	U:SCRB
U:SUN	U:TAP
U:SYK	U:TMA
U:TGX	U:USB
U:TRC	U:WB
U:TSS	U:WBS
U:UNS	U:WHI
U:VHI	U:WM
U:WAK	U:WTM
U:AAI	U:ZMX

Growth stocks	**Value stocks**
1996	
@BSN	@ALPC
@DNKG	@CRP
132835	@TH
141560	327284
154226	357062
321052	501006
325083	511131
328732	740787

357699
510110
542347
545524
702457
905258
921050
944370
951578
981524
998260
U:AZA
U:BOP
U:BOR
U:BRKA
U:BSX
U:CBR
U:CCU
U:CHK
U:CL
U:CRY
U:CVH
U:DLX
U:FCX
U:GDT
U:GGI
U:HDI
U:HET
U:IO
U:IOM
U:ITT
U:K
U:KAI
U:KMB
U:KO
U:KOL
U:MFE

741210
771809
904381
904849
905845
912236
923487
923700
981743
U:ABK
U:ACE
U:ACP
U:ANL
U:BNK
U:C
U:CBU
U:CGE
U:CHG
U:CNA
U:CV
U:CVO
U:CZC
U:DFG
U:EAS
U:EIX
U:FG
U:FMT
U:GMT
U:HVTA
U:ISH
U:KT
U:LFG
U:LTR
U:MCC
U:MDC
U:MHO
U:NMK

U:MLR	U:NU
U:NEM	U:NYM
U:OO	U:OLP
U:OSI	U:ORI
U:PDX	U:PAG
U:PEP	U:PCG
U:PLA	U:PKY
U:PLAA	U:PNM
U:PPP	U:PNW
U:RBD	U:PR
U:RHI	U:PRE
U:RXT	U:PS
U:SAM	U:PXT
U:SFE	U:RF
U:SGA	U:RRA
U:SLB	U:SCRA
U:SMS	U:SCRB
U:SY	U:SDW
U:SYK	U:SJW
U:SYX	U:SRE
U:TGX	U:TAP
U:TNI	U:THG
U:TRC	U:TSO
U:TRK	U:UB
U:TSS	U:UCM
U:VFI	U:UIL
U:VRI	U:WBS
U:VVI	U:WM
U:WAT	U:WR
U:WON	U:WTM
U:WPI	U:ZMX

Growth stocks	**Value stocks**
1997	
@BSN	131753
@BTL	154567

357841
510110
545524
700408
702457
777515
873136
874197
874363
883557
902221
904821
905062
905364
905682
905814
912912
916926
921050
951578
U:AES
U:AOS
U:BRKA
U:BSX
U:CBR
U:CCE
U:CTG
U:CVD
U:DLX
U:EK
U:ENQ
U:GAC
U:GDT
U:GGI
U:GLW
U:HAL
U:HSY

325527
510221
511131
545975
546276
702634
740787
771809
777001
873305
884049
902322
906823
912789
921146
923618
923700
938548
U:ACP
U:AKS
U:ALK
U:ANL
U:AP
U:BDY
U:BRE
U:CES
U:CGE
U:CHG
U:CLF
U:CNA
U:CTP
U:CV
U:CWL
U:EAS
U:ED
U:EUA
U:FAF

U:IOM
U:JNJ
U:JNY
U:K
U:KAI
U:KEA
U:KO
U:LLY
U:LSI
U:MFE
U:MIL
U:MLR
U:MRK
U:PEP
U:PFE
U:PLA
U:PLAA
U:PPP
U:RCA
U:RHI
U:ROL
U:RXR
U:SEE
U:SFE
U:SGA
U:SII
U:SLB
U:SNC
U:SNV
U:SWW
U:SYK
U:TGX
U:TRC
U:TRY
U:TSS
U:UVN
U:VFI

U:FE
U:FMT
U:FNF
U:GI
U:GMP
U:GPX
U:HVT
U:HVTA
U:IHC
U:KT
U:LFG
U:LTR
U:MDC
U:MHO
U:MMI
U:NMK
U:NYM
U:ORI
U:ORU
U:PEG
U:PHM
U:PKY
U:PNM
U:POR
U:PPL
U:PR
U:PRE
U:PSG
U:PXT
U:RS
U:SF
U:SKP
U:SRE
U:SSS
U:STC
U:THG
U:TMA

U:WAT	U:TRA
U:WMX	U:TSO
U:WON	U:UCM
U:WWW	U:UIC
U:WWY	U:UIL
U:XO	U:VRX
U:AAI	U:WES

Growth stocks	**Value stocks**
1998	
@DNKG	131753
154226	516654
326025	543628
327318	702634
328732	740787
510110	889931
674272	916466
702457	923618
874015	923700
883557	951502
902221	992224
905258	997223
905364	U:ACP
951578	U:AKS
U:AC	U:ALK
U:AES	U:AMH
U:ALX	U:ANL
U:ARB	U:AP
U:ASF	U:ASI
U:BSX	U:AWR
U:BTV	U:BED
U:CBR	U:BOY
U:CCE	U:BRE
U:CL	U:CHG
U:COF	U:CKH
U:CTG	U:CLF

U:CUL
U:CVS
U:DD
U:DLX
U:DVA
U:EK
U:EMC
U:FJ
U:GDT
U:GE
U:GGI
U:GTW
U:GTY
U:HLT
U:HNT
U:HTV
U:KAI
U:KEA
U:KO
U:LNM
U:LRW
U:MAT
U:NDN
U:NR
U:NTY
U:OMC
U:OO
U:PEP
U:PFE
U:PR
U:RCI
U:RHI
U:SEE
U:SGA
U:SGP
U:SGY
U:SNC
U:CNA
U:CPF
U:CPK
U:CV
U:CWL
U:CZC
U:DTE
U:EE
U:EGP
U:EUA
U:GMP
U:GND
U:IEC
U:IHC
U:ILA
U:IPX
U:KSE
U:LQI
U:LTR
U:MCC
U:MDC
U:MFW
U:MHO
U:MMI
U:MTH
U:NNN
U:NSS
U:NVP
U:NYM
U:OLP
U:ORU
U:PAG
U:PCU
U:PD
U:PEG
U:PNM
U:PRE

U:SNV	U:PXT
U:SPC	U:RRIA
U:SVM	U:SJW
U:SWW	U:SKP
U:SYK	U:SRE
U:T	U:SSS
U:TGX	U:TCI
U:TRC	U:TK
U:TSS	U:TMA
U:TWX	U:TRA
U:TYL	U:TUG
U:UVN	U:TXU
U:VRCZ	U:UIC
U:VRX	U:VSH
U:WAI	U:WES
U:WHI	U:WPC
U:WON	U:WPS
U:WPI	U:WR
U:WWY	U:WTM
U:XO	U:WXH

Growth stocks	**Value stocks**
1999	
154226	134665
325746	154567
357699	360186
510110	756431
545538	759807
687069	875661
867201	906823
874015	923618
883557	U:ACP
905005	U:AG
905027	U:AMH
905258	U:AP
905364	U:APN

906184
U:AIG
U:ARB
U:AT
U:BAX
U:BEC
U:BID
U:BMY
U:CCE
U:CL
U:COF
U:CVS
U:DD
U:DHR
U:DJ
U:ECL
U:EDS
U:EMC
U:ENQ
U:FDC
U:GE
U:GLW
U:HDI
U:HPC
U:IPG
U:JNJ
U:KO
U:KSU
U:LIN
U:LLY
U:LRW
U:LXK
U:MCD
U:MIL
U:NDN
U:ODP
U:OMC
U:ARW
U:ASI
U:BOY
U:CGI
U:CLF
U:CT
U:CTP
U:CWL
U:DFG
U:DSL
U:EE
U:EGP
U:ETR
U:FCN
U:GCW
U:GTNA
U:GWR
U:HOC
U:HSD
U:IHC
U:JAH
U:KT
U:LFG
U:MCC
U:MDC
U:MFW
U:MHO
U:MTH
U:NNN
U:NYM
U:NYM
U:OLP
U:OME
U:OMM
U:ORI
U:PAG
U:PDE

U:PBI	U:PHM
U:PCL	U:PNM
U:PER	U:RE
U:PFE	U:REG
U:ROL	U:RFS
U:RSH	U:RIG
U:SEE	U:RNR
U:SGA	U:RTI
U:SGP	U:RYL
U:SNC	U:SCG
U:SPC	U:SCRA
U:STT	U:SKP
U:SWY	U:SPF
U:SYK	U:SQAB
U:TNI	U:SQAA
U:TRC	U:STC
U:TRK	U:TCI
U:TSS	U:TIE
U:TWX	U:TK
U:TXN	U:TMA
U:UVN	U:TNH
U:VRI	U:TOA
U:WAT	U:WPC
U:WWY	U:WTS
U:WYE	U:XNR
U:XRX	U:ZAP

Growth stocks	**Value stocks**
2000	
510110	130669
670088	131753
674672	134665
687069	154567
902221	329189
905364	360186
905423	510221

945551
951578
U:AGN
U:AIG
U:ALX
U:APH
U:ASF
U:AVY
U:BID
U:BSX
U:CAM
U:CL
U:CRR
U:CTS
U:CTV
U:CVG
U:CY
U:DHR
U:DRQ
U:DS
U:ECL
U:EDS
U:EMC
U:FLA
U:GDT
U:GE
U:GLW
U:GTW
U:HAL
U:HDI
U:HRD
U:IPG
U:K
U:KO
U:LLY
U:LSI
U:LXK
680324
680654
689321
694011
884757
916466
921327
U:ACP
U:AHR
U:AMH
U:ANH
U:ANS
U:AP
U:ASI
U:BBX
U:BVC
U:CFC
U:CMO
U:CT
U:CV
U:CXW
U:EDO
U:ENC
U:FIX
U:GCW
U:GI
U:GPK
U:GWR
U:HOC
U:HVTA
U:IHC
U:IMH
U:IPX
U:ISH
U:KT
U:LFG
U:LII

U:MIL	U:LQI
U:MMC	U:MFW
U:MTZ	U:MHO
U:NDN	U:MHX
U:OMC	U:MTH
U:PFE	U:NHI
U:PR	U:NYM
U:RHI	U:OLP
U:ROL	U:ORI
U:RSH	U:OS
U:SBL	U:PCR
U:SEE	U:PDX
U:SFE	U:PHM
U:SGA	U:PNM
U:SII	U:PTA
U:SLB	U:RGF
U:SPW	U:RYL
U:SRT	U:SCRB
U:SYK	U:SOV
U:TER	U:SPF
U:TNO	U:SR
U:TRC	U:STC
U:TSS	U:TCI
U:TWX	U:TOA
U:TXN	U:UAG
U:UPR	U:UCI
U:UVN	U:WAKB
U:VRI	U:WES
U:WAT	U:WLV
U:WON	U:WTM
U:WYE	U:ZAP

Growth stocks	**Value stocks**
2001	
510110	132799
729024	134665

902221
U:AES
U:AGN
U:ALX
U:ASF
U:AZA
U:BAX
U:BHI
U:BRO
U:CAM
U:CL
U:COF
U:CPS
U:CRR
U:CRY
U:CVG
U:CVS
U:DGX
U:DJ
U:DST
U:DYN
U:EMC
U:ESV
U:FDC
U:FSH
U:GDT
U:GE
U:GLW
U:HAL
U:HCA
U:HDI
U:HON
U:HW
U:IPG
U:JNJ
U:KG
U:KO

329189
357980
360186
510221
519345
677088
689321
694011
771979
922170
923618
930543
U:ACO
U:ACP
U:AHR
U:ANS
U:AP
U:BDGA
U:BYD
U:BZ
U:CBU
U:CDI
U:CIX
U:CNA
U:COP
U:CT
U:CTB
U:CVO
U:DCO
U:EIX
U:ENC
U:FBC
U:GCW
U:GEFB
U:GEN
U:GPI
U:GWR

U:LLY
U:LSS
U:LXK
U:MAT
U:MSO
U:MVK
U:NDN
U:OAT
U:OMC
U:OO
U:PEP
U:PFE
U:PQ
U:PR
U:RHI
U:ROL
U:RX
U:SBL
U:SGA
U:SII
U:SKX
U:SLB
U:SNV
U:SSP
U:STJ
U:STT
U:SYK
U:TR
U:TSG
U:TSS
U:UNH
U:UVN
U:WAT
U:WGR
U:WWY
U:IHC
U:IM
U:IPX
U:KTO
U:LII
U:LNX
U:LTC
U:MFA
U:MFW
U:MHO
U:MHX
U:NHI
U:NLY
U:NNN
U:NOC
U:OLP
U:PHM
U:PIK
U:PNK
U:PTA
U:RCL
U:SAH
U:SCRB
U:SFN
U:SNH
U:SRI
U:TCI
U:TEX
U:TNH
U:TOA
U:TSO
U:USG
U:VLO
U:WLS
U:WLV

Growth stocks	Value stocks
2002	
510110	132799
905682	329189
U:ABT	329663
U:AGM	544117
U:AGN	694011
U:AH	U:ACP
U:AHS	U:AHM
U:ASF	U:ANH
U:AXP	U:AOI
U:BAX	U:ASI
U:BDK	U:BG
U:BEZ	U:CFC
U:BNT	U:COP
U:BRO	U:CPE
U:CIA	U:CSV
U:CNT	U:DNR
U:CPS	U:EIX
U:CRY	U:FAF
U:DGX	U:FBC
U:DJ	U:FED
U:DNA	U:FMT
U:DOV	U:FNF
U:EK	U:FRO
U:ELK	U:GCW
U:FSH	U:GEFB
U:FTI	U:GI
U:GRP	U:HNR
U:HDI	U:HOC
U:HON	U:IHC
U:HSY	U:ILA
U:IO	U:IMH
U:JOE	U:KND
U:KRI	U:LFG
U:LMT	U:MFA
U:MAR	U:MFW

U:MEL	U:MMA
U:MOT	U:NFI
U:MSO	U:NU
U:NDN	U:OIS
U:PQE	U:OMM
U:RHI	U:ORI
U:RRD	U:OSG
U:RSH	U:PHM
U:SEE	U:PIK
U:SGA	U:PKI
U:SIE	U:PNM
U:SLB	U:PTA
U:SLM	U:RGF
U:SRT	U:RLH
U:SSP	U:RRA
U:STJ	U:RRI
U:STN	U:SCRB
U:SYK	U:SPF
U:TDY	U:STC
U:TR	U:SWC
U:TRC	U:SXL
U:TSS	U:TCI
U:TWP	U:TIE
U:UIC	U:TK
U:UVN	U:TMA
U:VVI	U:TOA
U:VZ	U:TSO
U:WAB	U:UNM
U:WHR	U:VLO
U:WON	U:WLV
U:ZMH	U:WTM
U:AAP	U:Y

Growth stocks	**Value stocks**
2003	
357336	134624

501006
916926
U:ADS
U:AGN
U:ANT
U:BEZ
U:BHI
U:BRO
U:BSX
U:CAM
U:CEM
U:CNT
U:COG
U:CRR
U:DNA
U:ECL
U:EMN
U:EOG
U:EPD
U:ETM
U:ETP
U:EW
U:FCN
U:FOE
U:GB
U:GRP
U:GYI
U:IP
U:IRM
U:KO
U:LF
U:LMT
U:LUV
U:MKL
U:MRD
U:MAA
U:NDN

329189
510221
674639
U:ABG
U:ACP
U:ADC
U:AHM
U:ANH
U:ANS
U:AOI
U:ASI
U:AW
U:AZR
U:BG
U:CIT
U:CSV
U:CXW
U:DTG
U:EIX
U:ENC
U:EP
U:FBR
U:FIX
U:GEFB
U:GM
U:HNR
U:IHC
U:KND
U:LAD
U:LFG
U:LTR
U:LVB
U:MFA
U:NCT
U:NRP
U:NYM
U:OME

U:PKG	U:OS
U:RHI	U:PMI
U:ROG	U:POM
U:ROH	U:PTC
U:ROL	U:PXP
U:SBL	U:PXT
U:SGA	U:RAI
U:SII	U:RCL
U:SSP	U:RLH
U:STJ	U:S
U:STN	U:SCRB
U:SUI	U:SKX
U:SYK	U:SPF
U:TOC	U:SRI
U:TRC	U:STC
U:TSS	U:SWC
U:TWP	U:SWW
U:VHI	U:TK
U:WAB	U:TOA
U:WGR	U:TUC
U:WON	U:UNM
U:WPO	U:USG
U:WTW	U:WCI
U:WWY	U:WES
U:XRX	U:WG

Growth stocks	**Value stocks**
2004	
325746	U:AFG
U:ADS	U:AGMA
U:ANT	U:AHL
U:ASF	U:AHM
U:BA	U:AN
U:BCR	U:ANH
U:BHI	U:BG
U:BNT	U:CHK

U:BSX
U:CME
U:CNT
U:COG
U:CPS
U:CRR
U:CVO
U:DD
U:DJO
U:DNA
U:ELS
U:EMC
U:ETM
U:EYE
U:FLA
U:FOE
U:GB
U:GDP
U:GDT
U:GES
U:GGC
U:GR
U:GRP
U:GYI
U:HLT
U:IP
U:IRM
U:JOE
U:KWK
U:MOT
U:MAA
U:NTY
U:OLN
U:PFE
U:RHI
U:ROG
U:RX

U:CIT
U:CMO
U:CNO
U:COP
U:CPF
U:CQB
U:CT
U:CTL
U:DVN
U:EIX
U:ENH
U:FAF
U:FDP
U:FFG
U:GM
U:GMP
U:GMR
U:HUM
U:IFC
U:IMH
U:JNS
U:JPM
U:LFG
U:MBI
U:MFA
U:MFW
U:MHO
U:NI
U:NPO
U:OMM
U:ORH
U:ORI
U:OSG
U:PL
U:PRE
U:PXT
U:RDN

U:RYN
U:SBL
U:SGH
U:SII
U:SKT
U:SLB
U:SPG
U:SSP
U:STJ
U:STN
U:SUI
U:SWK
U:SYK
U:TXN
U:VZ
U:WAB
U:WAT
U:WDR
U:WPO
U:ZMH
U:RF
U:RGA
U:RML
U:SAH
U:SCRB
U:SF
U:SPF
U:SRZ
U:STC
U:TK
U:TMA
U:TMG
U:TNP
U:UCI
U:USG
U:VLO
U:WBS
U:WCI
U:WR
U:Y

Appendix 2. Data

This appendix consists of 1 CD-ROM with 2 Excel-files.

The first file labeled **'Stocks and Prices'** contains 38 worksheets. Each worksheet consists of either a growth or a value portfolio and represents 1 year. The daily price of each stock can be found in the worksheet. Furthermore, the geometric mean of the prices and the risk free rate of return are also included in each worksheet. The numbers written with blue are stocks that have ceased to exist during the year.

The second file labeled **'Technical Analysis'** contains the moving average price series and returns for each stock category and year. Furthermore, the worksheet 'Time Series' entails the full return series and calculation of various key figures.

Appendix 3 Yearly Return in Percentage and Standard Deviation

	Value Portfolio		Growth Portfolio	
	Return	Standard Deviation	Return	Standard Deviation
1986	0.62	11.9687	7.35	15.1130
1987	-7.76	24.5712	-18.91	32.2843
1988	18.99	9.4187	13.17	9.7379
1989	-21.05	9.9839	9.79	11.9443
1990	8.49	16.4244	10.75	15.2517
1991	28.71	9.9549	-3.87	13.3049
1992	24.33	8.5578	1.47	13.1618
1993	13.58	9.6716	14.05	10.5720
1994	4.09	7.5009	0.63	9.5127
1995	29.81	7.7437	32.51	10.2997
1996	15.17	7.0903	-13.09	14.2225
1997	41.46	8.8213	27.25	15.0830
1998	-17.55	10.8286	-8.47	20.8400
1999	-4.65	10.2803	1.30	16.5450
2000	29.26	12.3303	-22.06	22.3131
2001	25.31	13.1109	-12.88	16.7654
2002	-11.80	17.9579	-25.49	25.0048
2003	51.66	12.2608	21.09	12.2587
2004	14.85	12.6491	1.43	13.0568

Appendix 4 The Bootstrap Procedure

This appendix includes nine DVD's containing more than 20 GB data spread over various spreadsheets. The fact that the bootstrap procedure is spread over nine DVD's and a large number of workbooks and worksheets can be very confusing. However, this is simply a consequence of a computer power limitation. The memory of the computer only allows up to 100 series in one workbook and only up to 50 if the formula is very complex. However, the guide below can togethere with the bootstrap procedure in section 7.3.3 give one an overview of how the bootstrap algorithm is constructed in this thesis.

DVD 1 consists of four folders, one for each null model. Each folder captures the second (resampling of residuals/standardized residual) and third step (creating return series) in the bootstrap procedure. The random walk folder consists of only one workbook (returnandboot) containing six spreadsheets; one for the original return series copied 100 times and five spreadsheets containing 100 simulated random walk series each. The AR folder is a little more complex. Here step 2 and 3 of the bootstrap procedure is clearly separated. The AR folder consists of six workbooks. One workbook for the 500 residual series (residualsandboot) and five workbooks (return1-return5) each contain 100 return series. The GARCH and EGARCH folder differs from the AR folder in the way that step 3 are separated in variance and return workbooks. Both folders consist of 11 workbooks: one for the 500 standardized residual series (standardizedresidualsandboot), five variance workbooks (variance1-variance5) and five return workbooks (return1-return5).

DVD 2-9 captures steps 4-6 of the bootstrap procedure. Each null model consists of two DVD's. One for the trading rules without band and one for the trading rules with band. DVD 2 & 3 is the random walk without and with a band respectively. 4 & 5 is the AR model, 6 & 7 the GARCH and 8 & 9 is the EGARCH. The trading rules without band consist of ten workbooks: the first five contains the price and moving average series (PriceMA100-PriceMA500) and the last five contains the technical analysis and the mean return and standard deviation calculation (TA100-TA500). The trading rules with band are mainly constructed in the same way, however, with one exception. The TA books are divided in ten workbooks (TA50-TA500) instead of only five.

Appendix 5 Estimation Output for Linear Models

Random Walk with Drift

Dependent Variable: VALUE

Method: Least Squares

Date: 04/05/06 Time: 09:32

Sample: 4/30/1986 4/29/2005

Included observations: 4958

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.049021	0.010881	4.505122	0.0000

R-squared	0.000000	Mean dependent var	0.049021
Adjusted R-squared	0.000000	S.D. dependent var	0.766180
S.E. of regression	0.766180	Akaike info criterion	2.305402
Sum squared resid	2909.914	Schwarz criterion	2.306714
Log likelihood	-5714.091	Durbin-Watson stat	1.663174

Appendix 5 Estimation Output for Linear Models

MA (1)

Dependent Variable: VALUE

Method: Least Squares

Date: 04/05/06 Time: 09:30

Sample: 4/30/1986 4/29/2005

Included observations: 4958

Convergence achieved after 6 iterations

Backcast: 4/29/1986

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.049027	0.012443	3.939948	0.0001
MA(1)	0.158961	0.014031	11.32939	0.0000

R-squared	0.026527	Mean dependent var	0.049021
Adjusted R-squared	0.026331	S.D. dependent var	0.766180
S.E. of regression	0.756025	Akaike info criterion	2.278920
Sum squared resid	2832.722	Schwarz criterion	2.281545
Log likelihood	-5647.442	F-statistic	135.0514
Durbin-Watson stat	1.986091	Prob(F-statistic)	0.000000

Inverted MA Roots	-.16

Appendix 5 Estimation Output for Linear Models

AR (1)

Dependent Variable: VALUE

Method: Least Squares

Date: 04/05/06 Time: 09:27

Sample (adjusted): 5/01/1986 4/29/2005

Included observations: 4957 after adjustments

Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.049457	0.012888	3.837425	0.0001
AR(1)	0.167809	0.014002	11.98464	0.0000

R-squared	0.028171	Mean dependent var	0.049343
Adjusted R-squared	0.027975	S.D. dependent var	0.765921
S.E. of regression	0.755132	Akaike info criterion	2.276555
Sum squared resid	2825.461	Schwarz criterion	2.279181
Log likelihood	-5640.441	F-statistic	143.6317
Durbin-Watson stat	2.006674	Prob(F-statistic)	0.000000

Inverted AR Roots	.17

Appendix 5 Estimation Output for Linear Models

ARMA (1,1)

Dependent Variable: VALUE

Method: Least Squares

Date: 07/30/06 Time: 23:25

Sample (adjusted): 5/01/1986 4/29/2005

Included observations: 4957 after adjustments

Convergence achieved after 13 iterations

Backcast: 4/30/1986

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.049531	0.013455	3.681196	0.0002
AR(1)	0.370965	0.075033	4.944033	0.0000
MA(1)	-0.210693	0.079025	-2.666169	0.0077

R-squared	0.028905	Mean dependent var	0.049343
Adjusted R-squared	0.028513	S.D. dependent var	0.765921
S.E. of regression	0.754923	Akaike info criterion	2.276203
Sum squared resid	2823.327	Schwarz criterion	2.280142
Log likelihood	-5638.569	F-statistic	73.72764
Durbin-Watson stat	1.993972	Prob(F-statistic)	0.000000

Inverted AR Roots	.37
Inverted MA Roots	.21

Appendix 5 Estimation Output for Linear Models

ARMA (2,1)

Dependent Variable: VALUE

Method: Least Squares

Date: 07/30/06 Time: 23:15

Sample (adjusted): 5/02/1986 4/29/2005

Included observations: 4956 after adjustments

Convergence achieved after 10 iterations

Backcast: 5/01/1986

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.048724	0.019057	2.556702	0.0106
AR(1)	1.098847	0.028953	37.95300	0.0000
AR(2)	-0.132964	0.016540	-8.038826	0.0000
MA(1)	-0.939462	0.024643	-38.12347	0.0000

R-squared	0.032792	Mean dependent var	0.049361
Adjusted R-squared	0.032206	S.D. dependent var	0.765997
S.E. of regression	0.753562	Akaike info criterion	2.272795
Sum squared resid	2812.018	Schwarz criterion	2.278048
Log likelihood	-5627.985	F-statistic	55.96371
Durbin-Watson stat	1.998867	Prob(F-statistic)	0.000000

Inverted AR Roots	.96	.14
Inverted MA Roots	.94	

Appendix 5 Estimation Output for Linear Models

ARMA (2,2)

Dependent Variable: VALUE

Method: Least Squares

Date: 07/30/06 Time: 22:53

Sample (adjusted): 5/02/1986 4/29/2005

Included observations: 4956 after adjustments

Convergence achieved after 12 iterations

Backcast: 4/30/1986 5/01/1986

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.048730	0.019027	2.561126	0.0105
AR(1)	1.086137	0.124599	8.717070	0.0000
AR(2)	-0.121285	0.112763	-1.075574	0.2822
MA(1)	-0.926567	0.125277	-7.396141	0.0000
MA(2)	-0.011170	0.106661	-0.104721	0.9166

R-squared	0.032794	Mean dependent var	0.049361
Adjusted R-squared	0.032012	S.D. dependent var	0.765997
S.E. of regression	0.753637	Akaike info criterion	2.273196
Sum squared resid	2812.012	Schwarz criterion	2.279762
Log likelihood	-5627.980	F-statistic	41.96685
Durbin-Watson stat	1.999214	Prob(F-statistic)	0.000000

Inverted AR Roots	.96	.13
Inverted MA Roots	.94	-.01

Appendix 6 Estimation Output for GARCH Models

ARCH (6)

Dependent Variable: VALUE
Method: ML - ARCH
Date: 07/30/06 Time: 23:50
Sample (adjusted): 5/01/1986 4/29/2005
Included observations: 4957 after adjustments
Convergence achieved after 29 iterations
Variance backcast: ON
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-2)^2 + C(6)*RESID(-3)^2 + C(7)*RESID(-4)^2 + C(8)*RESID(-5)^2 + C(9)*RESID(-6)^2

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.077912	0.010569	7.372070	0.0000
AR(1)	0.153228	0.016924	9.054084	0.0000
		Variance Equation		
C	0.214668	0.007761	27.66087	0.0000
RESID(-1)^2	0.152002	0.006691	22.71676	0.0000
RESID(-2)^2	0.088658	0.011842	7.486453	0.0000
RESID(-3)^2	0.102600	0.013869	7.398022	0.0000
RESID(-4)^2	0.080070	0.012251	6.535982	0.0000
RESID(-5)^2	0.073523	0.011471	6.409201	0.0000
RESID(-6)^2	0.109734	0.006913	15.87428	0.0000

R-squared	0.026967	Mean dependent var	0.049343
Adjusted R-squared	0.025394	S.D. dependent var	0.765921
S.E. of regression	0.756134	Akaike info criterion	2.029451
Sum squared resid	2828.960	Schwarz criterion	2.041268
Log likelihood	-5020.994	F-statistic	17.14153
Durbin-Watson stat	1.974810	Prob(F-statistic)	0.000000

Inverted AR Roots	.15

Appendix 6 Estimation Output for GARCH Models

GARCH (1,1)

Dependent Variable: VALUE

Method: ML - ARCH

Date: 07/31/06 Time: 01:12

Sample (adjusted): 5/01/1986 4/29/2005

Included observations: 4957 after adjustments

Convergence achieved after 31 iterations

Bollerslev-Wooldrige robust standard errors & covariance

Variance backcast: ON

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.078107	0.010544	7.407579	0.0000
AR(1)	0.159934	0.014934	10.70932	0.0000
		Variance Equation		
C	0.021004	0.005000	4.200406	0.0000
RESID(-1)^2	0.104571	0.035954	2.908462	0.0036
GARCH(-1)	0.858454	0.036625	23.43880	0.0000

R-squared	0.027121	Mean dependent var	0.049343
Adjusted R-squared	0.026335	S.D. dependent var	0.765921
S.E. of regression	0.755769	Akaike info criterion	2.020165
Sum squared resid	2828.514	Schwarz criterion	2.026730
Log likelihood	-5001.980	F-statistic	34.51118
Durbin-Watson stat	1.988545	Prob(F-statistic)	0.000000

Inverted AR Roots	.16

Appendix 6 Estimation Output for GARCH Models

GARCH (1,2)

Dependent Variable: VALUE

Method: ML - ARCH

Date: 07/31/06 Time: 01:13

Sample (adjusted): 5/01/1986 4/29/2005

Included observations: 4957 after adjustments

Convergence achieved after 38 iterations

Bollerslev-Wooldrige robust standard errors & covariance

Variance backcast: ON

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) + C(6)
*GARCH(-2)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.076968	0.010495	7.333653	0.0000
AR(1)	0.161259	0.014928	10.80217	0.0000
		Variance Equation		
C	0.024851	0.008977	2.768256	0.0056
RESID(-1)^2	0.129547	0.059050	2.193851	0.0282
GARCH(-1)	0.471970	0.364075	1.296353	0.1949
GARCH(-2)	0.354511	0.306179	1.157856	0.2469

R-squared	0.027220	Mean dependent var	0.049343
Adjusted R-squared	0.026237	S.D. dependent var	0.765921
S.E. of regression	0.755806	Akaike info criterion	2.018492
Sum squared resid	2828.226	Schwarz criterion	2.026370
Log likelihood	-4996.833	F-statistic	27.70704
Durbin-Watson stat	1.991419	Prob(F-statistic)	0.000000

Inverted AR Roots	.16

Appendix 6 Estimation Output for GARCH Models

GARCH (2,1)

Dependent Variable: VALUE

Method: ML - ARCH

Date: 07/31/06 Time: 01:14

Sample (adjusted): 5/01/1986 4/29/2005

Included observations: 4957 after adjustments

Convergence achieved after 26 iterations

Bollerslev-Wooldrige robust standard errors & covariance

Variance backcast: ON

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-2)^2 + C(6)
*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.076527	0.010346	7.396747	0.0000
AR(1)	0.160054	0.014882	10.75478	0.0000
		Variance Equation		
C	0.014263	0.003321	4.294738	0.0000
RESID(-1)^2	0.148416	0.079013	1.878367	0.0603
RESID(-2)^2	-0.072561	0.072204	-1.004949	0.3149
GARCH(-1)	0.898525	0.016769	53.58203	0.0000

R-squared	0.027229	Mean dependent var	0.049343
Adjusted R-squared	0.026246	S.D. dependent var	0.765921
S.E. of regression	0.755803	Akaike info criterion	2.017540
Sum squared resid	2828.200	Schwarz criterion	2.025418
Log likelihood	-4994.472	F-statistic	27.71648
Durbin-Watson stat	1.989007	Prob(F-statistic)	0.000000
Inverted AR Roots	.16		

Appendix 6 Estimation Output for GARCH Models

GARCH (2,2)

Dependent Variable: VALUE

Method: ML - ARCH

Date: 07/31/06 Time: 01:14

Sample (adjusted): 5/01/1986 4/29/2005

Included observations: 4957 after adjustments

Convergence achieved after 49 iterations

Bollerslev-Wooldrige robust standard errors & covariance

Variance backcast: ON

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-2)^2 + C(6)
*GARCH(-1) + C(7)*GARCH(-2)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.077576	0.010173	7.625538	0.0000
AR(1)	0.158462	0.014857	10.66559	0.0000
		Variance Equation		
C	0.004669	0.003993	1.169255	0.2423
RESID(-1)^2	0.139207	0.072695	1.914959	0.0555
RESID(-2)^2	-0.115632	0.063191	-1.829881	0.0673
GARCH(-1)	1.481011	0.270377	5.477571	0.0000
GARCH(-2)	-0.513308	0.245395	-2.091758	0.0365

R-squared	0.027128	Mean dependent var	0.049343
Adjusted R-squared	0.025949	S.D. dependent var	0.765921
S.E. of regression	0.755918	Akaike info criterion	2.017104
Sum squared resid	2828.492	Schwarz criterion	2.026295
Log likelihood	-4992.392	F-statistic	23.00470
Durbin-Watson stat	1.985602	Prob(F-statistic)	0.000000

Inverted AR Roots	.16

Appendix 7 Estimation Output for EGARCH Models

EGARCH (1,1)

Dependent Variable: VALUE

Method: ML - ARCH

Date: 07/31/06 Time: 01:09

Sample (adjusted): 5/01/1986 4/29/2005

Included observations: 4957 after adjustments

Convergence achieved after 57 iterations

Bollerslev-Wooldrige robust standard errors & covariance

Variance backcast: ON

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.059430	0.011200	5.306489	0.0000
AR(1)	0.169448	0.015457	10.96226	0.0000
		Variance Equation		
C(3)	-0.159636	0.040162	-3.974792	0.0001
C(4)	0.167274	0.046439	3.602013	0.0003
C(5)	-0.091858	0.025601	-3.588126	0.0003
C(6)	0.957894	0.009840	97.35099	0.0000

R-squared	0.028051	Mean dependent var	0.049343
Adjusted R-squared	0.027069	S.D. dependent var	0.765921
S.E. of regression	0.755483	Akaike info criterion	2.003061
Sum squared resid	2825.809	Schwarz criterion	2.010939
Log likelihood	-4958.587	F-statistic	28.57774
Durbin-Watson stat	2.009778	Prob(F-statistic)	0.000000

Inverted AR Roots	.17

Appendix 7 Estimation Output for EGARCH Models

EGARCH (1,2)

Dependent Variable: VALUE
Method: ML - ARCH
Date: 07/31/06 Time: 01:08
Sample (adjusted): 5/01/1986 4/29/2005
Included observations: 4957 after adjustments
Convergence achieved after 71 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1)) +
C(7)*LOG(GARCH(-2))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.059052	0.011197	5.273859	0.0000
AR(1)	0.168148	0.015309	10.98337	0.0000
		Variance Equation		
C(3)	-0.193703	0.071329	-2.715622	0.0066
C(4)	0.205392	0.080445	2.553192	0.0107
C(5)	-0.112937	0.044404	-2.543409	0.0110
C(6)	0.645930	0.349432	1.848514	0.0645
C(7)	0.305311	0.336854	0.906359	0.3647

R-squared	0.028062	Mean dependent var	0.049343
Adjusted R-squared	0.026884	S.D. dependent var	0.765921
S.E. of regression	0.755555	Akaike info criterion	2.001554
Sum squared resid	2825.777	Schwarz criterion	2.010745
Log likelihood	-4953.851	F-statistic	23.81950
Durbin-Watson stat	2.007142	Prob(F-statistic)	0.000000

Inverted AR Roots	.17

Appendix 7 Estimation Output for EGARCH Models

EGARCH (2,1)

Dependent Variable: VALUE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/31/06 Time: 01:11
Sample (adjusted): 5/01/1986 4/29/2005
Included observations: 4957 after adjustments
Convergence achieved after 78 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(5)*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(6)*RESID(-1)
/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.060301	0.011137	5.414577	0.0000
AR(1)	0.169251	0.015431	10.96858	0.0000
		Variance Equation		
C(3)	-0.150012	0.032543	-4.609602	0.0000
C(4)	0.202403	0.099134	2.041710	0.0412
C(5)	-0.044047	0.078367	-0.562055	0.5741
C(6)	-0.087515	0.022614	-3.869887	0.0001
C(7)	0.961644	0.008334	115.3836	0.0000

R-squared	0.028030	Mean dependent var	0.049343
Adjusted R-squared	0.026852	S.D. dependent var	0.765921
S.E. of regression	0.755568	Akaike info criterion	2.003008
Sum squared resid	2825.869	Schwarz criterion	2.012199
Log likelihood	-4957.455	F-statistic	23.79181
Durbin-Watson stat	2.009332	Prob(F-statistic)	0.000000

Inverted AR Roots	.17

Appendix 7 Estimation Output for EGARCH Models

EGARCH (2,2)

Dependent Variable: VALUE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/31/06 Time: 01:10
Sample (adjusted): 5/01/1986 4/29/2005
Included observations: 4957 after adjustments
Convergence achieved after 79 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(5)*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(6)*RESID(-1)
/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*LOG(GARCH(-2))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.058890	0.011176	5.269579	0.0000
AR(1)	0.167194	0.015239	10.97154	0.0000
	Variance Equation			
C(3)	-0.206621	0.079872	-2.586893	0.0097
C(4)	0.192772	0.083189	2.317276	0.0205
C(5)	0.026276	0.055809	0.470824	0.6378
C(6)	-0.118978	0.046021	-2.585292	0.0097
C(7)	0.576717	0.372989	1.546204	0.1221
C(8)	0.371190	0.358984	1.034003	0.3011

R-squared	0.028065	Mean dependent var	0.049343
Adjusted R-squared	0.026690	S.D. dependent var	0.765921
S.E. of regression	0.755631	Akaike info criterion	2.001868
Sum squared resid	2825.768	Schwarz criterion	2.012372
Log likelihood	-4953.630	F-statistic	20.41491
Durbin-Watson stat	2.005200	Prob(F-statistic)	0.000000

Inverted AR Roots	.17