Technical Analysis in Financial Markets

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Technical Analysis in Financial Markets

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To my father and mother

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Chapter 1

Introduction

As long as financial markets have existed, people have tried to forecast them, in the hope that good forecasts would bring them great fortunes. In financial practice it is not the question *whether* it is possible to forecast, but *how* the future path of a financial time series can be forecasted. In academia, however, it is merely the question *whether* series of speculative prices can be forecasted than the question *how* to forecast. Therefore practice and academics have proceeded along different paths in studying financial time series data. For example, among practitioners fundamental and technical analysis are techniques developed in financial practice according to which guidelines financial time series should and could be forecasted. They are intended to give advice on what and when to buy or sell. In contrast, academics focus on the behavior and characteristics of a financial time series itself and try to explore whether there is certain dependence in successive price changes that could profitably be exploited by various kinds of trading techniques. However, early statistical studies concluded that successive price changes are independent. These empirical findings combined with the theory of Paul Samuelson, published in his influential paper "Proof that Properly Anticipated Prices Fluctuate Randomly" (1965), led to the efficient markets hypothesis (EMH). According to this hypothesis it is not possible to exploit any information set to predict future price changes. In another influential paper Eugene Fama (1970) reviewed the theoretical and empirical literature on the EMH to that date and concluded that the evidence in support of the EMH was very extensive, and that contradictory evidence was sparse. Since then the EMH is the central paradigm in financial economics.

Technical analysis has been a popular and heavily used technique for decades already in financial practice. It has grown to an industry on its own. During the 1990s there was a renewed interest in academia on the topic when it seemed that early studies which found technical analysis to be useless might have been premature. In this thesis a large number of trend-following technical trading techniques are studied and applied to various speculative price series. Their profitability as well as their forecasting ability will be statistically tested. Corrections will be made for transaction costs, risk and data snooping to answer the question whether one can really profit from perceived trending behavior in financial time series.

This introductory chapter is organized as follows. In section 1.1 the concepts of fundamental and technical analysis are presented and the philosophies underlying these techniques are explained. Also something will be said about the critiques on both methods. Next, in section 1.2 an overview of the academic literature on technical analysis and efficient markets is presented. Finally section 1.3 concludes with a brief outline of this thesis.

1.1 Financial practice

Fundamental analysis

Fundamental analysis found its existence in the *firm-foundation theory*, developed by numerous people in the 1930s, but finally worked out by John B. Williams. It was popularized by Graham and Dodd's book "Security Analysis" (1934) and by Graham's book "The Intelligent Investor" (1949). One of its most successful applicants known today is the investor Warren Buffet. The purpose of fundamental securities analysis is to find and explore all *economic* variables that influence the future earnings of a financial asset. These fundamental variables measure different economic circumstances, ranging from macro-economic (inflation, interest rates, oil prices, recessions, unemployment, etc.), industry specific (competition, demand/supply, technological changes, etc.) and firm specific (company growth, dividends, earnings, lawsuits, strikes etc.) circumstances. On the basis of these 'economic fundamentals' a fundamental analyst tries to compute the *true* underlying value, also called the fundamental value, of a financial asset.

According to the firm-foundation theory the fundamental value of an asset should be equal to the discounted value of all future cash flows the asset will generate. The discount factor is taken to be the interest rate plus a risk premium and therefore the fundamental analyst must also make expectations about future interest rate developments. The fundamental value is thus based on historical data and expectations about future developments extracted from them. Only 'news', which is new facts about the economic variables determining the true value of the fundamental asset, can change the fundamental value. If the computed fundamental value is higher (lower) than the market price, then the fundamental analyst concludes that the market over- (under-) values the asset. A long (short) position in the market should be taken to profit from this supposedly under- (over-) valuation. The philosophy behind fundamental analysis is that in the end, when enough traders realize that the market is not correctly pricing the asset, the market mechanism of demand/supply, will force the price of the asset to converge to its fundamental value. It is assumed that fundamental analysts who have better access to information and who have a more sophisticated system in interpreting and weighing the influence of information on future earnings will earn more than analysts who have less access to information and have a less sophisticated system in interpreting and weighing information. It is emphasized that sound investment principles will produce sound investment results, eliminating the psychology of the investors. Warren Buffet notices in the preface of "The Intelligent Investor" (1973): "*What's needed is a sound intellectual framework for making decisions and the ability to keep emotions from corroding that framework. The sillier the market's behavior, the greater the opportunity for the business-like investor.*"

However, it is questionable whether traders can perform a complete fundamental analysis in determining the true value of a financial asset. An important critique is that fundamental traders have to examine a lot of different economic variables and that they have to know the precise effects of all these variables on the future cash flows of the asset. Furthermore, it may happen that the price of an asset, for example due to overreaction by traders, persistently deviates from the fundamental value. In that case, *short term* fundamental trading cannot be profitable and therefore it is said that fundamental analysis should be used to make *long-term* predictions. Then a problem may be that a fundamental trader does not have enough wealth and/or enough patience to wait until convergence finally occurs. Furthermore, it could be that financial markets affect fundamentals, which they are supposed to reflect. In that case they do not merely discount the future, but they help to shape it and financial markets will never tend toward equilibrium. Thus it is clear that it is a most hazardous task to perform accurate fundamental analysis. Keynes (1936, p.157) already pointed out the difficulty as follows: "*Investment based on genuine long-term expectation is so difficult as to be scarcely practicable. He who attempts it must surely lead much more laborious days and run greater risks than he who tries to guess better than the crowd how the crowd will behave; and, given equal intelligence, he may make more disastrous mistakes.*"

On the other hand it may be possible for a trader to make a fortune by free riding on the expectations of all other traders together. Through the market mechanism of demand and supply the expectations of those traders will eventually be reflected in the asset price in a more or less gradual way. If a trader is engaged in this line of thinking, he leaves fundamental analysis and he moves into the area of technical analysis.

Technical analysis

Technical analysis is the study of past price movements with the goal to predict future price movements from the past. In his book "The Stock Market Barometer" (1922) William Peter Hamilton laid the foundation of the Dow Theory, the first theory of chart readers. The theory is based on editorials of Charles H. Dow when he was editor of the Wall Street Journal in the period 1889 – 1902. Robert Rhea popularized the idea in his 1930s market letters and his book "The Dow Theory" (1932). The philosophy underlying technical analysis can already for most part be found in this early work, developed after Dow's death in 1902. Charles Dow thought that expectations for the national economy were translated into market orders that caused stocks to rise or fall in prices over the long term together - usually in advance of actual economic developments. He believed that fundamental economic variables determine prices in the long run. To quantify his theory Charles Dow began to compute averages to measure market movements. This led to the existence of the Dow-Jones Industrial Average (DJIA) in May 1896 and the Dow-Jones Railroad Average (DJRA) in September 1896.

The Dow Theory assumes that all information is discounted in the averages, hence no other information is needed to make trading decisions. Further the theory makes use of Charles Dow's notion that there are three types of market movements: primary (also called major), secondary (also called intermediate) and tertiary (also called minor) upward and downward price movements, also called trends. It is the aim of the theory to detect the primary trend changes in an early stage. Minor trends tend to be much more influenced by random news events than the secondary and primary trends and are said to be therefore more difficult to identify. According to the Dow Theory bull and bear markets, that is primary upward and downward trends, are divisible in stages which reflect the moods of the investors.

The Dow Theory is based on Charles Dow's philosophy that "*the rails should take what the industrials make.*" Stated differently, the two averages DJIA and DJRA should confirm each other. If the two averages are rising it is time to buy; when both are decreasing it is time to sell. If they diverge, this is a warning signal. Also the Dow Theory states that volume should go with the prevailing primary trend. If the primary trend is upward (downward), volume should increase when price rises (declines) and should decrease when price declines (rises). Eventually the Dow Theory became the basis of what is known today as technical analysis. Although the theory bears Charles Dow's name, it is likely that he would deny any allegiance to it. Instead of being a chartist, Charles Dow as a financial reporter advocated to invest on sound fundamental economic variables, that is buying stocks when their prices are well below their fundamental values. His main purpose in developing the averages was to measure market cycles, rather than to use them to generate trading signals.

After the work of Hamilton and Rhea the technical analysis literature was expanded and refined by early pioneers such as Richard Schabacker, Robert Edwards, John Magee and later Welles Wilder and John Murphy. Technical analysis developed into a standard tool used by many financial practitioners to forecast the future price path of all kinds of financial assets such as stocks, bonds, futures and options. Nowadays a lot of technical analysis software packages are sold on the market. Technical analysis newsletters and journals flourish. Bookstores have shelves full of technical analysis literature. Every bank employs several chartists who write technical reports spreading around forecasts with all kinds of fancy techniques. Classes are organized to introduce the home investor to the topic. Technical analysis has become an industry on its own. Taylor and Allen (1992) conducted a questionnaire survey in 1988 on behalf of the Bank of England among chief foreign exchange dealers based in London. It is revealed that at least 90 percent of the respondents place some weight on technical analysis when forming views over some time horizons. There is also a skew towards reliance on technical, as opposed to fundamental, analysis at shorter horizons, which becomes steadily reversed as the length of the time horizon is increased. A high proportion of chief dealers view technical and fundamental analysis as complementary forms of analysis and a substantial proportion suggest that technical advice may be self-fulfilling. There is a feeling among market participants that it is important to have a notion of chartism, because many traders use it, and may therefore influence market prices. It is said that chartism can be used to exploit market movements generated by less sophisticated, 'noise traders'. Menkhoff (1998) holds a questionnaire survey among foreign exchange professionals from banks and from fund management companies trading in Germany in August 1992. He concludes that many market participants use non-fundamental trading techniques. Cheung and Chinn (1999) conduct a mail survey among US foreign exchange traders between October 1996 and November 1997. The results indicate that in that time period technical trading best characterizes 30% of traders against 25% for fundamental analysis. All these studies show that technical analysis is broadly used in practice.

The general consensus among technical analysts is that there is no need to look at the fundamentals, because everything that is happening in the world can be seen in the price charts. A popular saying among chartists is that "*a picture is worth a ten thousand words.*"

Price as the solution of the demand/supply mechanism reflects the dreams, expectations, guesses, hopes, moods and nightmares of all investors trading in the market. A true chartist does not even care to know which business or industry a firm is in, as long he can study its stock chart and knows its ticker symbol. The motto of Doyne Farmer's prediction company as quoted by Bass, 1999, p.102, was for example: "*If the market makes numbers out of information, one should be able to reverse the process and get information out of numbers.*" The philosophy behind technical analysis is that information is *gradually* discounted in the price of an asset. Except for a crash once in a while there is no 'big bang' price movement that immediately discounts all available information. It is said that price gradually moves to new highs or new lows and that trading volume goes with the prevailing trend. Therefore most popular technical trading rules are trend following techniques such as moving averages and filters. Technical analysis tries to detect changes in investors' sentiments in an early stage and tries to profit from them. It is said that these changes in sentiments cause certain patterns to occur repeatedly in the price charts, because people react the same in equal circumstances. A lot of 'subjective' pattern recognition techniques are therefore described in the technical analysis literature which have fancy names, such as head & shoulders, double top, double bottoms, triangles, rectangles, etc., which should be traded on after their pattern is completed.

An example: the moving-average technical trading rule.

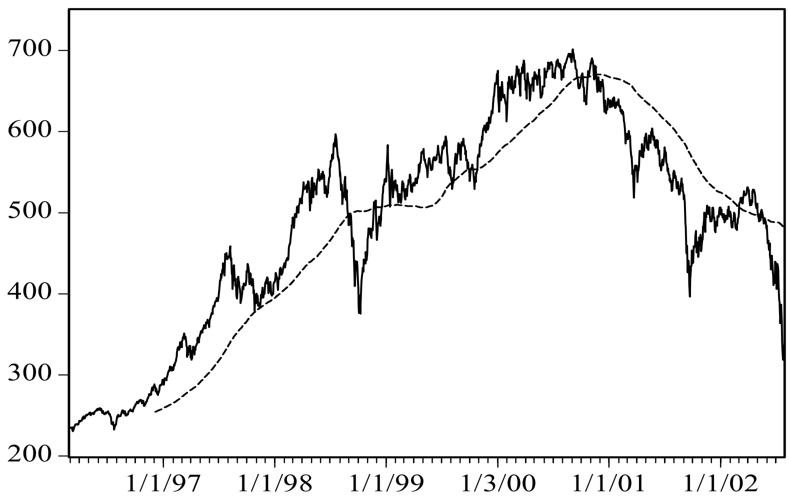

Figure 1.1: A 200-day moving-average trading rule applied to the AEX-index in the period March 1, 1996 through July 25, 2002.

At this point it is useful to illustrate technical trading by a simple example. One of the most popular technical trading rules is based on moving averages. A moving average is a recursively updated, for example daily, weekly or monthly, average of past prices. A moving average smoothes out erratic price movements and is supposed to reflect the underlying trend in prices. A buy (sell) signal is said to be generated at time t if the price crosses the moving average upwards (downwards) at time t. Figure 1.1 shows an example of a 200-day moving average applied to the Amsterdam Stock Exchange Index (AEX-index) in the period March 1, 1996 through July 25, 2002. The 200-day moving average is exhibited by the dotted line. It can be seen that the moving average follows the price at some distance. It changes direction after a change in the direction of the prices has occurred. By decreasing the number of days over which the moving average is computed, the distance can be made smaller, and trading signals occur more often. Despite that the 200-day moving-average trading rule is generating signals in some occasions too late, it can be seen that the trading rule succeeds in detecting large price moves that occurred in the index. In this thesis we will develop a technical trading rule set on the basis of simple trend-following trading techniques, such as the above moving-average strategy, as well as refinements with %-band-filters, time delay filters, fixed holding periods and stop-loss. We will test the profitability and predictability of a large class of such trading rules applied to a large number of financial asset price series.

Critiques on technical analysis

Technical analysis has been heavily criticized over the decades. One critique is that it trades when a trend is already established. By the time that a trend is signaled, it may already have taken place. Hence it is said that technical analysts are always trading too late.

As noted by Osler and Chang (1995, p.7), books on technical analysis fail in documenting the validity of their claims. Authors do not hesitate to characterize a pattern as frequent or reliable, without making an attempt to quantify those assessments. Profits are measured in isolation, without regard for opportunity costs or risk. The lack of a sound statistical analysis arises from the difficulty in programming technical pattern recognition techniques into a computer. Many technical trading rules seem to be somewhat vague statements without accurately mathematically defined patterns. However Neftci (1991) shows that most patterns used by technical analysts can be characterized by appropriate sequences of local minima and/or maxima. Lo, Mamaysky and Wang (2000) develop a pattern recognition system based on non-parametric kernel regression. They conclude (p.1753): "*Although human judgment is still superior to most computational algorithms in* *the area of visual pattern recognition, recent advances in statistical learning theory have had successful applications in fingerprint identification, handwriting analysis, and face recognition. Technical analysis may well be the next frontier for such methods.*"

Furthermore, in financial practice technical analysis is criticized because of its highly subjective nature. It is said that there are probably as many methods of combining and interpreting the various techniques as there are chartists themselves. The geometric shapes in historical price charts are often in the eyes of the beholder. Fundamental analysis is compared with technical analysis like astronomy with astrology. It is claimed that technical analysis is voodoo finance and that chart reading shares a pedestal with alchemy. The attitude of academics towards technical analysis is well described by Malkiel (1996, p.139): "*Obviously, I'm biased against the chartist. This is not only a personal predilection but a professional one as well. Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) after paying transaction costs, the method does not do better than a buy-and-hold strategy for investors, and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: It's your money we are trying to save.*"

However, technical analysts acknowledge that their techniques are by no means foolproof. For example, Martin Pring (1998, p.5) notices about technical analysis: "*It can help in identifying the direction of a trend, but there is no known method of consistently forecasting its magnitude.*" Edwards and Magee (1998, p.12) notice: "*Chart analysis is certainly neither easy nor foolproof* ." Finally, Achelis (1995, p.6) remarks:"*..., I caution you not to let the software lull you into believing markets are as logical and predictable as the computer you use to analyze them.*" Hence, even technical analysts warn against investment decisions based upon their charts alone.

Fundamental versus technical analysis

The big advantage of technical analysis over fundamental analysis is that it can be applied fairly easily and cheaply to all kinds of securities prices. Only some practice is needed in recognizing the patterns, but in principle everyone can apply it. Of course, there exist also some complex technical trading techniques, but technical analysis can be made as easy or as difficult as the user likes. Martin Pring (1997, p.3) for example notices that although computers make it more easy to come up with sophisticated trading rules, it is better to keep things as simple as possible.

Of course fundamental analysis can also be made as simple as one likes. For example, look at the number of cars parked at the lot of the shopping mall to get an indication of consumers' confidence in the national economy. Usually more (macro) economic variables are needed. That makes fundamental analysis more costly than technical analysis.

An advantage of technical analysis from an academic point of view is that it is much easier to test the forecasting power of well-defined objective technical trading rules than to test the forecasting power of trading rules based on fundamentals. For testing technical trading rules only data is needed on prices, volumes and dividends, which can be obtained fairly easily.

An essential difference between chart analysis and fundamental economic analysis is that chartists study only the price action of the market itself, whereas fundamentalists attempt to look for the reasons behind that action. However, both the fundamental analyst and the technical analyst make use of historical data, but in a different manner. The technical analyst claims that all information is gradually discounted in the prices, while the fundamental analyst uses all available information including many other economic variables to compute the 'true' value. The pure technical analyst will never issue a price goal. He only trades on the buy and sell signals his strategies generate. In contrast, the fundamental analyst will issue a price goal that is based on the calculated fundamental value. However in practice investors expect also from technical analysts to issue price goals.

Neither fundamental nor technical analysis will lead to sure profits. Malkiel shows in his book "A Random Walk down Wall Street" (1996) that mutual funds, the main big users of fundamental analysis, are not able to outperform a general market index. In the period 1974 – 1990 at least two thirds of the mutual funds were beaten by the Standard & Poors 500 (Malkiel, 1996, p.184). Moreover, Cowles (1933, 1944) already noticed that analysts report more bullish signals than bearish ones, while in his studies the number of weeks the stock market advanced and declined were equal. Furthermore, fundamental analysts do not always report what they think, as became publicly known in the Merrill Lynch scandal. Internally analysts judged certain internet and telecommunications stocks as 'piece of shit', abbreviated by 'pos' at the end of internal email messages, while they gave their clients strong advices to buy the stocks of these companies. In 1998 the "Long Term Capital Management" (LTCM) fund filed for bankruptcy. This hedge fund was trading on the basis of mathematical models. Myron Scholes and Robert Merton, well known for the development and extension of the Black & Scholes option pricing model, were closely involved in this company. Under leadership of the New York Federal Reserve Bank, one the twelve central banks in the US, the financial world had to raise a great amount of money to prevent a big catastrophe. Because LTCM had large obligations in the derivatives markets, which they could not fulfill anymore, default of payments would have an influence on the profits of the financial companies who had taken the counterpart positions in the market. A sudden bankruptcy of LTCM could have led to a chain reaction on Wall Street and the rest of the financial world.

1.2 Technical analysis and efficient markets. An overview

In this section we present a historical overview of the most important (academic) literature published on technical analysis and efficient markets.

Early work on technical analysis

Despite the fact that chartists have a strong belief in their forecasting abilities, in academia it remains questionable whether technical trading based on patterns or trends in past prices has any statistically significant forecasting power and whether it can profitably be exploited after correcting for transaction costs and risk. Cowles (1933) started by analyzing the weekly forecasting results of well-known professional agencies, such as financial services and fire insurance companies, in the period January 1928 through June 1932. The ability of selecting a specific stock which should generate superior returns, as well as the ability of forecasting the movement of the stock market itself is studied. Thousands of predictions are recorded. Cowles (1933) finds no statistically significant forecasting performance. Furthermore Cowles (1933) considered the 26-year forecasting record of William Peter Hamilton in the period December 1903 until his death in December 1929. During this period Hamilton wrote 255 editorials in the Wall Street Journal which presented forecasts for the stock market based on the Dow Theory. It is found that Hamilton could not beat a continuous investment in the DJIA or the DJRA after correcting for the effect of brokerage charges, cash dividends and interest earned if no position is held in the market. On 90 occasions Hamilton announced changes in the outlook for the market. Cowles (1933) finds that 45 of the changes of position were unsuccessful and that 45 were successful. Cowles (1944) repeats the analysis for 11 forecasting companies for the longer period January 1928 through July 1943. Again no evidence of forecasting power is found. However, although the number of months the stock market declined exceeded the number of months the stock market rose, and although the level of the stock market in July 1943 was lower than at the beginning of the sample period, Cowles (1944) finds that more bullish signals are published than bearish. Cowles (1944, p.210) argues that this peculiar result can be explained by the fact that readers prefer good news to bad, and that a forecaster who presents a cheerful point of view thereby attracts more followers without whom he would probably be unable to remain long in the forecasting business.

Random walk hypothesis

While Cowles (1933, 1944) focused on testing analysts' advices, other academics focused on time series behavior. Working (1934), Kendall (1953) and Roberts (1959) found for series of speculative prices, such as American commodity prices of wheat and cotton, British indices of industrial share prices and the DJIA, that successive price changes are linearly independent, as measured by autocorrelation, and that these series may be well defined by random walks. According to the random walk hypothesis trends in prices are spurious and purely accidentally manifestations. Therefore, trading systems based on past information should not generate profits in excess of equilibrium expected profits or returns. It became commonly accepted that the study of past price trends and patterns is no more useful in predicting future price movements than throwing a dart at the list of stocks in a daily newspaper.

However the dependence in price changes can be of such a complicated form that standard linear statistical tools, such as serial correlations, may provide misleading measures of the degree of dependence in the data. Therefore Alexander (1961) began defining filters to reveal possible trends in stock prices which may be masked by the jiggling of the market. A filter strategy buys when price increases by x percent from a recent low and sells when price declines by x percent from a recent high. Thus filters can be used to identify local peaks and troughs according to the filter size. He applies several filters to the DJIA in the period $1897-1929$ and the S&P Industrials in the period $1929-1959$. Alexander (1961) concludes that in speculative markets a price move, once initiated, tends to persist. Thus he concludes that the basic philosophy underlying technical analysis, that is prices move in trends, holds. However he notices that commissions could reduce the results found. Mandelbrot (1963, p.418) notes that there is a flaw in the computations of Alexander (1961), since he assumes that the trader can buy exactly at the low plus x percent and can sell exactly at the high minus x percent. However in real trading this will probably not be the case. Further it was argued that traders cannot buy the averages and that investors can change the price themselves if they try to invest according to the filters. In Alexander (1964) the computing mistake is corrected and allowance is made for transaction costs. The filter rules still show considerable excess profits over the buy-and-hold strategy, but transaction costs wipe out all the profits. It is concluded that an investor who is not a floor trader and must pay commissions should turn to other sources of advice on how to beat the buy-and-hold benchmark. Alexander (1964) also tests other mechanical trading rules, such as Dow-type formulas and old technical trading rules called formula Dazhi, formula Dafilt and finally the also nowadays popular moving averages. These techniques provided much better profits than the filter techniques. The results led Alexander (1964) still to conclude that the independence assumption of the random walk had been overturned.

Theil and Leenders (1965) investigate the dependence of the proportion of securities that advance, decline or remain unchanged between successive days for approximately 450 stocks traded at the Amsterdam Stock Exchange in the period November 1959 through October 1963. They find that there is considerable positive dependence in successive values of securities advancing, declining and remaining unchanged at the Amsterdam Stock Exchange. It is concluded that if stocks in general advanced yesterday, they will probably also advance today. Fama (1965b) replicates the Theil and Leenders test for the NYSE. In contrast to the results of Theil and Leenders (1965), Fama (1965b) finds that the proportions of securities advancing and declining today on the NYSE do not provide much help in predicting the proportions advancing and declining tomorrow. Fama (1965b) concludes that this contradiction in results could be caused by economic factors that are unique to the Amsterdam Exchange.

Fama (1965a) tries to show with various tests that price changes are independent and that therefore the past history of stock prices cannot be used to make meaningful predictions concerning its future behavior. Moreover, if it is found that there is some dependence, then Fama argues that this dependence is too small to be profitably exploited because of transaction costs. Fama (1965a) applies serial correlation tests, runs tests and Alexander's filter technique to daily data of 30 individual stocks quoted in the DJIA in the period January 1956 through September 1962. A runs test counts the number of sequences and reversals in a returns series. Two consecutive returns of the same sign are counted as a sequence, if they are of opposite sign they are counted as a reversal. The serial correlation tests show that the dependence in successive price changes is either extremely small or non-existent. Also the runs tests do not show a large degree of dependence. Profits of the filter techniques are calculated by trading blocks of 100 shares and are corrected for dividends and transaction costs. The results show no profitability. Hence Fama (1965a) concludes that the largest profits under the filter technique would seem to be those of the broker.

The paper of Fama and Blume (1966) studies Alexander's filters applied to the same data set as in Fama (1965a). A set of filters is applied to each of the 30 stocks quoted in the DJIA with and without correction for dividends and transaction costs. The data set is divided in days during which long and short positions are held. They show that the short positions initiated are disastrous for the investor. But even if positions were only held at buy signals, the buy-and-hold strategy cannot consistently be outperformed. Until the 1990s Fama and Blume (1966) remained the best known and most influential paper on mechanical trading rules. The results caused academic skepticism concerning the usefulness of technical analysis.

Return and risk

Diversification of wealth over multiple securities reduces the risk of investing. The phrase "*don't put all your eggs in one basket*" is already well known for a long time. Markowitz (1952) argued that every rule that does not imply the superiority of diversification must be rejected both as hypothesis to explain and as a principle to guide investment behavior. Therefore Markowitz (1952, 1959) published a formal model of portfolio selection embodying diversification principles, called the expected returns-variance of returns rule (E-V-rule). The model determines for any given level of anticipated return the portfolio with the lowest risk and for any given levels of risk the portfolio with the highest expected return. This optimization procedure leads to the well-known efficient frontier of risky assets. Markowitz (1952, 1959) argues that portfolios found on the efficient frontier consist of firms operating in different industries, because firms in industries with different economic characteristics have lower covariance than firms within an industry. Further it was shown how by maximizing a capital allocation line (CAL) on the efficient frontier the optimal risky portfolio could be determined. Finally, by maximizing a personal utility function on the CAL, a personal asset allocation between a risk-free asset and the optimal risky portfolio can be derived.

An expected positive price change can be the reward needed to attract investors to hold a risky asset and bear the corresponding risk. Then prices need not be perfectly random, even if markets are operating efficiently and rationally. With his work Markowitz (1952, 1959) laid the foundation of the capital asset pricing model (CAPM) developed by Sharpe (1964) and Lintner (1965). They show that under the assumptions that investors have homogeneous expectations and optimally hold mean-variance efficient portfolios, and in the absence of market frictions, a broad-weighted market portfolio will itself be a mean-variance efficient portfolio. This market portfolio is the tangency portfolio of the CAL with the efficient frontier. The great merit of the CAPM was, despite its strict and unrealistic assumptions, that it showed the relationship between the risk of an asset and its expected return. The notion of trade-off between risk and rewards also triggered the question whether the profits generated by technical trading rule signals were not just the reward of bearing risky asset positions.

Levy (1967) applies relative strength as a criterion for investment selection to weekly closing prices of 200 stocks listed on the NYSE for the 260-week period beginning October 24, 1960 and ending October 15, 1965. All price series are adjusted for splits, stock dividends, and for the reinvestment of both cash dividends and proceeds received from the sale of rights. The relative strength strategy buys those stocks that have performed well in the past. Levy (1967) concludes that the profits attainable by purchasing the historically strongest stocks are superior to the profits of the random walk. Thus in contrast to earlier results he finds stock market prices to be forecastable by using the relative strength rule. However Levy (1967) notices that the random walk hypothesis is not refuted by these findings, because superior profits could be attributable to the incurrence of extraordinary risk and he remarks that it is therefore necessary to determine the riskiness of the various technical measures he tested.

Jensen (1967) indicates that the results of Levy (1967) could be the result of selection bias. Technical trading rules that performed well in the past get most attention by researchers, and if they are back-tested, then of course they generate good results. Jensen and Benington (1969) apply the relative strength procedure of Levy (1967) to monthly closing prices of every security traded on the NYSE over the period January 1926 to March 1966, in total 1952 securities. They conclude that after allowance for transaction costs and correction for risk the trading rules did not on average earn significantly more than the buy-and-hold policy.

James (1968) is one of the firsts who tests moving-average trading strategies. That is, signals are generated by a crossing of the price through a moving average of past prices. He finds no superior performance for these rules when applied to end of month data of stocks traded at the NYSE in the period $1926 - 1960$.

Efficient markets hypothesis

Besides testing the random walk theory with serial correlation tests, runs tests and by applying technical trading rules used in practice, academics were searching for a theory that could explain the random walk behavior of stock prices. In 1965 Samuelson published his "*Proof that properly anticipated prices fluctuate randomly* ." He argues that in an informational efficient market price changes must be unforecastable if they are properly anticipated, i.e., if they fully incorporate the expectations and information of all market participants. Because news is announced randomly, since otherwise it would not be news anymore, prices must fluctuate randomly. This important observation, combined with the notion that positive earnings are the reward for bearing risk, and the earlier empirical findings that successive price changes are independent, led to the efficient markets hypothesis. Especially the notion of trade-off between reward and risk distinguishes the efficient markets hypothesis from the random walk theory, which is merely a purely statistical model of returns.

The influential paper of Fama (1970) reviews the theoretical and empirical literature on the efficient markets model until that date. Fama (1970) distinguishes three forms of market efficiency. A financial market is called weak efficient, if no trading rule can be developed that can forecast future price movements on the basis of past prices. Secondly, a financial market is called semi-strong efficient, if it is impossible to forecast future price movements on the basis of publicly known information. Finally, a financial market is called strong efficient if on the basis of all available information, also inside information, it is not possible to forecast future price movements. Semi-strong efficiency implies weak-form efficiency. Strong efficiency implies semi-strong and weak efficiency. If the weak form of the EMH can be rejected, then also the semi strong and strong form of the EMH can be rejected. Fama (1970) concludes that the evidence in support of the efficient markets model is very extensive, and that contradictory evidence is sparse. The impact of the empirical findings on random walk behavior and the conclusion in academia that financial asset prices are and should be unforecastable was so large, that it took a while before new academic literature on technical trading was published. Financial analysts heavily debated the efficient markets hypothesis. However, as argued by academics, even if the theory of Samuelson would be wrong, then there are still many empirical findings of no forecastability.

Market technicians kept arguing that statistical tests of any kind are less capable of detecting subtle patterns in stock price data than the human eye. Thus Arditti and McCollough (1978) argued that if stock price series have information content, then technicians should be able to differentiate between actual price data and random walk data generated from the same statistical parameters. For each of five randomly chosen stocks from the NYSE in the year 1969 they showed 14 New York based CFAs (Chartered Financial Analyst, the CFA® program is a globally recognized standard for measuring the competence and integrity of financial analysts) with more than five years of experience three graphs, the actual price series plus two random price series. The analysts were asked to pick the actual price series using any technical forecasting tool they wanted. The results reveal that the technicians were not able to make consistently correct selections. Thus Arditti and McCollough (1978) conclude that past price data provide little or no information useful for technical analysis, because analysts cannot differentiate between price series with information content and price series with no information content.

Technical analysis in the foreign currency markets

One of the earliest studies of the profitability of technical trading rules in foreign exchange markets is Dooley and Shafer (1983). Very high liquidity, low bid-ask spreads and round-the-clock decentralized trading characterize exchange rate markets for foreign currency. Furthermore, because of their size, these markets are relatively immune to insider trading. Dooley and Shafer (1983) address the question whether the observed short-run variability in exchange rates since the start of generalized floating exchange rates in March 1973 is caused by technical traders or is caused by severe fundamental shocks. In the former case the exchange rate path could be interpreted in terms of price runs, bandwagons, and technical corrections, while in the latter case frequent revisions on the basis of small information occurs and the market is efficient in taking into account whatever information is available. They follow the study of Fama (1965, 1970) by applying serial correlation tests, runs tests and seven filter trading rules in the range [1%, 25%] to the US Dollar (USD) prices of the Belgium Franc (BF), Canadian Dollar (CD), French Franc (FF), German Mark (DEM), Italian Lira (IL), Japanese Yen (JPY), Dutch Guilder (DGL), Swiss Franc (SF), and the British Pound (BP) in the period March 1973 through November 1981. Adjustment is made for overnight Eurocurrency interest rate differentials to account for the predictable component of changes in daily spot exchange rates. In an earlier study Dooley and Shafer (1976) already found that the filters yielded substantial profits from March 1975 until October 1975 even if careful account was taken of opportunity costs in terms of interest rate differentials and transactions costs. It is noted that these good results could be the result of chance and therefore the period October 1975 through November 1981 is considered to serve as an out-of-sample testing period for which it is unlikely that the good results for the filters continue to hold if the exchange markets are really efficient. Dooley and Shafer (1983) report that there is significant autocorrelation present in the data and that there is evidence of substantial profits to all but the largest filters, casting doubt on the weak form of the efficient markets hypothesis. Further, they find a relation between the variability of exchange rates, as measured by the standard deviation of the daily returns, and the filter rules' profits. A large increase in the variability is associated with a dramatic increase in the profitability of the filters. They also compare the results generated in the actual exchange rate data with results generated by random walk and autoregressive models, which in the end cannot explain the findings.

Sweeney (1986) develops a test of the significance of filter rule profits that explicitly assumes constant risk/return trade-off due to constant risk premia. Seven different filter rules in the range [0.5%, 10%] are applied to the US Dollar against the BF, BP, CD, DEM, FF, IL, JPY, SF, Swedish Krone (SK) and Spanish Peseta (SP) exchange rates in the period $1975-1980$. It is found that excess rates of return of filter rules persist into the 1980s, even after correcting for transaction costs and risk.

After his study on exchange rates, Sweeney (1988) focuses on a subset of the 30 stocks in the DJIA for which the 0.5% filter rule yielded the most promising results in the Fama and Blume (1966) paper, which comprehends the $1956-1962$ period. He finds that by focusing on the winners in the previous period of the Fama and Blume (1966) paper significant profits over the buy-and-hold can be made for all selected stocks in the period $1970-1982$ by investors with low but feasible transaction costs, most likely floor traders. Sweeney (1988) questions why the market seems to be weak-form inefficient according to his results. Sweeny argues that the costs of a seat on an exchange are just the risk-adjusted present value of the profits that could be made. Another possibility is that if a trader tries to trade according to a predefined trading strategy, he can move the market itself and therefore cannot reap the profits. Finally Sweeney (1988) concludes that excess return may be the reward for putting in the effort for finding the rule which can exploit irregularities. Hence after correcting for research costs the market may be efficient in the end.

Schulmeister (1988) observes that USD/DEM exchange rate movements are characterized by a sequence of upward and downward trends in the period March 1973 to March 1988. For two moving averages, two momentum strategies, two combinations of moving averages and momentum and finally one support-and-resistance rule, reported to be widely used in practice, it is concluded that they yield systematically and significant profits. Schulmeister (1988) remarks that the combined strategy is developed and truly applied in trading by Citicorp. No correction is made for transaction costs and interest rate differentials. However, for the period October 1986 through March 1988 a reduction in profits is noticed, which is explained by the stabilizing effects of the Louvre accord of February 22, 1987. The goal of this agreement was to keep the USD/DEM/JPY exchange rates stable. The philosophy behind the accord was that when those three key currencies were stable, then the other currencies of the world could link into the system and world currencies could more or less stabilize, reducing currency risks in foreign trade.

Renewed interest in the 1990s

Little work on technical analysis appeared during the 1970s and 1980s, because the efficient markets hypothesis was the dominating paradigm in finance. Brock, Lakonishok and LeBaron (1992) test the forecastability of a set of 26 simple technical trading rules by applying them to the closing prices of the DJIA in the period January 1897 through December 1986, nearly 90 years of data. The set of trading rules consists of moving average strategies and support-and-resistance rules, very popular trading rules among technical trading practitioners. Brock et al. (1992) recognize the danger of data snooping. That is, the performance of the best forecasting model found in a given data set by a certain specification search could be just the result of chance instead of truly superior forecasting power. They admit that their choice of trading rules could be the result of survivorship bias, because they consulted a technical analyst. However they claim that they mitigate the problem of data snooping by (1) reporting the results of all tested trading strategies, (2) utilizing a very long data set, and (3) emphasizing the robustness of the results across various non-overlapping subperiods for statistical inference. Brock et al. (1992) find that all trading rules yield significant profits above the buy-and-hold benchmark in all periods by using simple t-ratios as test statistics. Moreover they find that buy signals consistently generate higher returns than sell signals and that the returns following buy signals are less volatile than the returns following sell signals. However t-ratios are only valid under the assumption of stationary and time independent return distributions. Stock returns exhibit several well-known deviations from these assumptions like leptokurtosis, autocorrelation, dependence in the squared returns (volatility clustering or conditional heteroskedasticity), and changing conditional means (risk premia). The results found could therefore be the consequence of using invalid significance tests. To overcome this problem Brock et al. (1992) were the first who extended standard statistical analysis with parametric bootstrap techniques, inspired by Efron (1979), Freedman and Peters (1984a, 1984b) and Efron and Tibshirani (1986). Brock et al. (1992) find that the patterns uncovered by their technical trading rules cannot be explained by first order autocorrelation and by changing expected returns caused by changes in volatility. Stated differently, the predictive ability of the technical trading rules found is not consistent with a random walk, an AR(1), a GARCH-in-mean model, or an exponential GARCH model. Therefore Brock et al. (1992) conclude that the conclusion reached in earlier studies that technical analysis is useless may have been premature. However they acknowledge that the good results of the technical trading rules can be offset by transaction costs.

The strong results of Brock, Lakonishok and LeBaron (1992) led to a renewed interest in academia for testing the forecastability of technical trading rules. It was the impetus for many papers published on the topic in the 1990s. Notice however that Brock et al. (1992) in fact do not apply the correct t-test statistic, as derived in footnote 9, page 1738. See section 2.5 in Chapter 2 of this thesis for a further discussion on this topic.

Levich and Thomas (1993) criticize Dooley and Shafer (1983) for not reporting any measures of statistical significance of the technical trading rule profits. Therefore Levich and Thomas (1993) are the first who apply the bootstrap methodology, as introduced by Brock et al. (1992), to exchange rate data. Six filters and three moving averages are applied to the US Dollar closing settlement prices of the BP, CD, DEM, JPY and SF futures contracts traded at the International Monetary Market of the Chicago Mercantile Exchange in the period January 1973 through December 1990. Levich and Thomas (1993) note that the trading rules tested are very popular ones and that the parameterizations are taken from earlier literature. Just like Brock et al. (1992) they report that they mitigate the problem of data mining by showing the results for all strategies. It is found that the simple technical trading rules generate unusual profits (no corrections are made for transaction costs) and that a random walk model cannot explain these profits. However there is some deterioration over time in the profitability of the trading rules, especially in the $1986 - 1990$ period.

Lee and Mathur (1995) remark that most surveys, whose findings are in favor of technical trading if applied to exchange rate data, are conducted on US Dollar denominated currencies and that the positive results are likely to be caused by central bank intervention. Therefore to test market efficiency of European foreign exchange markets they apply 45 different crossover moving-average trading strategies to six European spot cross-rates (JPY/BP, DEM/BP, JPY/DEM, SF/DEM and JPY/SF) in the May, 1988 to December, 1993 period. A correction for 0.1% transaction costs per trade is made. They find that moving-average trading rules are marginally profitable only for the JPY/DEM and JPY/SF cross rates, currencies that do not belong to the European exchange rate mechanism (ERM). Further it is found that in periods during which central bank intervention is believed to have taken place, trading rules do not show to be profitable in the European cross rates. Finally Lee and Mathur (1995) propose to apply a recursively optimizing test procedure with a rolling window for the purpose of testing out-of-sample forecasting power. Every year the best trading rule of the previous half-year is applied. Also this out-of-sample test procedure rejects the null hypothesis that moving averages have forecasting power. It is concluded that the effect of target zones on the dynamics of the ERM exchange rates may be partly responsible for the lack of profitability of moving-average trading rules. The dynamics of ERM exchange rates are different from those of common exchange ranges in that they have smaller volatility.

Bessembinder and Chan (1995) test whether the trading rule set of Brock et al. (1992) has forecasting power when applied to the stock market indices of Japan, Hong Kong, South Korea, Malaysia, Thailand and Taiwan in the period January 1975 through December 1989. Break-even transaction costs that eliminate the excess return of a double or out strategy over a buy-and-hold are computed. The rules are most successful in the markets of Malaysia, Thailand and Taiwan, where the buy-sell difference is on average 51.9% yearly. Break-even round-trip transaction costs are estimated to be 1.57% on average (1.34% in the case if a one-day lag in trading is incorporated). It is concluded that excess profits over the buy-and-hold could be made, but emphasis is placed on the fact that the relative riskiness of the technical trading strategies is not controlled for.

For the UK stock market Hudson, Dempsey and Keasey (1996) test the trading rule set of Brock et al. (1992) on daily data of the Financial Times Industrial Ordinary index, which consists of 30 UK companies, in the period July 1935 to January 1994. They want to examine whether the same set of trading rules outperforms the buy-and-hold on a different market. It is computed that the trading rules on average generate an excess return of 0.8% per transaction over the buy-and-hold, but that the costs of implementing the strategy are at least 1% per transaction. Further when looking at the subperiod $1981 - 1994$, the trading rules seem to lose their forecasting power. Hence Hudson et al. (1996) conclude that although the technical trading rules examined do have predictive ability, their use would not allow investors to make excess returns in the presence of costly trading. Additionally Mills (1997) simultaneously finds in the case of zero transaction costs with the bootstrap technique introduced by Brock et al. (1992) that the good results for the period $1935 - 1980$ cannot be explained by an AR-ARCH model for the daily returns. Again, for the period after 1980 it is found that the trading rules do not generate statistically significant results. Mills (1997) concludes that the trading rules mainly worked when the market was driftless but performed badly in the period after 1980, because the buy-and-hold strategy was clearly dominating.

Kho (1996) tests a limited number of double crossover moving-average trading rules on weekly data of BP, DEM, JPY, SF futures contracts traded on the International Monetary Market (IMM) division of the Chicago Mercantile Exchange from January 1980 through December 1991. The results show that there have been profit opportunities that could have been exploited by moving-average trading rules. The measured profits are so high that they cannot be explained by transaction costs, serial correlation in the returns or a simple volatility expected return relation (GARCH-in-mean model). Next, Kho (1996) estimates a conditional CAPM model that captures the time-varying price of risk. It is concluded that the technical trading rule profits found can be well explained by time-varying risk premia.

Bessembinder and Chan (1998) redo the calculations of Brock et al. (1992) for the period $1926-1991$ to assess the *economic* significance of the Brock et al. (1992) findings. Corrections are made for transaction costs and dividends. One-month treasury bills are used as proxy for the risk-free interest rate if no trading position is held in the market. Furthermore, also a correction is made for non-synchronous trading by lagging trading signals for one day. It is computed that one-way break-even transaction costs are approximately 0.39% for the full sample. However they decline from 0.54% in the first subperiod $1926-1943$ to 0.22% in the last subperiod $1976-1991$. Knez and Ready (1996) estimate the average bid-ask spread between 0.11 and 0.13%, while Chan and Lakonishok (1993) estimate commissions costs to be 0.13%. Together this adds to approximately 0.24 to 0.26% transaction costs for institutional traders in the last subperiod. In earlier years trading costs were probably higher. Thus the break-even one-way transaction costs of 0.22% in the last subperiod are clearly smaller than the real estimated transaction costs of 0.26% per trade. Although Bessembinder and Chan (1998) confirm the results of Brock et al. (1992), they conclude that there is little reason to view the evidence of Brock et al. (1992) as indicative of market inefficiency.

Fernández-Rodríguez, Sosvilla-Rivero, and Andrada-Félix (2001) replicate the testing procedures of Brock et al. (1992) for daily data of the General Index of the Madrid Stock Exchange (IGBM) in the period January 1966 through October 1997. They find that technical trading rules show forecastability in the Madrid Stock Exchange, but acknowledge that they didn't include transaction costs. Furthermore, the bootstrap results show that several null models for stock returns such as the AR(1), GARCH and GARCH-in-mean models cannot explain the forecasting power of the technical trading rules.

Ratner and Leal (1999) apply ten moving-average trading rules to daily local index inflation corrected closing levels for Argentina (Bolsa Indice General), Brazil (Indice BOVESPA), Chile (Indice General de Precios), India (Bombay Sensitive), Korea (Seoul Composite Index), Malaysia (Kuala Lumpur Composite Index), Mexico (Indice de Precios y Cotaciones), the Philippines (Manila Composite Index), Taiwan (Taipei Weighted Price Index) and Thailand (Bangkok S.E.T.) in the period January 1982 through April 1995. After correcting for transaction costs, the rules appear to be significantly profitable only in Taiwan, Thailand and Mexico. However, when not looking at significance, in more than 80% of the cases the trading rules correctly predict the direction of changes in prices.

Isakov and Hollistein (1999) test simple technical trading rules on the Swiss Bank Corporation (SBC) General Index and to some of its individual stocks UBS, ABB, Nestle, Ciba-Geigy and Zurich in the period $1969-1997$. They are the first who extend moving-average trading strategies with momentum indicators or oscillators, so called relative strength or stochastics. These oscillators should indicate when an asset is overbought or oversold and they are supposed to give appropriate signals when to step out of the market. Isakov and Hollistein (1999) find that the use of oscillators does not add to the performance of the moving averages. For the basic moving average strategies they find an average yearly excess return of 18% on the SBC index. Bootstrap simulations show that an AR(1) or GARCH(1,1) model for asset returns cannot explain the predictability of the trading rules. However it is concluded that in the presence of trading costs the rules are only profitable for a particular kind of investor, namely if the costs are not higher than 0.3-0.7% per transaction, and that therefore weak-form efficiency cannot be rejected for small investors.

LeBaron (2000b) tests a 30-week single crossover moving-average trading strategy on weekly data at the close of London markets on Wednesdays of the US Dollar against the BP, DEM and JPY in the period June 1973 through May 1998. It is found that the strategy performed very well on all three exchange rates in the subperiod $1973-1989$, yielding significant positive excess returns of 8, 6.8 and 10.2% yearly for the BP, DM and JPY respectively. However for the subperiod $1990-1998$ the results are not significant anymore. LeBaron (2000b) argues that this reduction in forecastability may be explained by changes in the foreign exchange markets, such as lower transaction costs allowing traders to better arbitrage, foreign exchange intervention, the internet or a better general knowledge of technical trading rules. Another possibility is that trading rules are profitable only over very long periods, but can go through long periods in which they lose money, during which most users of the rules are driven out of the market.

LeBaron (2000a) reviews the paper of Brock et al. (1992) and tests whether the results found for the DJIA in the period $1897-1986$ also hold for the period after 1986. Two technical trading rules are applied to the data set, namely the 150-day single crossover moving-average rule, because the research of Brock et al. (1992) pointed out that this rule performed consistently well over a couple of subperiods, and a 150-day momentum strategy. LeBaron (2000a) finds that the results of Brock et al. (1992) change dramatically in the period $1988-1999$. The trading rules seem to have lost their predictive ability. For the period $1897-1986$ the results could not be explained by a random walk model for stock returns, but for the period $1988-1999$, in contrast, it is concluded that the null of a random walk cannot be rejected.

Coutts and Cheung (2000) apply the technical trading rule set of Brock et al. (1992) to daily data of the Hang Seng Index quoted at the Hong Kong Stock Exchange (HKSE) for the period October 1985 through June 1997. It is found that the trading range break-out rules yield better results than the moving averages. Although the trading rules show significant forecasting power, it is concluded that after correcting for transaction costs the trading rules cannot profitably be exploited. In contrast, Ming Ming, Mat Nor and Krishnan Guru (2000) find significant forecasting power for the strategies of Brock et al. (1992) when applied to the Kuala Lumpur Composite Index (KLCI) even after correction for transaction costs.

Detry and Gregoire (2001) test 10 moving-average trading rules of Brock et al. (1992) on the indices of all 15 countries in the European Union. They find that their results strongly support the conclusion of Brock et al. (1992) for the predictive ability of moving-average rules. However the computed break-even transaction costs are often of the same magnitude as actual transaction costs encountered by professional traders.

In his master's thesis Langedijk (2001) tests the predictability of the variable moving-average trading rules of Brock et al. (1992) on three foreign exchange rates, namely USD/DEM, JPY/DEM and USD/JPY, in the period July 1973 through June 2001. By using simple t-ratios he finds that technical trading rules have predictive ability in the subperiod July 1973 through June 1986, but that the results deteriorate for the period thereafter. Because for the USD/JPY exchange rate the strongest results in favor of technical trading are found, standard statistical analysis is extended by the bootstrap methodology of Brock et al. (1992). It is found that random walk, autoregressive and GARCH models cannot explain the results. However Langedijk (2001) shows that only large investors with low transaction costs can profitably exploit the trading rules.

Intra-day data

Most papers written on the profitability of technical trading rules use daily data. But there is also some literature testing the strategies on intra-day data. Ready (1997) shows that profits of technical trading rules applied to the largest 20% stocks of the NYSE in the period $1970-1995$ disappear, if transaction costs as well as the time delay between the signal of a trading rule and the actual trade are taken into account. Further, he also finds that trading rules perform much worse in the period $1990-1995$. Curcio, Goodhart, Guillaume and Payne (1997) apply technical trading rules, based on support-and-resistance levels, identified and supplied by technical analysts, to intra-daily data of foreign exchange markets (DEM/USD, JPY/USD, BP/USD). They find that no profits can be made on average when transaction costs, due to bid-ask spreads, are taken into account.

Pattern recognition

Academic research on the effectiveness of technical analysis in financial markets, as reviewed above, mainly implements filters, moving averages, momentum and support-and-resistance rules. These technical indicators are fairly easy to program into a computer. However the range of technical trading techniques is very broad and an important part deals with visual pattern recognition. The claim by technical analysts of the presence of geometric shapes in historical price charts is often criticized as being too subjective, intuitive or even vague. Levy (1971) was the first to examine 32 possible forms of five point chart patterns, i.e. a pattern with two highs and three lows or two lows and three highs, which are claimed to represent channels, wedges, diamonds, symmetrical triangles, (reverse) head-and-shoulders, triple tops, and triple bottoms. Local extrema are determined with the help of Alexander's (1961) filter techniques. After trading costs are taken into account it is concluded that none of the 32 patterns show any evidence of profitable forecasting ability in either bullish or bearish direction when applied to 548 NYSE securities in the period July 1964 through July 1969. Neftci (1991) shows that technical patterns can be fully characterized by using appropriate sequences of local minima and maxima. Hence it is concluded that any pattern can potentially be formalized. Osler and Chang (1995) were the first to evaluate the predictive power of head-and-shoulders patterns using a computer-implemented algorithm in foreign exchange rates. The features of the head-and-shoulders pattern are defined to be described by local minima and maxima that are found by applying Alexander's (1961) filter techniques. The pattern recognition algorithm is applied to six currencies (JPY, DEM, CD, SF, FF and BP against the USD) in the period March 1973 to June 1994. Significance is tested with the bootstrap methodology described by Brock et al. (1992) under the null of a random walk and GARCH model. It is found that the head-and-shoulders pattern had significant predictive power for the DEM and the JPY, also after correcting for transaction costs and interest rate differentials. Lo, Mamaysky and Wang (2000) develop a pattern recognition algorithm based on non-parametric kernel regression to detect (inverse) head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, rectangle tops and bottoms, and double tops and bottoms - patterns that are the most difficult to quantify analytically. The pattern recognition algorithm is applied to hundreds of NYSE and NASDAQ quoted stocks in the period $1962 - 1996$. It is found that technical patterns do provide incremental information, especially for NASDAQ stocks. Further it is found that the most common patterns are double tops and bottoms, and (inverted) head-and-shoulders.

The dangers of data snooping

Data snooping is the generic term of the danger that the best forecasting model found in a given data set by a certain specification search is just the result of chance instead of the result of truly superior forecasting power. Jensen (1967) already argued that the good results of the relative-strength trading rule used by Levy (1967) could be the result of survivorship bias. That is, strategies that performed well in the past get the most attention by researchers. Jensen and Benington (1969, p.470) go a step further and argue: "*Likewise given enough computer time, we are sure that we can find a mechanical trading rule which works on a table of random numbers - provided of course that we are allowed to test the same rule on the same table of numbers which we used to discover the rule. We realize of course that the rule would prove useless on any other table of random numbers, and this is exactly the issue with Levy's results.*"

Another form of data snooping is the publication bias. It is a well-known fact that studies presenting unusual results are more likely to be published than the studies that just confirm a well-known theory. The problem of data snooping was addressed in most of the work on technical analysis, but for a long time there was no test procedure to test for it. Finally White (2000), building on the work of Diebold and Mariano (1995) and West (1996), developed a simple and straightforward procedure for testing the null hypothesis that the best forecasting model encountered in a specification search has no predictive superiority over a given benchmark model. The alternative is of course that the best forecasting model is superior to the benchmark. Summarized in simple terms, the procedure bootstraps the original time series a great number of times, preserving the key characteristics of the time series. White (2000) recommends the stationary bootstrap of Politis and Romano (1994a, 1994b). Next, the specification search for the best forecasting model is executed for each bootstrapped series, which yields an empirical distribution of the performance of the best forecasting model. The null hypothesis is rejected at the α percent significance level if the performance of the best forecasting model on the original time series is greater than the α percent cut off level of the empirical distribution. This procedure was called White's Reality Check (RC) for data snooping.

Sullivan, Timmermann and White (1999, 2001) utilize the RC to evaluate simple technical trading strategies and calendar effects applied to the DJIA in the period $1897-1996$. Sullivan et al. (1999) take the study of Brock et al. (1992) as starting point and construct an extensive set of 7846 trading rules, consisting of filters, moving averages, support-and-resistance, channel break-outs and on-balance volume averages. It is demonstrated that the results of Brock et al. (1992) hold after correction for data snooping, but that the forecasting performance tends to have disappeared in the period after the end of 1986.

For the calendar effects, for example the January, Friday and the turn of the month effect, Sullivan et al. (2001) find that the RC in all periods does not reject the null hypothesis that the best forecasting rule encountered in the specification search does not have superior predictive ability over the buy-and-hold benchmark. If no correction were made for the specification search, then in both papers the conclusion would have been that the best model would have significant superior forecasting power over the benchmark. Hence Sullivan et al. (1999, 2000) conclude that it is very important to correct for data snooping for otherwise one can make wrong inferences about the significance of the best model found.

Hansen (2001) identifies a similarity condition for asymptotic tests of composite hypotheses, shows that this condition is a necessary condition for a test to be unbiased. He shows that White's RC does not satisfy this condition. This causes the RC to be an asymptotically biased test, which yields inconsistent p-values. Moreover, the test is sensitive to the inclusion of poor and irrelevant models in the comparison. Further, the test has poor power properties. Therefore, within the framework of White (2000), he applies the similarity condition to derive a test for superior predictive ability (SPA). The null hypothesis of this test is that none of the alternative models in the specification search is superior to the benchmark model, or stated differently, the benchmark model is not inferior to any alternative model. The alternative is that one or more of the alternative models are superior to the benchmark model. Hansen (2001) uses the RC and the SPA-test to evaluate forecasting models applied to US annual inflation in the period $1952 - 2000$. He shows that the null hypothesis is neither rejected by the SPA-test p-value, nor by the RC p-value, but that there is a large difference between both p-values, likely to be caused by poor models in the space of forecasting models.

Grandia (2002) utilizes in his master's thesis the RC and the SPA-test to evaluate the forecasting ability of a large set of technical trading strategies applied to stocks quoted at the Amsterdam Stock Exchange in the period January 1973 through December 2001. He finds that the best trading strategy out of the set of filters, moving averages and trading range break-out rules can generate excess profits over the buy-and-hold even in the presence of transaction costs, but is not superior to the buy-and-hold benchmark after correction for the specification search. The results are stable across the subperiods $1973 - 1986$ and $1987 - 2001$.

Conclusions from the literature

Technical analysis is heavily used in practice to make forecasts about speculative price series. However, early statistical studies found that successive price changes are linearly independent, as measured by autocorrelation, and that financial price series may be well defined by random walks. In that case technical trading should not provide valuable trading signals. However, it was argued that the dependence in price changes might be of such a complicated nonlinear form that standard linear statistical tools might provide misleading measures of the degree of dependence in the data. Therefore several papers appeared in the academic literature testing the profitability of technical analysis. The general consensus in academic research on technical analysis is that there is some but not much dependence in speculative prices that can be exploited by nonlinear technical trading rules. Moreover, any found profitability seems to disappear after correcting for transaction costs and risk. Only floor traders who face very small transaction costs can possibly reap profits from technical trading. Most papers consider a small set of technical trading rules that are said to be widely known and frequently used in practice. This causes the danger of data snooping. However, after correction for the specification search, it is still found that those technical trading rules show forecasting power in the presence of small transaction costs. It is noted by many authors that the forecasting power of technical trading rules seems to disappear in the stock markets as well as in the currency markets during the 1990s, if there was any predictive power before. It is argued that this is likely to be caused by computerized trading programs that take advantage of any kind of patterns discovered before the mid 1990s causing any profit opportunity to disappear.

1.3 Outline of the thesis

The efficient markets hypothesis states that in highly competitive and developed markets it is impossible to derive a trading strategy that can generate persistent excess profits after correction for risk and transaction costs. Andrew Lo, in the introduction of Paul Cootner's "The Random Character of Stock Prices" (2000 reprint, p.xi), suggests even to extend the definition of efficient markets so that profits accrue only to those who acquire and maintain a competitive advantage. Then, those profits may simply be the fair reward for unusual skill, extraordinary effort or breakthroughs in financial technology. The goal of this thesis is to test the weak form of the efficient markets hypothesis by applying a broad range of technical trading strategies to a large number of different data sets. In particular we focus on the question whether, after correcting for transaction costs, risk and data snooping, technical trading rules have statistically significant forecasting power and can generate economically significant profits. This section briefly outlines the different chapters of the thesis. The chapters are written independently from each other with a separate introduction for each chapter. Now and then there is some repetition in the text, but this is mainly done to keep each chapter self contained. Chapters 2 through 5 are mainly empirical, while Chapter 6 describes a theoretical model.

In Chapter 2 a large set of 5350 trend-following technical trading rules is applied to the price series of cocoa futures contracts traded at the London International Financial Futures Exchange (LIFFE) and the New York Coffee, Sugar and Cocoa Exchange (CSCE), in the period January 1983 through June 1997. The trading rule set is also applied to the Pound-Dollar exchange rate in the same period. It is found that 58% of the trading rules generates a strictly positive excess return, even if a correction is made for transaction costs, when applied to the LIFFE cocoa futures prices. Moreover, a large set of trading rules exhibits statistically significant forecasting power if applied to the LIFFE cocoa futures series. On the other hand the same set of strategies performs poor on the CSCE cocoa futures prices, with only 12% generating strictly positive excess returns and hardly showing any statistically significant forecasting power. Bootstrap techniques reveal that the good results found for the LIFFE cocoa futures price series cannot be explained by several popular null models like a random walk, autoregressive and GARCH model, but can be explained by a structural break in trend model. The large difference in the performance of technical trading may be attributed to a combination of the demand/supply mechanism in the cocoa market and an accidental influence of the Pound-Dollar exchange rate, reinforcing trends in the LIFFE cocoa futures but weakening trends in the CSCE cocoa futures. Furthermore, our case study suggests a connection between the success or failure of technical trading and the relative magnitudes of trend, volatility and autocorrelation of the underlying series.

In the next three chapters, Chapters 3-5, a set of trend-following technical trading rules is applied to the price history of several stocks and stock market indices. Two different performance measures are used to select the best technical trading strategy, namely the mean return and the Sharpe ratio criterion. Corrections are made for transaction costs. If technical trading shows to be profitable, then it could be the case that these profits are merely the reward for bearing the risk of implementing technical trading. Therefore Sharpe-Lintner capital asset pricing models (CAPMs) are estimated to test this hypothesis. Furthermore, if technical trading shows economically and statistically significant forecasting power after corrections are made for transaction costs and risk, then it is tested whether the selected technical trading strategy is genuinely superior to the buy-and-hold benchmark also after a correction is made for data snooping. Tests utilized to correct for data snooping are White's (2000) Reality Check (RC) and Hansen's (2001) test for superior predictive ability (SPA). Finally, it is tested with a recursively optimizing and testing method whether technical trading shows true out-of-sample forecasting power. For example, recursively at the beginning of each month the strategy with the highest performance during the preceding six months is selected to generate trading signals in that month.

In Chapter 3 a set of 787 trend-following technical trading rules is applied to the Dow-Jones Industrial Average (DJIA) and to 34 stocks listed in the DJIA in the period January 1973 through June 2001. Because numerous research papers found that technical trading rules show economically and statistically significant forecasting power in the era until 1987, but not in the period thereafter, we split our sample in two subperiods: $1973 - 1986$ and $1987 - 2002$. For the mean return as well as the Sharpe ratio selection criterion it is found that in all periods for each data series a technical trading rule can be found that is capable of beating the buy-and-hold benchmark, even if a correction is made for transaction costs. Furthermore, if no transaction costs are implemented, then for most data series it is found by estimating Sharpe-Lintner CAPMs that technical trading generates risk-corrected excess returns over the risk-free interest rate. However, as transaction costs increase the null hypothesis that technical trading rule profits are just the reward for bearing risk is not rejected for more and more data series. Moreover, if as little as 0.25% transaction costs are implemented, then the null hypothesis that the best technical trading strategy found in a data set is not superior to the buy-and-hold benchmark after a correction is made for data snooping, is neither rejected by the RC nor by the SPA-test for all data series examined. Finally, the recursive optimizing and testing method does not show economically and statistically significant risk-corrected out-of-sample forecasting power of technical trading. Thus, in this chapter no evidence is found that trend-following technical trading rules can forecast the direction of the future price path of the DJIA and stocks listed in the DJIA.

In Chapter 4 the same technical trading rule set is applied to the Amsterdam Stock Exchange Index (AEX-index) and to 50 stocks listed in the AEX-index in the period January 1983 through May 2002. For both selection criteria it is found that for each data series a technical trading strategy can be selected that is capable of beating the buy-and-hold benchmark, also after correction for transaction costs. Furthermore, by estimating Sharpe-Lintner CAPMs it is found for both selection criteria in the presence of 1% transaction costs that for approximately half of the data series the best technical trading strategy has statistically significant risk-corrected forecasting power and even reduces risk of trading. Next, a correction is made for data snooping by applying the RC and the SPA-test. If the mean return criterion is used for selecting the best strategy, then both tests lead for almost all data series to the same conclusion if as little as 0.10% transaction costs are implemented, namely that the best technical trading strategy selected by the mean return criterion is not capable of beating the buy-and-hold benchmark after correcting for the specification search that is used to select the best strategy. In contrast, if the Sharpe ratio selection criterion is used, then for one third of the data series the null of no superior forecasting power is rejected by the SPA-test, even after correction for 1% transaction costs. Thus in contrast to the findings for the stocks listed in the DJIA in Chapter 3, we find that technical trading has economically and statistically significant forecasting power for a group of stocks listed in the AEX-index, after a correction is made for transaction costs, risk and data snooping, if the Sharpe ratio criterion is used for selecting the best technical trading strategy. Finally, the recursive optimizing and testing method does show out-of-sample forecasting profits of technical trading. Estimation of Sharpe-Lintner CAPMs shows, after correction for 0.10% transaction costs, that the best recursive optimizing and testing method has statistically significant risk-corrected forecasting power for more than 40% of the data series examined. However, if transaction costs increase to 0.50% per trade, then for almost all data series the best recursive optimizing and testing procedure has no statistically significant risk-corrected forecasting power anymore. Thus only for sufficiently low transaction costs technical trading is economically and statistically significant for a group of stocks listed in the AEX-index.

In Chapter 5 the set of 787 trend-following technical trading strategies is applied to 50 local main stock market indices in Africa, North and South America, Asia, Europe, the Middle East and the Pacific, and to the MSCI World Index in the period January 1981 through June 2002. We consider the case of an US-based trader and recompute all profits in US Dollars. It is found that half of the indices could not even beat a continuous risk-free investment. However, as in Chapters 3 and 4 it is found for both selection criteria that for each stock market index a technical trading strategy can be selected that is capable of beating the buy-and-hold benchmark, also after correction for transaction costs. Furthermore, after implementing 1% costs per trade, still for half of the indices a statistically significant risk-corrected forecasting power is found by estimating CAPMs. If also a correction is made for data snooping, then we find as in Chapter 4 that both selection criteria yield different results. In the presence of 0.50% transaction costs the null hypothesis of no superior predictive ability of the best technical trading strategy selected by the mean return criterion over the buy-and-hold benchmark after correcting for the specification search is not rejected for most indices by both the RC and

SPA-test. However, if the Sharpe ratio criterion is used to select the best strategy, then for one fourth of the indices, mainly the Asian ones, the null hypothesis of no superior forecastability is rejected by the SPA-test, even in the presence of 1% transaction costs. Finally, the recursive optimizing and testing method does show out-of-sample forecasting profits, also in the presence of transaction costs, mainly for the Asian, Latin American, Middle East and Russian stock market indices. However, for the US, Japanese and most Western European stock market indices the recursive out-of-sample forecasting procedure does not show to be profitable, after implementing little transaction costs. Moreover, for sufficiently high transaction costs it is found, by estimating CAPMs, that technical trading shows no statistically significant risk-corrected out-of-sample forecasting power for almost all of the stock market indices. Only for low transaction costs ($\leq 0.25\%$ per trade) economically and statistically significant risk-corrected out-of-sample forecasting power of trend-following technical trading techniques is found for the Asian, Latin American, Middle East and Russian stock market indices.

In Chapter 6 a financial market model with heterogeneous adaptively learning agents is developed. The agents can choose between a fundamental forecasting rule and a technical trading rule. The fundamental forecasting rule predicts that the price returns back to the fundamental value with a certain speed, whereas the technical trading rule is based on moving averages. The model in this chapter extends the Brock and Hommes (1998) heterogeneous agents model by adding a moving-average technical trading strategy to the set of beliefs the agents can choose from, but deviates by assuming constant relative risk aversion, so that agents choosing the same forecasting rule invest the same fraction of their wealth in the risky asset. The local dynamical behavior of the model around the fundamental steady state is studied by varying the values of the model parameters. A mixture of theoretical and numerical methods is used to analyze the dynamics. In particular we show that the fundamental steady state may become unstable due to a Hopf bifurcation. The interaction between fundamentalists and technical traders may thus cause prices to deviate from their fundamental value. In this heterogeneous world the fundamental traders are not able to drive the moving average traders out of the market, but fundamentalists and technical analysts coexist forever with their relative importance changing over time.

Chapter 2

Success and Failure of Technical Trading Strategies in the Cocoa Futures Market

2.1 Introduction

This chapter is an attempt to answer questions raised by a financial practitioner, Guido Veenstra, employed at the leading Dutch cocoa-trading firm, Unicom International B.V. at Zaandam. Unicom is part of a bigger consortium that buys crops of cocoa at the Ivory Coast, where it has a plant to make some first refinements of the raw cocoa. The cocoa beans are shipped to Europe where they are transformed to cocoa-butter, cocoa-powder and cocoa-mass in plants in France and Spain. These raw cocoa products serve as production factors in the chocolate industry. The first goal of Unicom is to sell the raw cocoa beans as well as the raw cocoa products to chocolate manufacturers. A second important task of Unicom is to control the financial risks of the whole consortium. The consortium faces currency risk as well as cocoa price risk. Unicom monitors the product streams and uses cocoa futures contracts, mainly those traded at the London International Financial Futures Exchange (LIFFE), to hedge the price risk. Unicom trades cocoa futures through brokers. However, the commission fees give the brokers an incentive to contact their clients frequently and to give them sometimes unwanted advice to trade as much as possible. Brokers' advices are partly based on technical analysis.

In addition to cocoa producers, more and more speculators seem to be trading on the cocoa futures markets who use technical analysis as a forecasting tool. If a lot of speculators with a large amount of money are trading in a market, they may affect realized futures prices through their behavior. The question *"Can cocoa futures prices be predicted by technical analysis?"* thus becomes important from a practitioner's viewpoint. This question is not only important to cocoa producers, but in general to producers of any commodity hedging price risk. If technical analysis has forecasting power and speculators take positions in the market on the basis of technical analysis, these speculators can affect market prices. Why should a (cocoa) producer go short in the futures market to hedge his price risk exposure if he knows that a lot of speculators in the market are buying long positions driving up the price? Knowledge of the behavior of speculators in the market may be useful to adapt a producers' price hedging strategy.

Until fairly recently, the academic literature has paid little attention to technical trading strategies. Until the 1980s the efficient markets hypothesis (EMH) was the dominating paradigm in finance, see e.g. Fama (1970) and Samuelson (1965). According to a strong form of the EMH, financial time series follow a random walk and are thus inherently unpredictable. All information is discounted in the prices already and prices will only adapt if new information becomes available. Because news arrives randomly, prices will move randomly. According to the EMH, financial time series are unpredictable and technical analysis is useless and cannot lead to statistically significant prediction or economically significant profits.

In the last decade however, technical analysis has regained the interest of many economic researchers. Several authors have shown that financial prices and returns are forecastable to some extent, either from their own past or from some other publicly available information, see e.g. Fama and French (1988), Lo and MacKinlay (1988, 1997, 1999) and Pesaran and Timmermann (1995, 2000). In particular, it has been shown that simple technical trading rules used in financial practice can generate positive profits and can have statistically significant forecasting power. For example Brock, Lakonishok and LeBaron (1992) test 26 simple technical trading rules on daily data of the Dow-Jones Industrial Average (DJIA) in the period 1897-1986. Each of the trading rules Brock et al. (1992) test generates higher returns during buy days, that is periods following buy signals, than during sell days, that is periods following sell signals. Further they find that returns following buy signals are less volatile than returns following sell signals. By applying bootstrap techniques they show that their results are not consistent with some popular null models like the random walk, the AR(1), the GARCH-in-mean and the exponential GARCH model. LeBaron (2000) performs the same analysis as Brock et al. (1992) for the period 1988-1999 and finds that trading rules perform much worse in this period, but that volatility remains different between buy and sell periods. Levich and Thomas (1993) test filter and moving-average trading rules on foreign currency futures prices in the period

1976-1990. Applying bootstrap techniques they conclude that the profits of the technical trading strategies cannot be explained by a random walk model or by autocorrelation in the data. LeBaron (1993) applies trading rules to exchange rates based on interest rate differentials, moving averages and volatility comparison and concludes that the trading rules tested have forecasting power.

Several authors have emphasized the danger of data snooping, meaning that if one searches long enough in a data set, there will always appear one trading strategy that seems to work. Many authors mitigate this problem by using only trading rules that are frequently used in financial practice or by reporting the robustness of their results across different subperiods. However, Sullivan, Timmermann and White (1999) noted that such trading strategies could be the result of survivorship bias, since the currently used trading rules in practice can be the result of a continuous search for the best strategy. Therefore they propose to use White's (2000) Reality Check bootstrap methodology to correct for data snooping. Sullivan et al. (1999) take the results of Brock et al. (1992) on the DJIA in the period 1897-1986 as starting point. They find that the results of Brock et al. (1992) are robust to data snooping in the period 1897-1986, but that in the period 1987-1997 the performance of the best trading rule is not significant when corrected for data snooping. Sullivan et al. (1999) show that the same results hold for a universe of 7846 trading rules and conclude that the worse performance of trading rules in the period 1987-1997 may be explained by a change of the market mechanism, e.g. an increase of market efficiency due to lower transaction costs and increased liquidity.

The present chapter is empirical and tests the profitability and predictability of objective trend-following technical trading techniques in the cocoa futures markets in the period 1983:1-1997:6. In order to avoid the problem of data snooping our approach is to test a large set of more than 5000 trading strategies, moving average, trading range break-out and filter rules, and to investigate the magnitude of the fraction generating strictly positive excess returns and statistically significant forecasting power. Cocoa futures contracts are traded at two different exchanges, namely at the Coffee, Sugar and Cocoa Exchange (CSCE) in New York and the London International Financial Futures Exchange (LIFFE). The results for the two cocoa futures contracts are strikingly different. When applied to the LIFFE cocoa futures prices, 58.3% of all trading rules generate strictly positive excess returns, even when correcting for transaction costs. Furthermore, a large set of trading rules exhibits statistically significant forecasting power of the LIFFE cocoa futures series, with e.g. 26.6% having significantly positive mean buy minus sell return; for the 5 year subperiod 1983:1-1987:12 even 46.7% of all trading rules has a significantly positive mean buy minus sell return. However, the same set of strategies performs poorly on the CSCE cocoa futures prices, with only 12.2% generating positive net excess returns and hardly any statistically significant forecasting power. The large difference in the performance of technical trading is surprising, because the underlying asset in both markets is more or less the same. Our findings may be attributed to a combination of the demand/supply mechanism in the cocoa market and an accidental influence of the Pound-Dollar exchange rate. Due to a spurious relation between the level of the Pound-Dollar exchange rate and the excess demand/supply mechanism in the cocoa market, especially in the period 1983:1-1987:12, trends caused by the demand/supply mechanism were reinforced in the LIFFE cocoa futures price, but the same trends were weakened in the CSCE cocoa futures price. Many technical trading rules are able to pick up these sufficiently strong trends in the LIFFE cocoa futures but almost none of them pick up the weaker trends in the CSCE cocoa futures.

The chapter is organized as follows. In section 2.2 we describe our data set and the construction of a long, continuous time series of 15 years out of 160 different (overlapping) futures contracts of 18 months. Section 2.3 gives an overview of the 5350 trading rules we apply; the parameterizations of these rules can be found in Appendix B. In section 2.4 the performance measure, i.e. the excess return net of transaction costs generated by the trading rules, is calculated. Section 2.5 focuses on the economic performance as well as the statistical significance of the predictability of returns by technical trading rules. The statistical tests are performed first under the assumption of iid returns but later also by correcting for dependence in the data. This is done by estimating exponential GARCH models with a dummy for the trading position in the regression equation, but also by applying bootstrap techniques, the results of which are presented in section 2.6. In section 2.7 a possible explanation of the large differences in the performance between CSCE and the LIFFE cocoa futures prices is given. Finally, section 2.8 concludes.

2.2 Data

2.2.1 Data series

A commodity futures contract is an agreement between two parties to trade a certain asset at some future date. The contract specifies the quality and quantity of the good as well as the time and place of delivery. The price against which the contract is traded is called the futures price. The expiry months of cocoa futures contracts are March, May, July, September and December. Each contract asks for the delivery of ten tons of cocoa. The LIFFE contract specifies that at each trading day ten expiry months are available for trading. The CSCE and LIFFE cocoa futures contracts differ somewhat in their specifications. First, cocoa is grown in many regions in Africa, Asia and Latin America and therefore the crops differ in quality. In the futures contracts a benchmark is specified and the other crops are traded at premiums. The benchmark in the LIFFE contract has a higher quality than the benchmark in the CSCE contract. Therefore the benchmark in the LIFFE contract is traded at a $160/ton[1] premium in the CSCE contract. Second, the place of delivery in the CSCE contract is near New York, while the places of delivery in the LIFFE contract are nominated warehouses at different places in Europe. Third, the tick sizes of the CSCE and LIFFE contract are respectively one Dollar and one Pound.

Cocoa producers and farmers hedge their price risk exposure with futures contracts. This guarantees them that they buy or sell cocoa against a predetermined price. The futures price will depend on the current and expected future demand and supply. When new information becomes available the price will adapt. Normally a futures price is the derivative of the spot price and can be computed by the cost of carry relationship. But in the case of soft commodities such as cocoa the spot price is not relevant, because a farmer with his crop on the land only wants to know what he can get in the future. For cocoa there is no actual spot price, but the "notional" spot price is in fact determined by the futures prices.

We investigate data on the settlement prices of 160 cocoa futures contracts that expire in the period January 1982 through December 1997 at the CSCE and the LIFFE[2], as well as data on the Pound-Dollar exchange rate (WM/Reuters) and 1-month UK and US certificates of deposit (COD) interest rates in the same period.

2.2.2 A continuous time series of futures prices

Each futures contract covers a limited time span of approximately 18 months. Thus there is no continuous time series of futures prices over a couple of years. In this section we describe how a continuous time series can be constructed out of the prices of the separate contracts. The well-known formula of the price of a futures contract at day t which expires at day T is

$$F_t = S_t e^{(r_t^f + u_t - y_t)(T-t)}. \tag{2.1}$$

Here S_t is the spot price of the underlying asset at time t, and r_t^f, u_t, y_t are respectively the daily risk-free interest rate, storage costs and convenience yield averaged over the period

[1] Contract specifications of January 26, 1998.

[2] We thank the cocoa-trading firm Unicom International B.V. and ADP Financial Information Services for providing the data.

$(t, T]$ at time t with continuous compounding. The convenience yield can be described as the utility of having the asset in stock. The term $(r_t^f + u_t - y_t)$ is called the *cost of carry* and (2.1) is called the cost of carry relationship. The daily return r_t^F of the futures contract, expressed as the log difference, is given by

$$r_t^F = r_t^S + (\Delta r_t^f + \Delta u_t - \Delta y_t)\ (T - t) - (r_{t-1}^f + u_{t-1} - y_{t-1}). \tag{2.2}$$

This formula shows that a change in one of the factors of the cost of carry has an impact on the futures price. Otherwise, the return of a futures contract is equal to the excess return of the underlying asset over the cost of carry.

Assume that we have two futures contracts, 1 and 2, with futures prices $F_t^{(1)}$ and $F_t^{(2)}$ and expiry dates $T_2 > T_1$. It follows from (2.2) that two futures contracts traded in the same period have the same trends in prices. The futures price of contract 2 can be expressed in terms of the futures price of contract 1 as

$$F_t^{(2)} = F_t^{(1)} e^{(r_t^f + u_t - y_t)(T_2 - T_1)}. \tag{2.3}$$

Notice that r_t^f, u_t and y_t are numbers averaged over $(t, T]$. Thus in equation (2.3) it is assumed that r_t^f, u_t and y_t averaged over $(t, T_1]$ is equal to r_t^f, u_t and y_t averaged over $(t, T_2]$. Formula (2.3) shows that if, as is usual, the cost of carry is positive, the futures price of contract 2 which expires later is higher than the futures price of contract 1 which expires earlier. But if the utility of having an asset in stock is high, e.g. when there is a shortage of the commodity in the short run, then the futures price of contract 2 can be lower than the futures price of contract 1. Thus the prices of different futures contracts can move at different price levels.

A long continuous time series of futures prices will be constructed, in order to be able to test technical trading strategies with long memory. The continuous time series must be constructed out of the many price series of the different futures contracts that have the same price trends, but move at different price levels. In particular *roll over dates* must be defined at which the price movements of the different contracts are pasted together. In practice most trading occurs in the second nearest contract, that is the futures contract that has the one but nearest expiration date. We investigated the liquidity of the cocoa futures contracts and decided to take as roll over dates the date one month before most of the practitioners switch to the next contract, so that the continuous time series always represents a high liquidity futures contract. Figure 2.1 exhibits graphically the roll over procedure used in this chapter.

Murphy (1986) suggests pasting the prices of two successive futures contracts to study price movements over a long period of time. But the pasting of prices will introduce price

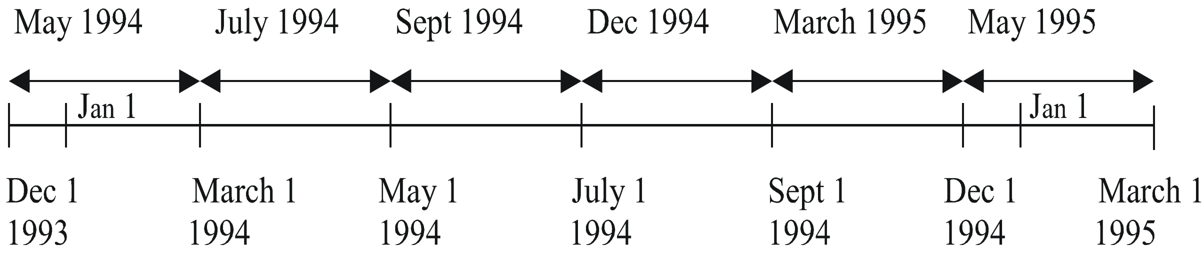

Figure 2.1: Roll over scheme. The time axis shows the roll over dates from Dec. 1, 1993 until March 1, 1995. The arrows above the time axis show in which period which futures contract is used in constructing the continuous futures price series.

jumps in the continuous time series, because the prices of two different contracts move at different levels. These price jumps can have an impact on the results and may trigger spurious trading signals if technical trading rules are tested. Therefore a continuous time series must be constructed in another way.

The holder of the long position in a futures contract pays a time premium to the holder of the short position. According to (2.1) the time premium paid at time t is

$$TP_t = F_t - S_t = (e^{(r_t^f + u_t - y_t)(T-t)} - 1)\ S_t. \tag{2.4}$$

According to (2.4) the time premium that must be paid will be less when the duration of the contract is shorter other things being equal. However, (2.4) also implies that if a continuous time series of futures prices is constructed by pasting the prices of different contracts, at each pasting date[3] a new time premium to the time series is added, because at each pasting date the time until expiration will be longer than before the pasting date. This time premium will create price jumps and therefore an upward force in the global price development. In fact, if the return of the underlying asset is not greater than the cost of carry a spurious upward trend can be observed in the continuous price series, as illustrated in figure 2.2, which may affect the performance of long memory trading strategies. Therefore we constructed a continuous time series of futures prices by pasting the returns of each futures contract at the roll over dates and choosing an appropriate starting value; see figure 2.2. For this continuous series, discontinuous price jumps and spurious trends will disappear and the trends will show the real profitability of trading positions in futures contracts.

[3]The pasting date is equal to the roll over date.

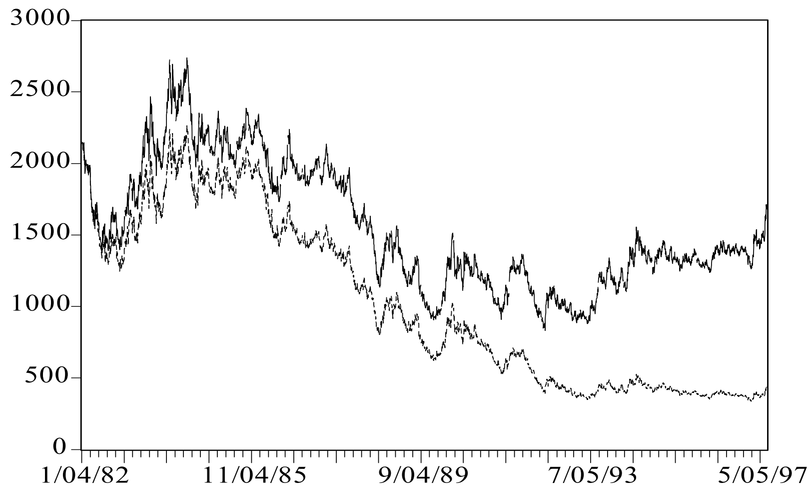

Figure 2.2: Two continuous time series of CSCE cocoa futures prices in the period 1982:1-1997:6. The upper time series is constructed by pasting the futures *prices* at the roll over dates. The time premium of a futures contract leads to price jumps and spurious trends. In this chapter we use the lower continuous time series, constructed by pasting the *returns* of the futures prices at the roll over dates and by choosing as starting value the futures price of the May contract at January 3, 1983. Any trends that are present in the lower series reflect real profitability of trading positions.

2.2.3 Summary statistics

In figure 2.3 time series are shown of the continuation of the CSCE and LIFFE cocoa futures prices and returns as well as the Pound-Dollar exchange rates and returns for the period 1982:1-1997:6. The long-term and short-term trends can be seen clearly. Each technical trading strategy needs a different time horizon of past prices to generate its first signal. Therefore the first 260 observations in each data set will be used to initialize the trading rules, so that on January 3, 1983 each rule advises some position in the market. All trading rules will be compared from this date. Table 2.1 shows the summary statistics of the daily returns of the sample 1983:1-1997:6 and three subperiods of five years. Returns are calculated as the natural log differences of the level of the data series.

The first subperiod, 1983:1-1987:12, covers the period in which the price series exhibit first a long term upward trend and thereafter a downward trend; see figure 2.3. It is remarkable that the upward and downward trends of both cocoa futures series CSCE and LIFFE (accidentally) coincide with similar trends in the Pound-Dollar exchange rate series. In the second subperiod, 1988:1-1992:12, the cocoa series exhibit a downward trend, while the Pound-Dollar series is fluctuating upwards and downwards. The third subperiod, 1993:1-1997:6, covers a period in which the cocoa series as well as the Pound-Dollar series seem to show no significant long term trends anymore. From table 2.1 it

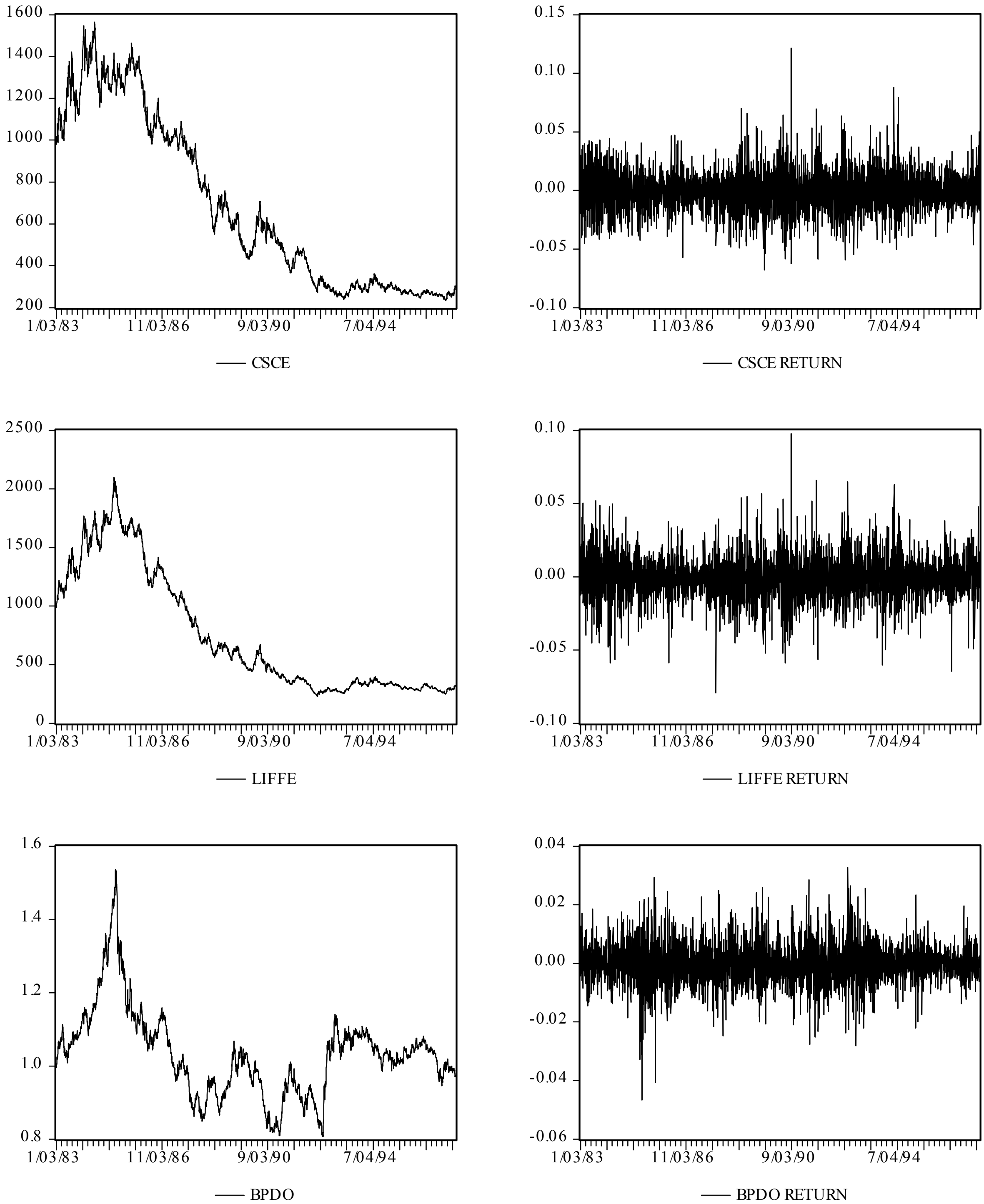

Figure 2.3: Time series, over the period 1983:1-1997:6, of CSCE (top left) and LIFFE (middle left) cocoa futures prices, the Pound-Dollar exchange rate (bottom left) and corresponding returns series (right).

can be seen that the mean daily returns are close to zero for all periods. The largest (absolute) mean daily return is negative 9.5 basis points per day, -21.2% per year, for the CSCE series in the second subperiod. The daily standard deviation of the CSCE returns series is slightly, but significantly[4] greater than the daily standard deviation of the LIFFE returns series in all periods. The daily volatility of the Pound-Dollar series is much smaller, by a factor more than two measured in standard deviations, than the volatility of both cocoa series in all subperiods. All data series show excess kurtosis in comparison with a normal distribution and show some sign of skewness. The table also shows the maximum consecutive decline of the data series in each period. For example the CSCE cocoa futures continuation series declined with 85.1% in the period May 23, 1984 until February 20, 1997. The Pound lost 47.5% of its value against the Dollar in the period February 27, 1985 until September 2, 1992. Hence, if objective trend-following trading techniques can avoid being in the market during such periods of great depreciation, large profits can be made.

Table 2.2 shows the estimated autocorrelation functions, up to order 20, for all data series over all periods. Typically autocorrelations are small with only few lags being significant.[5] The CSCE series shows little autocorrelation. Only for the first subperiod the second order autocorrelation is significant at a 5% significance level. The LIFFE series shows some signs of low order autocorrelation, significant at the 10% level, in the first two subperiods. The Pound-Dollar series has a significant first order autocorrelation at a 1% significance level, mainly in the first two subperiods.

2.3 Technical trading strategies

Murphy (1986) defines technical analysis as the study of past price movements with the goal to forecast future price movements, perhaps with the aid of certain quantitative summary measures of past prices such as "momentum" indicators ("oscillators"), but without regard to any underlying economic, or "fundamental" analysis. Another description is given by Pring (1998) who defines technical analysis as the "art" of detecting a price trend in an early stage and maintaining a market position until there is enough weight of evidence that the trend has reversed.

[4] $H_0 : \sigma^2_{r(csce)} = \sigma^2_{r(liffe)}$ vs $H_1 : \sigma^2_{r(csce)} \neq \sigma^2_{r(liffe)}$; $F = S^2_{r(csce)}/S^2_{r(liffe)}$;

[5] Because sample autocorrelation may be spurious in the presence of heteroskedasticity we also tested for significance by computing Diebold (1986) heteroskedasticity-consistent estimates of the standard errors, $se(k) = \sqrt{1/n\ (1 + \gamma(r^2, k)/\sigma^4)}$, where n is the number of observations, $\gamma(r^2, k)$ is the k-th order sample autocovariance of the squared returns, and σ is the standard error of the returns. ***, **, * in table 2.2 then indicates whether the corresponding autocorrelation is significantly different from zero.

There are three principles underlying technical analysis. The first is that all information is gradually discounted in the prices. Through the market mechanism the expectations, hopes, dreams and believes of all investors are reflected in the prices. A technical analyst argues that the best adviser you can get is the market itself and there is no need to explore fundamental information. Second, technical analysis assumes that prices move in upward, downward or sideways trends. Therefore most technical trading techniques are trend-following instruments. The third assumption is that history repeats itself. Under equal conditions investors will react the same leading to price patterns which can be recognized in the data. Technical analysts claim that if a pattern is detected in an early stage, profitable trades can be made.

In this thesis we confine ourselves to *objective* trend-following technical trading techniques which can be implemented on a computer. In this chapter we test in total 5350 technical trading strategies divided in three different groups: moving-average rules (in total 2760), trading range break-out (also called support-and-resistance) rules (in total 1990) and filter rules (in total 600). These strategies are also described by Brock, Lakonishok and LeBaron (1992), Levich and Thomas (1993) and Sullivan, Timmermann and White (1999). Lo, Mamaysky and Wang (2000) use non-parametric methods to implement other, geometrically based technical trading rules such as head-and-shoulder pattern formation. We use the parameterizations of Sullivan et al. (1999) as a starting point to construct our sets of trading rules. These parameterizations are presented in Appendix B. The strategies will be computed on the continuous cocoa time series and the Pound-Dollar exchange rate. If a buy (sell) signal is generated at the end of day t, we assume that a long (short) position is taken in the market at day t against the settlement price of day t.

2.3.1 The moving-average trading rule

Moving-average (MA) trading rules are the most commonly used and most commonly tested technical trading strategies. Moving averages are recursively updated averages of past prices. They yield insight in the underlying trend of a price series and also smooth out an otherwise volatile series. In this thesis we use equally weighted moving averages

$$MA_t^n = \frac{1}{n}\sum_{j=0}^{n-1} P_{t-j},$$

where MA_t^n is the moving average at time t of the last n observed prices. Short (long) term trends can be detected by choosing n small (large). The larger n, the slower the MA adapts and the more the volatility is smoothed out. Technical analysts therefore refer to a MA with a large n as a slow MA and to a MA with a small n as a fast MA.

MA trading rules make use of one or two moving averages. A special case is the *single crossover* MA trading rule using the price series itself and a MA of the price series. If the price crosses the MA upward (downward) this is considered as a buy (sell) signal. The *double crossover* MA trading rule on the other hand uses two moving averages, a slow one and a fast one. The slow MA represents the long run trend and the fast MA represents the short run trend. If the fast MA crosses the slow MA upward (downward) a buy (sell) signal is given. The signal generating model is given by[6]

$$
\begin{aligned}
Pos_{t+1} &= 1, && \text{if } MA_t^k > MA_t^n \\
Pos_{t+1} &= Pos_t, && \text{if } MA_t^k = MA_t^n \\
Pos_{t+1} &= -1, && \text{if } MA_t^k < MA_t^n,
\end{aligned}
$$

where $k < n$ and $Pos_{t+1} = -1, 0, 1$ means holding a short, neutral respectively long position in the market in period $t+1$.

We call the single and double crossover MA rules described above, the basic MA trading rules. These basic MA rules can be extended with a %-band filter, a time delay filter, a fixed holding period and a stop-loss. The %-band filter and time delay filter are developed to reduce the number of false signals. In the case of the %-band filter, a band is introduced around the slow MA. If the price or fast MA crosses the slow MA with an amount greater than the band, a signal is generated; otherwise the position in the market is maintained. This strategy will not generate trading signals as long as the fast MA is within the band around the slow MA. The extended MA model with a $b \cdot 100\%$ filter is given by

$$
\begin{aligned}
Pos_{t+1} &= 1, && \text{if } MA_t^k > (1+b)MA_t^n \\
Pos_{t+1} &= Pos_t, && \text{if } (1-b)MA_t^n \leq MA_t^k \leq (1+b)MA_t^n \\
Pos_{t+1} &= -1, && \text{if } MA_t^k < (1-b)MA_t^n.
\end{aligned}
$$

According to the time delay filter a signal must hold for d consecutive days before a trade is implemented. If within these d days different signals are given, the position in the market will not be changed. A MA rule with a fixed holding period holds a long (short) position in the market for a fixed number of f days after a buy (sell) signal is generated. After f days the market position is liquidated and a neutral market position is held up to the next buy or sell signal. This strategy tests whether the market behaves different in a time period after the first crossing. All signals that are generated during the fixed holding period are ignored. The last extension is the stop-loss. The stop-loss is based on the popular phrase: "*Let your profits run and cut your losses short.*" If a short (long) position is held in the market, the stop-loss will liquidate the position if the price rises

[6] Positions are unchanged until the moving averages really cross.

(declines) from the most recent low (high) with $x\%$. A neutral market position is held up to the next buy or sell signal. In total our group of MA rules consists of 2760 trading strategies.

2.3.2 Trading range break-out

Our second group of trading rules consists of trading range break-out (TRB) strategies, also called support-and-resistance strategies. The TRB strategy uses *support* and *resistance* levels. If during a certain period of time the price does not fall below (rise beyond) a certain price level, this price level is called a support (resistance) level. According to technical analysts, there is a "battle between buyers and sellers" at these price levels. The market buys at the support level after a price decline and sells at the resistance level after a price rise. If the price breaks through the support (resistance) level, an important technical trading signal is generated. The sellers (buyers) have won the "battle". At the support (resistance) level the market has become a net seller (buyer). This indicates that the market will move to a subsequent lower (higher) level. The support (resistance) level will change into a resistance (support) level. To implement the TRB strategy, support-and-resistance levels are defined as local minima and maxima of the closing prices. If the price falls (rises) through the local minimum (maximum) a sell (buy) signal is generated and a short (long) position is taken in the market. If the price moves between the local minimum and maximum the position in the market is maintained until there is a new breakthrough. The TRB strategy will also be extended with a %-band filter, a time delay filter, a fixed holding period and a stop-loss. The basic TRB strategy, extended with a %-band filter, is described by

$$
\begin{aligned}
&Pos_{t+1} = 1, && \text{if } P_t > (1+b)\max\{P_{t-1}, P_{t-2}, ..., P_{t-n}\} \\
&Pos_{t+1} = Pos_t, && \text{if } (1-b)\min\{P_{t-1}, ..., P_{t-n}\} \leq P_t \leq (1+b)\max\{P_{t-1}, ..., P_{t-n}\} \\
&Pos_{t+1} = -1, && \text{if } P_t < (1-b)\min\{P_{t-1}, P_{t-2}, ..., P_{t-n}\}
\end{aligned}
$$

Our group of TRB strategies consists of 1990 trading strategies.

2.3.3 Filter rule

The final group of trading strategies we test is the group of filter rules, introduced by Alexander (1961). These strategies generate buy (sell) signals if the price rises (falls) by $x\%$ from a previous low (high). We implement the filter rule by using a so called moving stop-loss. In an upward trend the stop-loss is placed below the price series. If the price goes up, the stop-loss will go up. If the price declines, the stop-loss will not be changed.

If the price falls through the stop-loss, a sell signal is generated and the stop-loss will be placed above the price series. If the price declines, the stop-loss will decline. If the price rises, the stop-loss is not changed. If the price rises through the stop-loss a buy signal is generated and the stop-loss is placed below the price series. The stop-loss will follow the price series at a $x\%$ distance. On a buy (sell) signal a long (short) position is maintained. This strategy will be extended with a time delay filter and a fixed holding period. In total our group of filter rules consists of 600 trading strategies.

As can be seen in Appendix B we can construct a total of 5350 trading strategies (2760 MA-rules, 1990 TRB-rules, and 600 Filter-rules) with a limited number of values for each parameter. Each trading strategy divides the data set of prices in three subsets. A buy (sell) period is defined as the period after a buy (sell) signal up to the next trading signal. A neutral period is defined as the period after a neutral signal up to the next buy or sell signal. The subsets consisting of buy, sell or neutral periods will be called the set of buy, sell or neutral days.

2.4 Performance measure

2.4.1 Cocoa futures prices

Suppose P_t is the level of the continuous futures price series at the end of day t and Pos_t is the position held in the market by the trader at day t. When trading a futures contract, it is required to hold some margin on a margin account to protect the broker against defaults of the traders. Profits and losses are directly added and subtracted from the margin. A risk-free interest rate can be earned on the margin account. Suppose a trader takes a long or short position in the market against the settlement price at day $t-1$, P_{t-1}, and assume that he deposits P_{t-1} on his margin account. In this case the broker is fully protected against defaulting[7]. Then the margin of the trader at the end of day t is equal to

$$M_t = (1 + r_t^f)M_{t-1} + (P_t - P_{t-1})Pos_t,$$

where $M_{t-1} = P_{t-1}$, if as in the case described above the position is held for the first day, otherwise M_{t-1} is just the margin build up until time $t-1$. Further, r_t^f is the daily

[7] In practice traders can hold a margin of 10% of the underlying value. The broker issues frequently a margin call, that is to add money to the margin, if the trader is in a losing position. However, to keep things as simple as possible we assume a fully protected trading position by setting the required margin to 100% of the underlying value.

risk-free interest rate. The profit or loss of the trader on the futures position in period t directly added to or subtracted from the margin account is equal to $(P_t - P_{t-1})Pos_t$.

We will also consider transaction costs. Costs are calculated as a fraction c of the price. Some strategies generate trading signals very often, others not. If a strategy does not generate trading signals very often and a position in the market is maintained for a long time, then there are also trading costs due to the limited life span of a futures contract. In particular, we assume that if a certain position in the market is maintained for 20 days after a roll over date, a trade takes place since the position has to be rolled over to the next futures contract and transaction costs must be paid. This approach leads to a fair comparison of the cost structure of strategies that generate many signals with strategies that generate only a few signals.

Finally, the gross return on time t is calculated as

$$
\begin{aligned}
&M_{t-1} = P_{t-1} \quad \text{if there is a trade (i.e. } Pos_t \neq Pos_{t-1}) \\
&\qquad\qquad\qquad \text{else } M_{t-1} \text{ remains the same;} \\
&M_t = (1 + r_t^f)M_{t-1} + (P_t - P_{t-1})Pos_t; \\
&1 + r_t = \begin{cases} \frac{M_t}{M_{t-1}} & \text{, if there is no trade;} \\ \frac{M_t}{M_{t-1}} \frac{1-c|Pos_{t-1}|}{1+c|Pos_t|} & \text{, if there is a trade.} \end{cases}
\end{aligned}
\tag{2.5}
$$

If no position is held in the market, i.e. $Pos_t = 0$, then according to the formula above a risk-free interest rate is earned. Formula (2.5) represents in the best way the daily return generated by a long as well as a short position in a futures contract. The net return with continuous compounding can be computed by taking the natural logarithm of (2.5). The excess return over the risk-free interest rate and after correcting for transaction costs of trading futures contracts we compute as $r_t^e = \ln(1 + r_t) - \ln(1 + r_t^f)$. If we take the cumulative excess return, $\sum_{t=1}^{T} r_t^e$, to the power e, then we get

$$A = \exp\left(\sum_{t=1}^{T} r_t^e\right) = \prod_{t=1}^{T} \frac{1 + r_t}{1 + r_t^f}. \tag{2.6}$$

Equation (2.6) determines how much better a technical trading strategy performs relatively to a continuous risk free investment. Hence $(A - 1) * 100\%$ determines how much percent the strategy performs better than a risk free investment.

We take as a proxy for the risk-free interest rates the 1-month US and UK certificates of deposits (COD), which we recompute to daily interest rates. Costs of trading c are set equal to 0.1% per trade, which is close to real transaction costs in futures trading.

2.4.2 Pound-Dollar exchange rate

This section describes how the excess return of a trading strategy applied to an exchange rate E_t is computed. On a buy signal the foreign currency is bought and the foreign risk-free interest rate $r^F_{f,t}$ is earned. If there is a position in the foreign currency and the trading rule generates a sell signal or advises to hold no position, then the foreign currency will be exchanged for the domestic currency and the domestic risk-free interest rate $r^D_{f,t}$ is earned. Costs are calculated as a fraction c of the exchange rate. The following formula gives the gross return of the trading strategy used:

$$(1 - costs) = \begin{cases} \frac{1}{1+c} & \text{, if foreign currency is bought;} \\ 1 - c & \text{, if foreign currency is sold;} \\ 1 & \text{, if there is no change in position.} \end{cases}$$

$$1 + r_t = \begin{cases} \frac{E_t}{E_{t-1}}(1 + r^F_{f,t})(1 - costs), & \text{if a position is held in the foreign currency;} \\ (1 + r^D_{f,t})(1 - costs), & \text{if a position is held in the domestic currency.} \end{cases} \tag{2.7}$$

The net return with continuous compounding can be computed by taking the natural logarithm of (2.7). The excess return over the risk free domestic interest rate and after correcting for transaction costs of trading currency we compute as $r^e_t = \ln(1+r_t) - \ln(1+r^D_{f,t})$. With equation (2.6) we can determine how much better a trading strategy performs over a continuous risk free investment, for example a domestic deposit. For the foreign and domestic interest rates we use as proxies the US and UK 1-month CODs, which are recomputed to daily interest rates. Costs for trading are set equal to 0.1%.

2.5 Profitability and predictability of trading rules

2.5.1 The best 5 strategies

Panel A of table 2.3 shows the results of the best five technical trading strategies applied to the CSCE cocoa futures price series in the period 1983:1-1997:6. Panel B of the table lists the results of the best strategy in each subperiod. The first column of the table lists the strategy parameters. MA, TRB and FR are abbreviations for the moving average, trading range break-out and filter rules respectively. $\%b$, td, fhp, and stl are abbreviations for the %-band filter, the time delay filter, the fixed holding period and the stop-loss respectively. For example, the best technical trading strategy in the full sample period is the trading range break-out strategy with a history of five days, a two %-band filter and a 50 day fixed holding period. The second column lists the mean daily excess return of the strategy on a yearly basis, that is the mean daily return times the number of trading days in a year, which is set to 252. The third column lists the mean daily excess returns of the trading rules net of 0.1% transaction costs, with the t-ratios beneath these numbers. The t-test statistic tests whether the mean daily excess return is significantly different from zero under the assumption of iid returns. The fourth and fifth column list the number of days classified as a buy or sell day. The number of buy and sell trades is listed beneath these numbers. The sixth (seventh) column list the total number of days buy (sell) trades with a strictly positive excess return last, as a fraction of the total number of buy (sell) days. The fraction of buy and sell trades with a strictly positive excess return is listed beneath these numbers. The eight and ninth column list the mean daily return of the data series itself during buy and sell days. T-ratios to test whether the mean daily return during buy and sell days is significantly different from zero are listed beneath these numbers. In this way we can detect whether the data series itself rises during buy days and declines during sell days. The last column lists the differences between the mean daily buy and sell returns and the corresponding t-ratios, which test whether the mean daily buy return is significantly different from the mean daily sell return. These t-ratios are computed as

$$t_{B-S} = \frac{\overline{r_B} - \overline{r_S}}{\sqrt{\frac{S_B^2}{N_B} + \frac{S_S^2}{N_S}}},$$

where $\overline{r_B}$ and $\overline{r_S}$ is the mean return of the data series during buy and sell days, and S_B and S_S is the standard error of the mean buy and sell return. This test statistic is not Student-t distributed. Satterthwaite (1946) derived an approximation for the degrees of freedom, so that the critical values from the t-table can be used. If the number of observations is sufficiently large this test statistic will have a limiting standard normal distribution.

Notice that Brock et al. (1992) in fact do not use the correct t-test statistic, as derived in footnote 9, page 1738. To test whether the mean daily return of the DJIA during buy and sell periods is significantly different from the unconditional mean daily return it is assumed that returns are iid distributed and the following t-statistic is used:

$$\frac{\mu_k - \mu}{\sqrt{\frac{\sigma^2}{N_k} + \frac{\sigma^2}{N}}}, \tag{2.8}$$

where μ_k is the mean return during buy or sell periods, N_k is the number of buy or sell days, μ is the mean market return, σ^2 is the variance of the daily returns and N is the total number of observations. However the variance of $\mu_k - \mu$ is equal to

$$\begin{aligned} V(\mu_k - \mu) &= V(\mu_k) + V(\mu) - 2Cov(\mu_k, \mu) \\ &= V(\tfrac{1}{N_k}\sum_{t\in k} r_t) + V(\tfrac{1}{N}\sum_{t=1}^{N} r_t) - 2Cov(\tfrac{1}{N_k}\sum_{t\in k} r_t, \tfrac{1}{N}\sum_{t=1}^{N} r_t) \\ &= \tfrac{1}{N_k}\sigma^2 + \tfrac{1}{N}\sigma^2 - 2\tfrac{1}{N_k}\tfrac{1}{N}N_k\sigma^2 \\ &= \tfrac{1}{N_k}\sigma^2 - \tfrac{1}{N}\sigma^2. \end{aligned} \tag{2.9}$$

Thus the expression in the denominator of (2.8) is not correct, because the covariance term in (2.9) is unequal to zero. This is because the set of buy or sell days is a subset of the total set of observations. However the adjustment would have little effect on the results of Brock et al. (1992), because as we have shown the variance of their test statistic is actually smaller than the one they used and therefore their tests are too conservative.

The best strategy applied to the full sample has a significantly positive mean daily excess return of 0.039%, 10.38% yearly, which is considerably large. The mean daily excess return of the CSCE series during buy (sell) days is equal to 0.056% (−0.101%), 15.2% (−22.5%) yearly. The mean daily sell return is significantly negative at a 5% significance level using a one tailed test, while the mean daily buy return is not significantly positive. The mean buy-sell difference is significantly positive at a 5% significance level and equal to 0.158% (48.9% yearly). The four other strategies yield similar results. The mean daily excess return is significantly positive in all cases at a 10% significance level using a one tailed t-test. The mean return of the CSCE series during buy days is positive, but not significant, and the mean return during sell days is significantly negative. For all five strategies the mean buy-sell differences are significantly positive at a 5% significance level using a one sided test. The sixth and seventh column show that for all five listed strategies more than 50% of the buy and sell trades have a strictly positive excess return and that these trades consist of more than 50% of the total number of buy and sell days. The results above show that the best five technical trading strategies applied to the CSCE series in the period 83:1-97:6 have an economically as well as a statistically significant forecasting power.

For the three subperiods similar results are found, but now the best five strategies found have a higher mean daily excess return. The best strategy has a significantly positive mean yearly excess return of about 20%. Thus when looking at subperiods, strategies can be found that perform better than when applied to the full period.

Panel A of table 2.4 shows the results of the best five technical trading strategies applied to the LIFFE cocoa series in the period 83:1-97:6. Now the best five strategies consist entirely of moving-average trading strategies. The best strategy is a MA strategy that compares the price series with a 40-day MA. The strategy is extended with a 0.5 %-band filter. The results of the mean daily excess returns and the mean daily buy and sell returns are similar to the CSCE cocoa series in the same period, but the mean excess returns are higher and the t-ratios show that the results are strongly significant. The results for the number of trades with a strictly positive excess return differ. Now in most cases $20 - 40\%$ of the buy and sell trades generate an excess return, but these trades consists of more than 70% of the total number of buy and sell days. Thus most of the time the strategies are making a positive excess return, but there are a lot of short run trades that make a loss.

Also for the three subperiods of the LIFFE series it is found that the best strategies perform better than the best strategy applied to the total period. But for the three subperiods the best five strategies generate buy and sell trades that are in more than 50% of the cases profitable and these trades consist of more than 70% of the total number of buy and sell days in most cases. The above results show that also for the LIFFE series the best five strategies have an economically and statistically significant forecasting power in all periods.

Table 2.5 shows the results of the best technical trading strategies applied to the Pound-Dollar exchange rate for the full sample. The best strategy is a 100 day trading range break-out rule with a one %-band filter and a 50 day fixed holding period. This strategy has a mean daily excess return of 0.007% (1.64% yearly). The mean daily return during buy (sell) days of the Pound-Dollar series itself is equal to 0.161% (-0.017%), which corresponds to 50% (-4.2%) on a yearly basis. The mean daily buy return is significantly positive in all cases, but the mean daily sell return is not significantly negative for most of the best five strategies. The mean buy-sell difference is significantly positive for all best five strategies and for the best strategy equal to 0.178% (56.6% yearly). All strategies generate buy trades with a strictly positive excess return in more than 50% of the cases, and these trades consist of more than 50% of the total number of buy days. The percentage of sell trades with a strictly positive excess return is equal to zero, because in the case of a sell trade, the domestic currency is bought and the domestic interest rate is earned. Hence the excess return during sell days is always equal to zero. The results for all three subperiods are similar. Thus also in the case of the Pound-Dollar exchange rate the results show that the best five technical trading strategies have an economically and statistically significantly forecasting power. However the mean daily excess returns of the best five strategies are smaller in comparison with the excess returns of the best five strategies applied to the cocoa series, and much less profits could be made in comparison with the cocoa series.

We have found technical trading rules that perform very well when applied to the CSCE and LIFFE cocoa futures series and the Pound-Dollar exchange rate. However, there will always be a strategy that generates a large profit if a large set of trading rules is tested as we have seen in the results above. In practice technical traders will optimize their set of trading rules and use the best one for future forecasting. Therefore Brock et al. (1992) and Levich and Thomas (1993) test a small set of strategies that are used in practice. In their bootstrap procedure which corrects for data snooping Sullivan et al. (1999) only use the best strategy. Instead, in the next section, to deal with the data snooping problem we shall look at the forecasting results of the 5350 constructed technical trading rules as a group.

2.5.2 The set of 5350 trading rules: economic significance

Cocoa futures series

We test for economic significance of the set of technical trading strategies by looking at the percentage of strategies that generate a strictly positive excess return. These numbers are shown in table 2.6 in the case of no transaction costs and in table 2.7 in the case of 0.1% transaction costs, for the CSCE, LIFFE and Pound-Dollar series, for all sets of technical trading rules and for all periods. Comparing table 2.6 with table 2.7 shows that after correcting for transaction costs, the percentage of trading rules generating a strictly positive excess return declines substantially. In the full period 83:1-97:6 the complete set of trading rules performs very well on the LIFFE cocoa futures prices, but much worse on the CSCE cocoa prices; 58.34% of the strategies generate a strictly positive excess return when applied to the LIFFE series, but only 12.18% generate a strictly positive excess return when applied to the CSCE series, after correcting for transaction costs. This large difference is remarkable, because the underlying asset in both markets is the same, except for small differences in quality of the cocoa. The table shows that the good results for the LIFFE series mainly appear in the first subperiod 1983:1-1987:12, where 73.25% of the rules generate a strictly positive net excess return for the LIFFE series against 14.14% for the CSCE series. In the second subperiod, 1988:1-1992:12, the trading rules seem to work equally well and fairly well on both series, although the results for the LIFFE series are now weaker than in the first subperiod, with 50.55% (53.90%) of the rules generating a strictly positive net excess return for the CSCE (LIFFE) series. In the third subperiod

1993:1-1997:6, the trading rules perform poorer on both series, since only 15.19% (29.25%) generate a strictly positive net excess return for the CSCE (LIFFE) series. As can be seen in the tables, the results for the different subsets of technical trading rules do not differ from the complete set of trading rules for all periods.

Pound-Dollar exchange rate

For the full sample the trading rules do not show much economically significant forecasting power, with only 10.14% of the trading rules generating a strictly positive excess return net of 0.1% transaction costs. The same result is found for the first subperiod, with 9.32% generating a strictly positive net excess return. The trading rules seem to work better when they are applied to the Pound-Dollar exchange rate in the second subperiod, with 30.81% of the trading rules generating a strictly positive net excess return. In the third subperiod the strategies work badly and only 2.07% generate a strictly positive net excess return. Thus for all three data series it is found that the set of technical trading strategies performs poorly in the subperiod 1993:1-1997:6, when compared with the preceding period 83:1-92:12.

Notice that, for example under the null hypothesis of a random walk, the net excess return of technical trading rules will be negative due to transaction costs. The fact that a large set of technical trading rules generates a strictly positive net excess return, especially for the LIFFE cocoa futures series, is therefore surprising and suggestive of economically significant profit opportunities. It is hard however, to evaluate the statistical significance of this observation. Therefore, in the next subsection we focus on the question whether the forecasting power of returns is statistically significant.

2.5.3 The set of 5350 trading rules: statistical significance

2.5.3.1 Significance under the assumption of iid returns: simple t-ratios

We test for the statistical forecasting significance of the set of technical trading rules by looking at the percentage of strategies which have a mean excess return, mean buy return, mean sell return, mean buy-sell difference significantly different from zero. Table 2.8 summarizes the results. The table shows for both the LIFFE and CSCE cocoa futures series and the Pound-Dollar exchange rate series for the full sample period 1983:1-1997:6 as well as for the three five year subperiods the percentages of MA, TRB and Filter trading rules, and the percentage of the complete set of trading rules for which a statistically significantly positive mean excess return is found. The table also shows the percentage of strategies that have a significantly positive (negative) mean return during buy (sell) days. Further the table shows the percentage of strategies for which the difference in mean return of the data series during buy and sell days is significantly positive. Finally, the percentage of strategies for which the data series at the same time has a significantly positive mean return during buy days as well as a significantly negative mean return during sell days is shown. A correction is made for 0.1% transaction costs.

Table 2.9 shows in contrast to table 2.8 the percentage of strategies which generate statistically significant bad results, i.e. the percentage of strategies with a significantly negative mean excess return, with a significantly negative (positive) mean buy (sell) return, with a significantly negative mean buy-sell difference and the percentage of strategies which have a significantly negative mean buy return as well as a significantly positive mean sell return. These statistics are computed to test whether technical trading rules as a group show statistically significant bad forecasting power.

The tables lists only the results of one sided tests with a 10% significance level, the results for a 5% significance level are similar but of course weaker. For a 1% significance level most significant results disappear.

Cocoa futures series

For the full sample period the strategies applied to the CSCE cocoa series show hardly any statistically significant forecasting power. For example, the difference in mean return during buy and sell days is significantly positive only in 1.38% of the trading rules, whereas a significantly negative mean return during sell days occurs only in 5.92% of all strategies. Only in 0.3% of the cases the mean excess return is significantly positive, hence no significant profits could be made. For the LIFFE series on the other hand the results are remarkably different. For 26.58% of the strategies the mean buy-sell difference is significantly positive. In particular, the strategies seem to forecast the sell days very well, with more than half (50.53%) of all strategies having a significantly negative mean return during sell days. In contrast, the mean buy return is significantly positive only in 6.86% of all strategies. 13.86% of the strategies have a significantly positive mean excess return when applied to the LIFFE series. Looking at table 2.9 a lot of strategies perform statistically very bad when applied to the CSCE series, while the percentage of strategies that performs statistically badly is much less for the LIFFE series. Thus for the full sample the set of strategies applied to the LIFFE series shows a lot of economic significance, which is also statistically significant, and a lot of trading rules have a statistically significant forecasting power, i.e. they detect periods in which the data series rises and declines, while the percentage of trading rules which performs statistically badly is smaller than the percentage of trading rules which performs statistically good.

For the first subperiod the trading rules show almost no statistically significant forecasting power when applied to the CSCE series. Most t-ratios stay within the critical values. The percentage of strategies that perform badly is even larger than the percentage of strategies that perform well. For example 24.17% of all strategies generate a significantly negative mean excess return. For the LIFFE series the results are totally different. All subsets of trading rules show some forecasting power. 34.52% of all strategies generate a significantly positive mean excess return. For 26.73% of the strategies the mean return of the data series during buy days is significantly positive, for 39.47% of the strategies the mean return during sell days is significantly negative and for 46.65% of the strategies the Buy-Sell difference is significantly positive. The percentage of strategies that performs statistically badly is small. For 5.87% of the strategies the mean excess return is significantly negative. Hence, for the LIFFE series the trading rules show economic as well as statistically significant forecasting power in the first subperiod.

The second subperiod is characterized by a long term downward trend with short term upward corrections in both cocoa series. Economically the strategies behave quite well in the second subperiod, but the statistical significance of the mean excess return of the strategies is very poor (CSCE: 1.85% $> t_{crit}$; LIFFE 6.31% $> t_{crit}$). Hence the economic significance found is not statistically significant. All subsets of trading rules show a significantly negative mean return of the data series during sell days (CSCE: 44.57% $< -t_{crit}$; LIFFE: 54.62% $< -t_{crit}$), which is in line with the downward trend. The upward corrections are not predicted well by the strategies, and for many trading rules the mean return of the data series during buy days is even significantly negative (CSCE: 26.55% $< -t_{crit}$; LIFFE: 31.96% $< -t_{crit}$). The results found for the second subperiod are in line with the advices of technical analysts only to trade in the direction of the main trend and not reverse the position in the market until there is enough weight of evidence that the trend has reversed. Apparently, the short term upward corrections did not last long enough to be predictable or profitable.

The third subperiod is characterized by upward and downward trends in prices. The trading rules show no economic significance for this period and neither do they show statistical forecasting significance. 29.25% of the strategies applied to the LIFFE series generated a strictly positive excess return, but only for 2.13% of the strategies the mean excess return is significantly positive. For the CSCE series even 32.26% of the strategies generate a significantly negative mean excess return. If there was any predictability in the data it has disappeared in the third subperiod.

Pound-Dollar exchange rate

For the full sample 83:1-97:6 table 2.8 shows that 13.08% of the strategies have a significantly positive mean buy return and 17.13% have a significantly negative mean sell return. In 28.19% of the cases the mean Buy-Sell difference is significantly positive. Thus the trading rules seem to generate good trading signals. However, the mean excess return is significantly positive only in 2.07% of the trading rules, while even in 62.32% of the cases the trading rules generate a significantly negative mean excess return. Especially the moving-average trading rules perform badly.

For the first subperiod the results are similar (Buy: 12.42% $> t_{crit}$; Sell: 44.29% $< -t_{crit}$; Buy-Sell: 41.9% $> t_{crit}$). Sell days are forecasted much better than the buy days. However, only for 0.35% of the strategies the mean excess return is significantly positive, while in 27.11% of the cases the mean excess return is even significantly negative. According to the Buy-Sell difference the trading rules as a group seem to have a statistically significant forecasting power in this period, but the economic significance is poor.

In the second subperiod the strategies forecast the upward trends better than the downward trends, 29.63% of the strategies have a significantly positive mean buy return, while 7.73% of the trading rules have a significantly negative mean sell return. For 26.13% of the trading rules the Buy-Sell difference is significantly positive. Only 4.78% of the strategies have a significantly positive mean excess return, while even 17.32% of the strategies have a significantly negative mean excess return. Hence, also in this subperiod there are signs of forecastability according to the Buy-Sell difference, which cannot be exploited economically.

In the third subperiod the Pound-Dollar exchange rate exhibits some upward and downward trends. The trading rules show hardly any signs of forecasting power in this subperiod for the Pound-Dollar exchange rate. Only in 0.09% of the cases a significantly positive mean excess return is generated, while in 66.02% of the cases a significantly negative mean excess return is generated.

2.5.3.2 Significance after correction for dependence: an estimation based approach

In the previous subsection we showed that in the period 1983:1-1987:12 the technical trading strategies as a group seem to have forecasting power when applied to the LIFFE cocoa futures prices. This is the only period and data series for which good results in favor of technical analysis are found. We tested on statistical significance under the assumption of iid returns. It is well known, however, that returns show dependence in the second moments (volatility clustering) and in section 2.2.3 we showed that our data series also exhibit some autocorrelation. Therefore we further explore the statistical significance found in the first subperiod by estimating for each trading rule an econometric time series model which incorporates volatility clustering, autoregressive variables and a dummy for buy (sell) days in the regression function. We then determine the percentage of cases for which the dummy coefficients are significant, to check whether the trading rules as a group show signs of forecasting power.

We estimated some econometric time series models on the daily LIFFE cocoa return series for the period 1983:1-1987:12 and we find that the following exponential GARCH model developed by Nelson (1991)[8] fits the data best[9]:

$$\begin{aligned}
r_t &= \alpha + \phi_{16} r_{t-16} + \epsilon_t \\
\epsilon_t &= \eta_t \sqrt{h_t}; \quad \eta_t \text{ iid } N(0,1) \\
\ln(h_t) &= \alpha_0 + g(\eta_{t-1}) + \beta_1 \ln(h_{t-1}) \\
g(\eta_t) &= \theta \eta_t + \gamma(|\eta_t| - \sqrt{\tfrac{2}{\pi}}).
\end{aligned} \tag{2.10}$$

This model allows that future volatility depends differently on the sign of the current return. The coefficient θ measures the leverage effect. If θ is negative (positive), then a negative (positive) return is followed by larger volatility than a positive (negative) return. Table 2.10 shows the estimation results. The coefficient θ is significantly positive. This indicates that there is a positive correlation between return and volatility. Note that this is in contrast with the results found on stock markets and exchange rates where a negative correlation between return and volatility is found, see for example Nelson (1991). The estimation of γ is also significantly positive and this shows that there is volatility clustering in the data. The (partial) autocorrelation function of the (squared) standardized residuals shows no sign of dependence in the (squared) standardized residuals. Hence we conclude that this model fits the data well.

To explore the significance of the trading rules after correction for dependence the following regression function in the exponential GARCH model is estimated:

$$r_t = \alpha + \delta_m \, D_{m,t} + \phi_{16} \, r_{t-16} + \epsilon_t,$$

[8]Nelson (1991) replaces the normal distribution used here with a generalized error distribution.

[9]We checked for significance of the estimated coefficients. We did diagnostic checking on the standardized residuals, to check whether there was still dependence. We used the (partial) autocorrelation function, Ljung-Box (1978) Q-statistics and the Breusch-Godfrey LM-test. The Schwartz Bayesian criterion was used for model selection.

Table 2.10: **Coefficient estimates EGARCH-model**

α	ϕ_{16}	α_0	θ	γ	β_1
-0.000339	0.066843	-0.194617	0.037536	0.125153	0.976722
(-1.11)	(2.49)	(-2.83)	(2.11)	(3.41)	(97.58)

Estimates on the daily return series of the LIFFE cocoa futures prices in the period December 12th 1981 until December 31, 1987. The exponential GARCH model is estimated using maximum likelihood using the Marquardt iterative algorithm and Bollerslev-Wooldridge (1992) heteroskedasticity-consistent standard errors and covariance. The numbers within parenthesis are t-ratios.

where $m = B$ ($m = S$) indicates that we insert a dummy for buy (sell) days, and we will refer to $D_{m,t}$ as the buy (sell) dummy. Thus $D_{B,t} = 1$ ($D_{S,t} = 1$) if day t is a buy (sell) day. For every trading strategy the coefficient for the buy dummy and for the sell dummy are estimated separately. Panel A of table 2.11 shows the percentage of trading rules for which the coefficient of the buy (sell) dummy is significantly positive (negative) at the 10% significance level (second and third column) using a one tailed t-test. The fourth column shows the percentage of trading rules for which the coefficient of the buy dummy is significantly positive and the coefficient of the sell dummy is significantly negative. The results again indicate that the technical trading strategies have forecasting power in the first subperiod. For 40.6% of all trading rules we find that the coefficient of the buy dummy is significantly positive. 27.4% of all trading rules show a significantly negative coefficient of the sell dummy. Finally, 22.8% of all trading rules have a significantly positive coefficient of the buy dummy as well as a significantly negative coefficient of the sell dummy. Panel B of table 2.11 shows that the strategies as a group do not perform statistically badly. For example 1.6% of all trading rules show a significantly negative coefficient of the buy dummy as well as a significantly positive coefficient of the sell dummy. This number is small compared to the 22.8% of the strategies that show statistically significant forecasting power. In comparison with the tests under the assumption of iid returns, it now seems that the trading rules forecast the buy days better than the sell days, while first it was the other way around.

2.6 Bootstrap

2.6.1 Bootstrap tests: methodology

The results reported in the last section show again that simple trend-following technical trading techniques have forecasting power when applied to the LIFFE series in the period 1983:1-1987:12. In this section we investigate whether the good results found can be explained by some popular time series models like a random walk, autoregressive or an exponential GARCH model using a bootstrap method.

The bootstrap methodology compares the percentage of trading rules with a significantly positive mean buy return, with a significantly negative mean sell return, with a significantly positive mean buy-sell difference and with a significantly positive mean buy as well as a significantly negative mean sell return, when applied to the original data series, with the percentages found when the same trading rules are applied to simulated comparison series. The distributions of these percentages under various null hypotheses for return movements will be estimated using the bootstrap methodology inspired by Efron (1982), Freedman (1984), Freedman and Peters (1984a, 1984b), and Efron and Tibshirani (1986). According to the estimation based bootstrap methodology of Freedman and Peters (1984a, 1984b) a null model is fit to the original data series. The estimated residuals are standardized and resampled with replacement to form a new residual series. This scrambled residual series is used together with the estimated model parameters to generate a new data series with the same properties as the null model.

For each null model we generate 500 bootstrapped data series. The set of 5350 technical trading rules is applied to each of the 500 bootstrapped data series to get an approximation of the distributions of the percentage of strategies with a significantly positive mean buy return, with a significantly negative mean sell return, with a significantly positive buy-sell difference and with a significantly positive mean buy as well as a significantly negative mean sell return under the null model. The null hypothesis that our strong results found can be explained by a certain time series model is rejected at the α percent significance level if the percentage found in the original data series is greater than the α percent cutoff level of the simulated percentages under the null model.

Random walk process

The random walk with a drift is bootstrapped by resampling the returns of the original data series with replacement. If the price series is defined as $\{P_t : t = 1, 2, ..., T\}$, then the return series is defined as $\{r_t = \ln(P_t) - \ln(P_{t-1}) : t = 2, 3, ..., T\}$. Finally the bootstrapped price series is equal to $\{P_t^* = \exp(r_t^*)P_{t-1}^* : t = 2, 3, ..., T\}$, where r_t^* is the redrawn return series. The initial value of the bootstrapped price series is set equal to the initial original price: $P_1^* = P_1$. By construction the returns in the bootstrapped data series are iid. There is no dependence in the data anymore that can be exploited by technical trading rules. Only by chance a trading rule will generate good forecasting results. Hence under the null of a random walk with a drift we test whether the results of the technical trading rules in the original data series are just the result of pure luck.

Autoregressive process

The second null model we test upon is an AR model:

$$r_t = \alpha + \phi_{16} r_{t-16} + \epsilon_t, \ |\phi_{16}| < 1, \tag{2.11}$$

where r_t is the return on day t and ϵ_t is iid[10]. The coefficients α, ϕ_{16} and the residuals ϵ_t are estimated with ordinary least squares. The estimated residuals are redrawn with replacement and the bootstrapped return series are generated using the estimated coefficients and residuals:

$$r_t^* = \hat{\alpha} + \hat{\phi_{16}} r_{t-16}^* + \epsilon_t^*,$$

for $t = 18, ..., T$ and where ϵ_t^* is the redrawn estimated residual at day t and where r_t^* is the bootstrapped return at day t. For $t = 2, .., 17$ we set $r_t^* = r_t$. The bootstrapped price series is now equal to $\{P_t^* = \exp(r_t^*)P_{t-1}^* : t = 2, ..., T\}$ and $P_1^* = P_1$. The autoregressive model tests whether the results of the technical trading strategies can be explained by the high order autocorrelation in the data. OLS estimation with White's (1980) heteroskedasticity-consistent standard errors gives the following results with t-ratios within parenthesis:

α	ϕ_{16}
-0.000235	0.110402
(-0.68)	(4.00)

The coefficient of the lagged return is significantly different from zero. This shows that the LIFFE series contains high order autocorrelation.

Exponential GARCH process

The third null model we test upon is the exponential GARCH model as given by (2.10). The model is estimated with maximum likelihood. The estimated coefficients and standardized residuals are used to generate new bootstrapped price series. The estimated

[10] This model is found to fit the data the best, see page 58.

standardized residuals, $\hat{\eta}_t$, are resampled with replacement to form the resampled standardized residual series $\{\eta_t^* : t = 18, ..., T\}$. The bootstrapped log conditional variance series is equal to

$$\{\ln(h_t^*) = \hat{\alpha_0} + g(\eta_{t-1}^*) + \hat{\beta_1}\ln(h_{t-1}^*) : t = 19, ..., T\}.$$

We set h_{18}^* equal to the unconditional variance. Under the assumption that the η_t are iid $N(0,1)$ the unconditional variance of ϵ_t is equal to

$$E(h_t) = \{\exp(\alpha_0)E[\exp(g(\eta_{t-1}))]\}^{\frac{1}{1-\beta_1}},$$

where

$$E[\exp(g(\eta_{t-1}))] =$$
$$\left\{\Phi(\gamma+\theta)\cdot\exp\left(\frac{1}{2}(\gamma+\theta)^2\right) + \Phi(\gamma-\theta)\cdot\exp\left(\frac{1}{2}(\gamma-\theta)^2\right)\right\}\cdot\exp\left(-\gamma\sqrt{\frac{2}{\pi}}\right).$$

Here $\Phi(.)$ is the cumulative normal distribution. Now the bootstrapped residual series is $\{\epsilon_t^* = \eta_t^*\sqrt{h_t^*} : t = 19, ..., T\}$ and the bootstrapped return series is equal to $\{r_t^* = \hat{\alpha} + \hat{\phi_{16}}r_{t-16}^* + \epsilon_t^* : t = 19, ..., T\}$. For $t = 2, ..., 18$ we set $r_t^* = r_t$. The bootstrapped price series is equal to $\{P_t^* = \exp(r_t^*)P_{t-1}^* : t = 2, ..., T\}$ and $P_1^* = P_1$. Table 2.10 contains the estimation results for the exponential GARCH model.

Structural break in trend

Figure 2.4 reveals that the LIFFE cocoa futures price series contains an upward trend in the period January 5, 1983 until February 4, 1985, when the price peaks, and a downward trend in the period February 5, 1985 until December 31, 1987. Therefore, we split the first subperiod in two periods, which separately contain the upward and downward trend. By doing this we allow for a structural change in the return process. The final bootstrap procedure we consider will simulate comparison series that will have the same change in trends. For the first period we estimate and bootstrap the autoregressive model (2.11). We don't find signs of volatility clustering for this period. However on the second period we find significant volatility clustering and therefore we estimate and bootstrap the following GARCH model:

$$\begin{aligned} r_t &= \alpha + \phi_2 r_{t-2} + \epsilon_t \\ \epsilon_t &= \eta_t\sqrt{h_t}; \quad \eta_t \text{ iid } N(0,1) \\ h_t &= \alpha_0 + \alpha_1 h_{t-1} + \beta_1 h_{t-1}. \end{aligned}$$

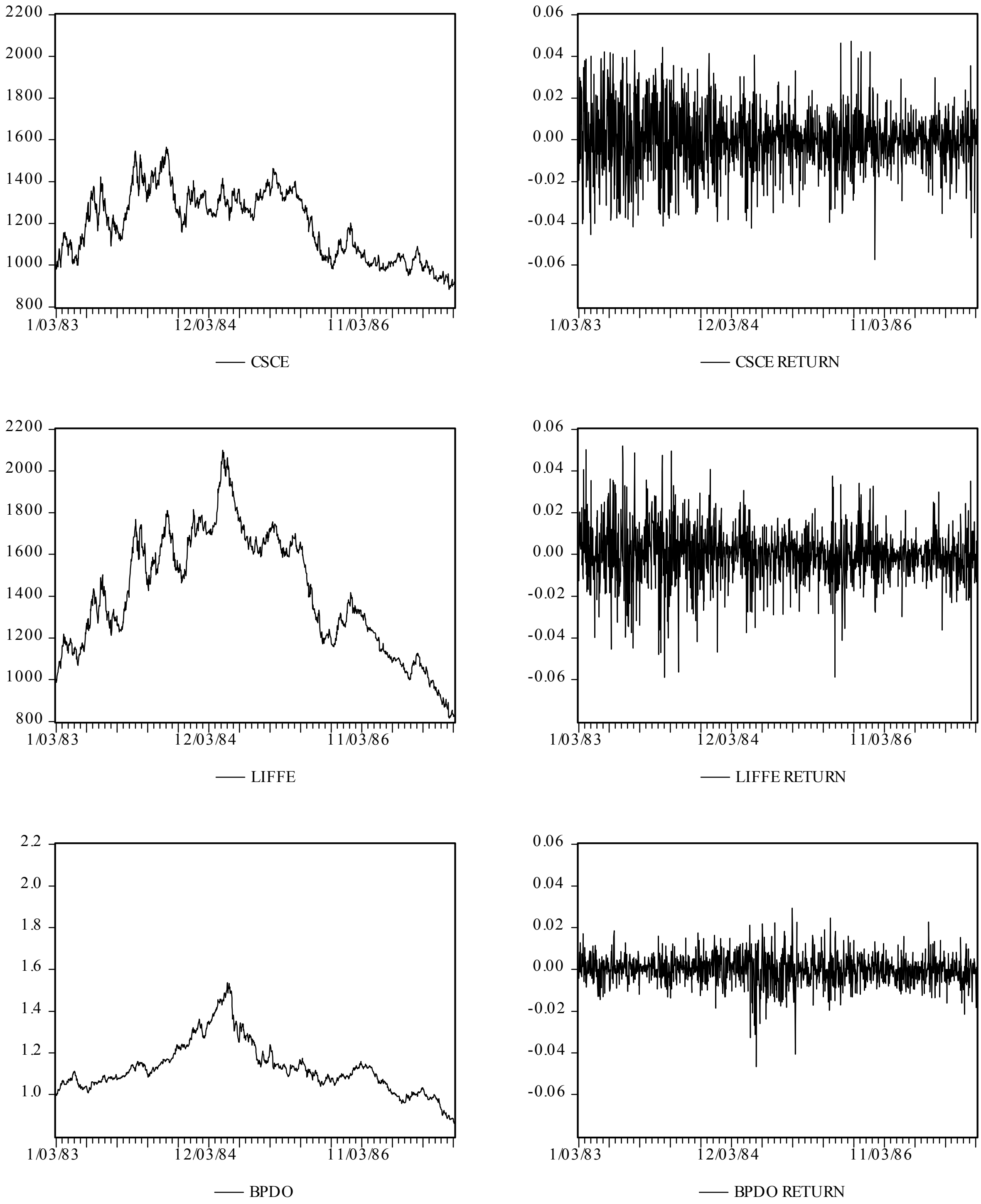

Figure 2.4: Time series, over the period 1983:1-1987:12, of CSCE (top left) and LIFFE (middle left) cocoa futures prices on the same scale [800, 2200], the Pound-Dollar exchange rate on scale [0.8, 2.2] (bottom left) and corresponding returns series (right) all on the same scale [-0.08, 0.06].

This model fits the data the best[9]. Table 2.12 contains the estimation results of the autoregressive model in the period January 5, 1983 until February 4, 1985 and of the GARCH model in the period February 5, 1985 until December 31, 1987 with the t-ratios within parenthesis.

Table 2.12: **Coefficient estimates structural break in trend model**

The autoregressive model coefficients estimates 1/5/1983 - 2/4/1985				
α	ϕ_{16}			
0.001213	0.161887			
(1.74)	(3.67)			
The GARCH-model coefficients estimates 2/5/1985 - 12/31/1987				
α	ϕ_2	α_0	α_1	β_1
-0.001511	-0.113115	3.85E-06	0.064247	0.905622
(-3.95)	(-2.85)	(1.48)	(1.68)	(18.6)

Estimates of an autoregressive model on the daily return series of the LIFFE cocoa futures prices in the period January 5, 1983 until February 4, 1985 and of a GARCH model in the period February 5, 1985 until December 31, 1987. The autoregressive model is estimated using OLS and White's (1980) heteroskedasticity-consistent standard errors. The GARCH model is estimated using maximum likelihood using the Marquardt iterative algorithm and Bollerslev-Wooldridge (1992) heteroskedasticity-consistent standard errors and covariance. The numbers within parenthesis are t-ratios.

The returns in the first period show significantly positive 16-th order autocorrelation, while the returns in the second period show significantly negative second order autocorrelation. The constant is in the first period significantly positive at the 10% significance level, while in the second period it is significantly negative at the 1% significance level. This is an indication that the drift is first positive and then negative. With this final bootstrap procedure we can test whether the good results of the technical trading rules can be explained by the trend structure in the data series and the strong autocorrelation in returns.

2.6.2 Bootstrap tests: empirical results

Random walk process

In table 2.13 we display the bootstrap results under the null of a random walk, an autoregressive model, an exponential GARCH model and the structural break in trend model when the complete set of technical trading strategies is applied to the LIFFE cocoa futures prices in the period 1983:1-1997:6. All the results presented are the fractions of simulation results that are larger than the results for the original data series. In panel A the fractions of the 500 bootstrapped time series are reported for which the percentage of trading rules with a significantly positive mean excess return, with a significantly positive mean buy return, with a significantly negative mean sell return, with a significantly positive mean buy-sell difference, and with a significantly positive mean buy as well as significantly negative mean sell return at a ten percent significance level using a one sided t-test is larger than the same percentage found when the same trading rules are applied to the original data series. Panel B on the other hand reports the bootstrap results for the bad significance of the trading rules. It shows the fraction of the 500 bootstrapped time series for which the percentage of trading rules with a bad significance is even larger than the percentage of trading rules with a bad significance at a 10% significance level using a one sided t-test when applied to the original data series.

For the cocoa series the mean excess return is approximately equal to the return on the futures position without correcting for the risk-free interest rate earned on the margin account, because

$$r_t^e = \ln(1+r_t^f + \frac{P_t - P_{t-1}}{M_{t-1}} Pos_t) - \ln(1+r_t^f) \approx r_t^f + \frac{P_t - P_{t-1}}{M_{t-1}} Pos_t - r_t^f = \frac{P_t - P_{t-1}}{M_{t-1}} Pos_t.$$

Therefore the mean excess return of a trading rule applied to the bootstrapped cocoa series is calculated as the mean return of the positions taken by the strategy, so that we don't need to bootstrap the risk-free interest rate.

We have already seen in table 2.8 that for 34.5% of the strategies the mean excess return is significantly positive in the first subperiod for the LIFFE cocoa futures series. The number in the column of the random walk results in the row $t_{Perf} > t_c$, which is 0.002, shows that for 0.2% of the 500 random walk simulations the percentage of strategies with a significantly positive mean excess return is larger than the 34.5% found when the strategies are applied to the original data series. This number can be thought of as a simulated "p-value". Hence the good results for the excess return found on the original data series cannot be explained by the random walk model. For 26.7% of the strategies the mean buy return is significantly positive. The fraction in the row $t_{Buy} > t_c$ shows that in only 3.2% of the simulations the percentage of strategies with a significantly positive mean buy return is larger than the 26.7% found in the original data series. However, the fraction in the row $t_{Sell} < -t_c$, shows that in 14% of the simulations the percentage of strategies with a significantly negative mean sell return is larger than the 39.5% of strategies with a significantly negative mean sell return when applied to the original data series. Thus the random walk model seems to explain the significantly negative mean sell return. For 46.7% of the strategies the buy-sell difference is significantly positive, but the fraction in the row $t_{Buy-Sell} > t_c$ shows that for none of the random walk bootstraps the percentage of trading rules with a significantly positive mean buy-sell return is larger than this number. 14.7% of the strategies have a significantly positive mean buy return as well as a significantly negative mean sell return. The number in the row $t_{Buy} > t_c \wedge t_{Sell} < -t_c$, which is 0.006, shows that in only 0.6% of the simulations this percentage is larger than the 14.7% found in the original data series.

Table 2.9 showed the percentage of strategies with a bad significance when applied to the original data series. For the LIFFE cocoa futures series in the first subperiod the strategies as a group show no real signs of bad significance. For 5.9% of the strategies the mean excess return is significantly negative, for 3.5% of the strategies the mean buy return is significantly negative, for 3.3% of the strategies the mean sell return is significantly positive, for 3.3% of the strategies the mean buy-sell difference is significantly negative and for 0.82% of the strategies the mean buy return is significantly negative and also the mean sell return is significantly positive. Panel B of table 2.13 shows that under the null of a random walk the strategies as a group perform even much worse. The number in the row $t_{Perf} < -t_c$ shows that for 96.4% of the simulations the percentage of strategies with a significantly negative mean excess return is larger than the 5.9% found in the original data series. For 87% of the simulations the percentage of strategies with a significantly negative mean buy return is larger than the 3.5% found on the original data series. For 57.2% (96.8%, 34.2%) of the simulations the percentage of strategies with a significantly positive mean sell (significantly negative mean buy-sell difference, a significantly negative mean buy as well as a significantly positive mean sell return) is larger than the 3.3% (3.3%,0.82%) found in the original data series.

From the results reported above we can conclude that the good results found when the technical trading strategies are applied to the LIFFE cocoa futures prices in the period 1983:1-1997:6 cannot be explained by a random walk model.

Autoregressive process

The third column of table 2.13 repeats the previous results under the null of an autoregressive process. Now we can detect whether the good results of the technical trading strategies can be explained by the high order autocorrelation in the data. The results change indeed in comparison with the null of a random walk. Now for 3.8% of the 500 AR bootstraps the percentage of strategies with a significantly positive mean excess return is larger than the 34.5% found in the original data series. For 7.4% (27.4%) of the simulations the percentage of strategies with a significantly positive mean buy return (significantly negative mean sell return) is larger than the 26.7% (39.5%) found in the original data series. Hence the autoregressive model seems to explain the good significant results of the technical trading rules as a group for selecting buy and sell days. On the other hand the autoregressive model does not explain the results found for the percentage of strategies with a significantly positive mean buy-sell difference and the percentage of strategies with a significantly positive mean buy as well as a significantly negative mean sell return. Panel B shows again, as in the case of the null of a random walk, that the strategies as a group perform much worse on the simulated autoregressive data series than on the original data series. We can conclude that the autoregressive model neither can explain the good results of the technical trading rules.

Exponential GARCH process

The results of the bootstrap procedure under the null of an exponential GARCH model are similar to those under the null of an autoregressive model. Therefore the good results of the technical trading strategies can also not be explained by the leverage effect, which is accounted for in the exponential GARCH formulation.

Structural break in trend

The last column of table 2.13 lists the bootstrap results of applying the set of trading strategies to simulated autoregressive series with a structural change to account for the different trending behavior of the LIFFE cocoa futures prices. The results change completely in comparison with the other null models. For 41.4% of the simulations the percentage of strategies with a significantly positive mean excess return is larger than the 34.5% found when the same set is applied to the original data series. For 47.8% (52.8%, 24.8%) of the simulations the percentage of strategies with a significantly positive mean buy (significantly negative mean sell, significantly positive mean buy-sell difference) return is larger than the 26.7% (39.5%, 46.7%) found when the same set is applied to the original data series. Even for 42.6% of the simulations the percentage of strategies with a significantly positive mean buy as well as a significantly negative mean sell is larger than the 14.7% found for the original data series. Hence the final model, which allows a structural change, because there is first an upward trend and then a downward trend in the price series, seems to explain the good results found when the set of technical trading strategies is applied to the LIFFE cocoa futures price series in the period 1983:1-1987:12. Probably the trading rules performed well because of the strong trends in the data. Panel

B shows the bootstrap results for testing whether the bad significance of the technical trading rules can be explained by the several null models. In the case of the structural break in trend model the results show again that the set of technical trading rules behaves statistically worse when applied to the simulated series than to the original data series. For example in 96% of the simulations the percentage of strategies with a significantly negative mean excess return is larger than the 5.9% found when the same strategies are applied to the original data series. Despite that the structural break in trend model can explain the statistically significant forecasting power of the trading rules, also this model cannot explain the good results found when testing for bad significance of the strategies in the original data series. Thus the original time series has characteristics which causes the trend-following technical trading techniques to show signs of forecasting power, most probably the characteristic of the strong change in direction of the price trend. However this characteristic is not the only explanation, because it cannot explain the relatively low percentage of trend-following technical trading techniques which performed statistically badly on the original time series.

2.7 Success and failure of technical trading

The technical trading strategies as a group show economic and statistically significant forecasting power when applied to the LIFFE cocoa series, especially in the period 1983:1-1987:12. On the other hand the same technical trading strategies show no sign of forecasting power when applied to the CSCE cocoa series in the same period. The futures contracts differ in their specification of quality, currency and place of delivery, but it is surprising that the difference in economic and statistical significance is so large. Why are these differences so pronounced?

The daily CSCE cocoa returns show somewhat stronger autocorrelation in the first two lags than the LIFFE returns, which suggests more predictability. The variance of the CSCE series is slightly bigger across all subperiods than the variance of the LIFFE series, which may be an indication why trend-following rules have more difficulty in predicting the CSCE cocoa series. However, it seems that this somewhat higher variance cannot explain the large differences. For example, in the second subperiod, when the volatility is the strongest across all subperiods for both time series, the trading rules perform almost equally well on the CSCE and LIFFE cocoa futures prices and show forecasting power of the sell days for both series. Hence, there must be some other explanation for the differences of technical trading performance.

Figure 2.3 already showed that, in the period 1983:1-1987:12, the LIFFE and CSCE cocoa futures prices first exhibit an upward trend from 83:1-84:6 for the CSCE in New York and from 83:1-85:2 for the LIFFE in London, whereas from 85:2-87:12 both cocoa series exhibit a downward trend. The upward trend until mid 84 was due to excess demand on the cocoa market, whereas after January 1986 cocoa prices declined for several years due to excess supply. See for example the graphs of gross crops and grindings of cocoa beans from 1960-1997 in the International Cocoa Organization Annual Report 1997/1998 (see e.g. p.15, Chart I).[11] The demand-supply mechanism thus caused the upward and downward trends in cocoa futures prices in the subperiod 1983:1-1987:12. Figure 2.3 suggests that these trends were more pronounced in London for the LIFFE than in New York for the CSCE.

2.7.1 The influence of the Pound-Dollar exchange rate

Figure 2.3 also showed that the Pound-Dollar exchange rate moved in similar trends in the same subperiod 1983:1-1987:12. More precisely, the Pound-Dollar exchange rate increased (the Pound weakened against the Dollar) from January 1983 to reach its high in February 1985. This caused an upward force on the LIFFE cocoa futures price in Pounds, and a downward force on the CSCE cocoa futures price in Dollars. The LIFFE cocoa futures price also peaked in February 1985, while the CSCE cocoa futures price reached its high already in June 1984. After February 1985, the Pound strengthened against the Dollar until April 1988 and the Pound-Dollar exchange rate declined. This caused a downward force on the LIFFE cocoa futures price in Pounds, but an upward force on the CSCE futures price in Dollars. Until January 1986 the LIFFE cocoa price declined, while the CSCE cocoa price rose slightly. After January 1986 cocoa prices fell on both exchanges for a long time, due to excess supply of cocoa beans. We therefore conclude that, by coincidence, the upward and downward trends in the cocoa prices coincide with the upward and downward trends in the Pound-Dollar exchange rate. For the LIFFE in London the trends in exchange rates reinforced the trends in cocoa futures, whereas for the CSCE in New York the trends in the exchange rates weakened the trends in cocoa futures prices.

Table 2.14 shows the cross-correlations between the levels of the three data series across all subperiods. It is well known that if two independently generated integrated time series of the order one are regressed against each other in level, with probability one a spurious, but significant relation between the two time series will be found (Phillips

[11]We would like to thank Guido Veenstra, employed at the Dutch cocoa firm Unicom, for pointing this out to us.

1986). Although the Pound-Dollar exchange rate should be independently generated from the cocoa futures series, it has some impact on the price level of the cocoa series as described above. The table shows that the Pound-Dollar exchange rate is correlated strongly with the level of the LIFFE cocoa continuation series and also (although a little bit weaker) with the CSCE cocoa continuation series. In particular, in the first subperiod 1983:1-1987:12 the Pound-Dollar exchange rate is correlated strongly with the level of the LIFFE cocoa futures series (cross correlation coefficient 0.88) and also (although a little bit weaker) with the CSCE cocoa futures series (cross correlation coefficient 0.58). In the other subperiods, there is little cross correlation between the Pound-Dollar exchange rate and the LIFFE and/or the CSCE cocoa futures series.

Apparently, due to the accidental correlation (spurious relation) in the period 1983:1-1987:12 between the Pound-Dollar exchange rate movements and the demand-supply mechanism in the cocoa market, trends in the LIFFE cocoa futures price are reinforced and trends in the CSCE cocoa futures price are weakened. Because the technical trading rules we tested are mainly trend-following techniques, this gives a possible explanation for the large differences in the performance of technical trading in the LIFFE and CSCE cocoa futures.

In order to explore further the possible impact of the Pound-Dollar exchange rate on the profitability of trend-following technical trading techniques when applied to the cocoa data series, we test the trading rules on the LIFFE cocoa price series expressed in Dollars and on the CSCE cocoa price series expressed in Pounds. If the LIFFE and CSCE cocoa futures prices are expressed in the other currency, then the results of testing technical trading strategies change indeed. In order to test for economic significance table 2.15 lists the percentage of trading rules with a strictly positive mean excess return for all trading rules sets across all subperiods. For the full sample, 83:1-97:6, for the LIFFE cocoa series in Dollars 33.85% (versus 58.34% in Pounds) of all trading rules generate a strictly positive mean excess return, while for CSCE cocoa futures in Pounds 19.30% (versus 12.18% in Dollars) of the trading rules generate a strictly positive mean excess return. Especially in the first subperiod 1983:1-1987:12 the results change dramatically. For the LIFFE cocoa series in Dollars 23.71% (versus 73.25% in Pounds) of all trading rules generate a strictly positive mean excess return, while for CSCE cocoa futures in Pounds 57.93% (versus 14.14% in Dollars) of the trading rules generate a strictly positive mean excess return.

Table 2.16 summarizes the results concerning the statistical forecasting power of the trading rules applied to the LIFFE cocoa futures in Dollars and the CSCE cocoa futures in Pounds. The table shows for all periods for both data series the percentage of trading rules generating a significantly positive mean excess return. The table also shows the percentage of trading rules generating a significantly positive (negative) mean return during buy (sell) days. Further the table shows the percentage of trading rules for which the mean Buy-Sell difference of the data series is significantly positive and for which buy and sell days at the same time generate significantly positive respectively negative returns. The table summarizes only the results of one sided tests at the 10% significance level. The results of table 2.16 should be compared to the corresponding results of table 2.8.

For the full sample, the statistical properties of the trading rules applied to the CSCE cocoa series in Pounds are only slightly better than for the CSCE cocoa series in Dollars. For example, only 2.73% (versus 1.38%) of all rules yields a significantly positive difference between Buy-Sell returns. The sell days are predicted better, with 14.25% (versus 5.92% of the trading rules showing significantly negative mean return during sell days. For the LIFFE series in Dollars the statistical results of the trading rules are poorer than for to the LIFFE series in Pounds. Now only 1.31% of the strategies generate a significantly positive mean excess return, while this percentage is 13.86% for the LIFFE series in Pounds. The mean Buy-Sell difference is significantly positive only for 5.10% (versus 26.58%) of all trading rules. The trading rules still forecast the sell days well, with 25.97% of the trading rules having significantly negative mean return during sell days, but not nearly as good as for the LIFFE cocoa series in Pounds for which 50.53% of all rules has significantly negative mean return during sell days.

For the first subperiod the trading rules showed no statistically significant forecasting power on the CSCE series in Dollars. When applied to the CSCE series in Pounds the results are much better. For example 8.33% (versus 0.92%) of the strategies has a significantly positive mean excess return. 19.65% (versus 0.77%) of all trading rules has a significantly negative mean return during sell days. For the buy days most t-ratios stay within the critical values and only 6.13% (versus 1.27%) has significantly positive returns. For 19.41% (versus 1.46%) of all strategies the mean Buy-Sell difference is significant. The strongly significant forecasting power of the strategies applied to the LIFFE series in Pounds totally vanishes when applied to the LIFFE series in Dollars. The percentage of trading rules which generates a significantly mean excess return decreases from 34.52% to 1.03%. For most trading rules the t-ratios of the mean return of the data series during buy or sell days stay within the critical values. Only 1.18% (versus 39.47%) of all trading rules has a significantly negative mean return during sell days and only 1.70% (versus 26.73%) has significantly positive returns during buy days. The percentage of strategies for which the mean Buy-Sell difference is significant drops from 46.65% to 2.13%.

We conclude that, especially in the first subperiod, the Pound-Dollar exchange rate had a strong influence on the forecasting power of the trading rules applied to the LIFFE cocoa futures price in Pounds. There is a dramatic change in predictability when the LIFFE cocoa futures price is transformed to Dollars. On the other hand the forecasting power of the strategies on the CSCE cocoa series transformed to Pounds is not as strong as the forecasting power of the strategies applied to the LIFFE cocoa series in Pounds. The Pound-Dollar exchange rate mechanism thus provides only a partial explanation, in addition to the demand-supply mechanism on the cocoa market, of the predictability of trading rules applied to cocoa futures.

2.7.2 What causes success and failure of technical trading?

An important theoretical and practical question is: *"What are the characteristics of speculative price series for which technical trading can be successful?"* In order to get some insight into this general question from our case-study, it is useful to plot the price and returns series all on the same scale, as shown in figure 2.4. The returns series clearly show that the volatility in the Pound-Dollar exchange rate is lower than the volatility in both cocoa futures series. Furthermore, the price series on the same scale show that the trends in the LIFFE cocoa series are much stronger than in the CSCE cocoa series and the Pound-Dollar exchange rate. One might characterize the three series as follows: (i) CSCE has weak trends and high volatility; (ii) LIFFE has strong trends and high volatility, and (iii) Pound-Dollar has weak trends and low volatility.

Recall from section 5 that the performance of technical trading may be summarized as follows: (i) no forecasting power and no economic profitability for CSCE; (ii) good forecasting power and substantial net economic profitability for LIFFE, and (iii) good forecasting power but no economic profitability for Pound-Dollar.

Our case-study of the cocoa futures series and the Pound-Dollar exchange rate series suggest the following connection between performance of technical trading rules and the trend and volatility of the corresponding series. When trends are weak and volatility is relatively high, as for the CSCE cocoa futures series, technical trading does not have much forecasting power and therefore also cannot lead to economic profitability. Volatility is too high relative to the trends, so that technical trading is unable to uncover these trends. When trends are weak but volatility is also relatively low, as for the Pound-Dollar exchange rates, technical trading rules can have statistically significant forecasting power without economically significant profitability. In that case, because volatility is low technical trading can still pick up the weak trends, but the changes in returns, although predictable, are too small to account for transaction costs. Finally, when trends are strong and volatility is relatively high, as for the LIFFE cocoa futures series, a large set of technical trading rules may have statistically significant forecasting power leading to economically significant profit opportunities. In that case, the trends are strong enough to be picked up by technical trading even though volatility is high. Moreover, since volatility is high, the magnitude of the (predictable) changes in returns is large enough to cover the transaction costs.

2.8 Concluding remarks

In this chapter the performance of a large set of 5350 technical trading rules has been tested on the prices of cocoa futures contracts, traded at the CSCE and the LIFFE, and on the Pound-Dollar exchange rate in the period 1983:1-1997:6. The large set of trading rules consists of three subsets: 1990 moving average, 2760 trading range break-out and 600 filter strategies. The strategies perform much better on the LIFFE cocoa prices than on the CSCE cocoa prices, especially in the period 1983:1-1987:12. In this period a large group of the trading rules applied to the LIFFE cocoa futures price has statistically significant forecasting power and is economically profitable after correcting for transaction costs. Applied to the CSCE cocoa futures series the trading rules show little forecasting power and are not profitable. The forecasting power of the strategies applied to the Pound-Dollar exchange rate in the period 1983:1-1997:6 is also statistically significant, but most trading strategies are not profitable.

The large difference in the performance of technical trading in the LIFFE or CSCE cocoa futures contracts may be explained by a combination of the demand/supply mechanism in the cocoa market and the Pound-Dollar exchange rate. In the period 1983:1-1987:12 the price level of the cocoa futures contracts and the level of the Pound-Dollar exchange rate were, accidentally, strongly correlated. This spurious correlation reinforced upward and downward price trends of the LIFFE cocoa futures contracts in London, while weakening the price trends of the CSCE cocoa futures contracts in New York. For the LIFFE cocoa futures price series the trends are strong enough to be picked up by a large class of technical trading rules; for the CSCE cocoa futures price series most trading rules do not pick up the trends, which are similar to the trends in the LIFFE cocoa futures but weaker. We also performed a bootstrap analysis showing that benchmark models such as a random walk, an autoregressive and an exponential GARCH cannot explain the good performance of the technical trading rules in the period 1983:1-1987:12. However a structural break in the trend model cannot be rejected as explanation of the results. Apparently many technical trading rules are able to pick up this structural break in trend.

For the period 1993:1-1997:12 we find that the forecasting power of the technical trading strategies applied to the cocoa futures prices and the Pound-Dollar exchange rate is much less than in the preceding period 1983:1-1992:12. This is in line with many papers that found that forecasting power of trading strategies tends to disappear in the 1990s.

Although the present chapter only documents the economic and statistical performance of technical trading rules applied to a single commodity market, some general conclusions that may be useful for other financial series as well are suggested by our case-study. First, in order to assess the success or failure of technical trading it is useful to test a large class of trading rules, as done in this chapter. A necessary condition for reliable success of technical trading seems to be that a large class of trading rules, not just a few, should work well. If only a few trading rules are successful this may simply be due to "chance" or to data snooping. It should also be emphasized that even if a large class of trading rules has statistically significant forecasting power this is *not* a sufficient condition for economically significant trading profits after correcting for transaction costs. An example is the Pound-Dollar exchange rate for which a large fraction of trading rules exhibits statistically significant forecasting power, but these trading rules hardly generate economic net profitability.

Our case-study of the cocoa futures series and the Pound-Dollar exchange rate series suggest a connection between the success or failure of technical trading rules and the trend and volatility of the corresponding series. When trends are weak and volatility is relatively high, technical trading does not have much forecasting power and therefore also cannot lead to economic profitability. Technical trading is unable to uncover these trends, because volatility is too high. When trends are weak but volatility is relatively low, technical trading rules can have statistically significant forecasting power without economically significant profitability. In that case, because volatility is low technical trading can still pick up the weak trends, but the changes in returns, although predictable, are too small to account for transaction costs. Finally, when trends are strong and volatility is relatively high, a large set of technical trading rules may have statistically significant forecasting power leading to economically significant profit opportunities. In that case, even though volatility is high the trends are strong enough to be picked up by technical trading. Moreover, since volatility is high, the magnitude of the (predictable) changes in returns is large enough to cover the transaction costs. We emphasize that this connection between predictive and economic performance of technical trading is suggestive and only documented by the market studied here. Further research, of interest from a theoretical as well as a practical viewpoint, is needed to uncover whether the success and failure of technical trading is explained by the relative magnitudes of trend and volatility.

Technical analysis may pick up sufficiently strong trends in asset prices and even may pick up a structural break in trends, without knowing or understanding the economic forces behind these trends. It seems wise however that a technical analyst does not trust his charts only, but also tries to trace economic fundamentals that may cause or reinforce detected trends. For the LIFFE cocoa futures series the trends were caused by two forces, namely the supply-demand mechanism in the cocoa market and the exchange rate movements. Apparently, at the same time as the trend break point, these forces changed direction. If both the technical charts and fundamental indicators point in the same direction technical trading can be successful; otherwise failure seems a real possibility.

Appendix

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Table 2.1: **Summary statistics for daily returns.** Results are presented for the full sample and for three subperiods. Returns are calculated as the log differences of the prices. The maximum loss is the largest consecutive decline in percentage terms during a certain period. The t-ratio tests whether the mean return is significantly different from zero.

	Full Sample	83:1-87:12	88:1-92:12	93:1-97:6
CSCE				
N	3654	1254	1262	1136
Yearly effective return	-0.078914	-0.016746	-0.21364	0.020661
Mean	-0.000326	-0.000067	-0.000954	0.000081
Std. Dev.	0.016616	0.015787	0.018842	0.014773
t-ratio	-1.186689	-0.150324	-1.798208	0.185154
Skewness	0.243951	-0.049036	0.341313	0.477601
Kurtosis	4.971493	3.39366	5.199822	5.495766
Maximum loss	-0.8507	-0.4355	-0.7234	-0.3546
Period of maximum loss	05/23/84 - 02/20/97	05/23/84 - 12/08/87	01/22/88 - 06/24/92	07/18/94 - 02/20/97
LIFFE				
N	3673	1260	1264	1147
Yearly effective return	-0.073934	-0.035598	-0.198199	0.030482
Mean	-0.000305	-0.000144	-0.000877	0.000119
Std. Dev.	0.014056	0.013538	0.015521	0.012851
t-ratio	-1.314172	-0.377152	-2.007875	0.314005
Skewness	0.08106	-0.249777	0.353273	0.040053
Kurtosis	5.797402	5.85137	5.564294	5.721865
Maximum loss	-0.8919	-0.6115	-0.7513	-0.3749
Period of maximum loss	02/05/85 - 06/24/92	02/05/85 - 12/09/87	01/19/88 - 06/24/92	08/01/94 - 02/12/97
BPDo				
N	3780	1303	1304	1171
Yearly effective return	-0.0019	-0.028517	0.042569	-0.020163
Mean	-0.000008	-0.000115	0.000165	-0.000081
t-ratio	-0.070642	-0.587341	0.832657	-0.537031
Std. Dev.	0.006567	0.007056	0.007174	0.00515
Skewness	-0.021897	-0.448886	0.391937	-0.086657
Kurtosis	6.133925	6.487253	4.839026	6.362086
Maximum loss	-0.4748	-0.4397	-0.244	-0.1714
Period of maximum loss	02/27/85 - 09/02/92	02/27/85 - 12/31/87	06/15/89 - 09/02/92	02/15/93 - 12/31/96

Table 2.2: **Autocorrelation functions of daily returns.** For every data series the estimated autocorrelations are shown up to order 20. a, b, c means that the corresponding autocorrelation is significant at the 1%, 5%, 10% significance level with Bartlett (1946) standard errors. $***$, $**$, $*$ means that the corresponding autocorrelation is significant at the 1%, 5%, 10% significance level with Diebold (1986) heteroskedasticity-consistent standard errors.

	CSCE				**LIFFE**			
k	83:1-97:6	83:1-87:12	88:1-92:12	93:1-97:6	83:1-97:6	83:1-87:12	88:1-92:12	93:1-97:6
1	-0.0007	0.0328	-0.0112	-0.0277	0.0300c	0.0083	0.0456	0.0253
2	-0.0515a***	-0.0611b*	-0.0524c	-0.0438	-0.0378b**	-0.0178	-0.0437	-0.0567c*
3	0.0038	0.0004	0.0086	-0.0036	0.0122	0.0538c*	0.0155	-0.047
4	-0.0023	-0.0007	0.0031	-0.017	0.0368b*	-0.0065	0.0493c	0.0671b*
5	0.0106	-0.012	0.0141	0.0314	0.0163	0.0605b*	-0.0027	-0.0048
6	-0.0192	-0.0263	0.0022	-0.0519c	-0.0279c	0.0016	-0.026	-0.0704b**
7	-0.0065	-0.0155	-0.0101	0.0115	-0.0087	-0.0193	-0.036	0.0454
8	0.0062	-0.0499c	0.0255	0.0344	0.0066	-0.0068	0.0188	-0.0063
9	-0.0072	0.005	-0.0167	-0.0078	0.0217	0.0202	0.0293	0.0041
10	-0.0014	-0.0387	0.0094	0.0265	0.0398b**	-0.0198	0.0662b**	0.0654b*
11	-0.024	-0.0352	-0.022	-0.0162	0.0001	-0.0012	-0.0216	0.026
12	-0.018	0.0431	-0.0613b**	-0.0236	-0.0173	0.0409	-0.0649b**	-0.0168
13	-0.0135	-0.0112	-0.0008	-0.046	-0.0011	0.0471c	-0.0131	-0.0426
14	0.0052	0.0372	0.0005	-0.0302	0.0176	0.0002	0.0444	-0.0098
15	0.0193	0.0024	0.0437	-0.0041	0.0151	0.0357	0.0239	-0.0223
16	-0.0141	0.0049	-0.0377	0.001	0.0098	0.1279a***	-0.0775a**	0.004
17	-0.0076	0.0312	-0.0384	0.0011	-0.0193	-0.0307	-0.0257	0.0054
18	0.0156	-0.0295	0.0565b*	0.0003	0.004	-0.0209	0.0488c	-0.0287
19	0.0093	-0.005	0.0135	0.0194	0.0399b**	0.0089	0.0433	0.0669b**
20	0.0135	-0.0083	0.0475c	-0.0243	0.0072	-0.0306	0.0221	0.0152

	BPDo			
k	83:1-97:6	83:1-87:12	88:1-92:12	93:1-97:6
1	0.0833a***	0.1025a***	0.1085a***	-0.0132
2	0.0241	0.0201	0.0165	0.0477
3	-0.0158	-0.0099	-0.0192	-0.0151
4	0.0016	-0.0313	0.0359	-0.0029
5	0.0343b*	0.0266	0.0958a***	-0.0605b
6	-0.0034	0.0286	-0.0135	-0.0411
7	-0.0303c	-0.0081	-0.0598b**	-0.022
8	0.0280c	0.0479c	0.025	-0.0074
9	0.0121	-0.0221	0.0357	0.0299
10	-0.0048	-0.0570b*	0.0414	0.0158
11	-0.0021	-0.0127	0.0203	-0.0246
12	-0.0203	-0.0439	-0.0068	-0.0044
13	-0.0079	-0.0087	0.0031	-0.0114
14	0.0268	0.0211	0.0386	0.0128
15	0.0305c	0.0527c	0.0478c	-0.0641b*
16	-0.0009	-0.0305	0.0277	-0.0079
17	0.0131	-0.0053	0.0085	0.0487
18	-0.0341b*	-0.0051	-0.0635b**	-0.0059
19	-0.0131	0.0143	-0.01	-0.0366
20	0.0103	0.0232	0.0035	-0.0177

Table 2.3: **Results of the best strategies applied to the CSCE cocoa futures prices.** Panel A shows the results of the best five technical trading strategies applied to the CSCE cocoa futures prices for the period 1983:1-1997:6. Panel B shows the results of the best technical trading strategy in each of the three subperiods: 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6. The first column lists the strategy parameters. %b, td, fhp, and stl are abbreviations for the %band filter, the time delay filter, the fixed holding period and the stop-loss respectively. The second column lists the mean daily excess returns $\overline{r_Y^e}$ on a yearly basis, that is the mean daily return times the number of trading days in a year, which is set to 252. The third column lists the mean daily excess returns of the trading rules net of 0.1% transaction costs, with the t-ratios beneath these numbers. The fourth and fifth column list the number of days classified as a buy or sell day. The number of buy and sell trades are listed beneath these numbers. The sixth and seventh column list the total number of days buy (sell) trades with a strictly positive excess return last, as a fraction of the total number of buy (sell) days. The fraction of buy and sell trades with a strictly positive excess return are listed beneath these numbers. The eight and ninth column list the mean daily return of the data series itself during buy and sell days, t-ratios are listed beneath these numbers. The last column lists the differences between the mean daily buy and sell returns and the corresponding t-ratios are listed beneath these numbers.

Panel A: Full sample, best five strategies														
Strategy [		%b	td	fhp	stl]	$\overline{r_Y^e}$	$\overline{r^e}$	N_B	N_S	Buy>0	Sell>0	Buy	Sell	Buy-Sell
1983-1997														
[TRB	5	2%		50	]	0.1038	0.00039	1450	950	0.517	0.737	0.00056	-0.00101	0.00158
							1.71767	28	19	0.5	0.737	1.20175	-1.96037	2.25978
[FR	1%		3	10	]	0.0935	0.00036	1150	1001	0.478	0.649	0.00068	-0.00118	0.00187
							1.63535	111	97	0.477	0.649	1.33110	-2.23745	2.53246
[TRB	15	2%		50	]	0.0832	0.00032	1000	750	0.65	0.733	0.00046	-0.00126	0.00172
							1.60974	20	15	0.65	0.733	0.85819	-1.93654	2.03745
[FR	1.5%		5	25	]	0.0782	0.00030	1117	1050	0.62	0.69	0.00041	-0.00105	0.00146
							1.37787	46	40	0.63	0.7	0.81153	-2.04345	2.02312
[FR	8%		3	50	]	0.0755	0.00029	1270	752	0.567	0.801	0.00034	-0.00117	0.00151
							1.36795	26	16	0.577	0.813	0.71020	-1.80930	1.87465
Panel B: Subperiods, best strategy														
1983-1987														
[FR	0.5%		3	50	]	0.2016	0.00073	429	630	0.767	0.635	0.00158	-0.00057	0.00215
							1.82085	9	13	0.778	0.615	1.99680	-0.94078	2.15951
1988-1992														
[MA	1, 2			25	]	0.2156	0.00078	652	560	0.617	0.732	0.00022	-0.00221	0.00243
							1.45504	21	21	0.524	0.762	0.29297	-2.76492	2.22314
1993-1997														
[FR	1%		3	10	]	0.2105	0.00076	385	311	0.481	0.74	0.00157	-0.00145	0.00302
							2.12162	38	30	0.5	0.7	2.01350	-1.66264	2.58211

Table 2.4: **Results of the best strategies applied to the LIFFE cocoa futures prices.** Panel A shows the results of the best five technical trading strategies applied to the LIFFE cocoa futures prices for the period 1983:1-1997:6. Panel B shows the results of the best technical trading strategy in each of the three subperiods: 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6.

Strategy [	%b	td	fhp	stl]	$\overline{r^e_Y}$	$\overline{r^e}$	N_B	N_S	Buy>0	Sell>0	Buy	Sell	Buy-Sell
Panel A: Full sample, best five strategies													
1983-1997													
[MA 1,40	0.5%			]	0.1495	0.00055	1505	2168	0.728	0.816	0.00059	-0.00092	0.00151
						2.60018	70	69	0.357	0.391	1.50434	-3.25995	3.13221
[MA 10,75				7.5%]	0.148	0.00055	1102	1914	0.691	0.869	0.00057	-0.00104	0.00161
						3.05696	33	32	0.424	0.625	1.32464	-3.59837	3.10298
[MA 5,50	0.5%			]	0.1459	0.00054	1489	2184	0.666	0.748	0.00052	-0.00087	0.00139
						2.55433	41	40	0.415	0.425	1.31265	-3.10160	2.85916
[MA 1,30				7.5%]	0.1442	0.00053	1485	2170	0.692	0.796	0.00067	-0.00097	0.00164
						2.50284	130	129	0.292	0.287	1.72202	-3.36952	3.38854
[MA 1,30	0.1%			]	0.1422	0.00053	1510	2163	0.689	0.791	0.00063	-0.00096	0.00158
						2.46005	118	117	0.297	0.308	1.61817	-3.34207	3.28657
Panel B: Subperiods, best strategy													
1983-1987													
[MA 2,40				5%]	0.3547	0.00121	388	691	0.866	0.925	0.00211	-0.00146	0.00357
						3.88278	19	19	0.526	0.579	2.79621	-3.19459	4.04603
1988-1992													
[FR 4%		5	50	]	0.2517	0.00089	498	417	0.703	1	0.00078	-0.00218	0.00296
						2.53028	10	9	0.7	1	1.16035	-2.72535	2.83447
1993-1997													
[FR 0.5%		2	50	]	0.1923	0.00070	400	675	0.75	0.75	0.00128	-0.00069	0.00197
						1.98085	8	13	0.75	0.769	1.92902	-1.46915	2.42358

Table 2.5: **Results of the best strategies applied to the Pound-Dollar exchange rate.** Panel A shows the results of the best five technical trading strategies applied to the Pound-Dollar exchange rate for the period 1983:1-1997:6. Panel B shows the results of the best technical trading strategy in each of the three subperiods: 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6.

Strategy [		%b	td	fhp	stl]	$\overline{r^e_Y}$	$\overline{r^e}$	N_B	N_S	Buy>0	Sell>0	Buy	Sell	Buy-Sell
Panel A: Full sample, best five strategies														
1983-1997														
[TRB	100	1%		50	]	0.0164	0.00007	215	250	0.767	0	0.00161	-0.00017	0.00178
							1.93088	5	5	0.8	0	2.75658	-0.36090	2.38333
[TRB	50	1%		50	]	0.0127	0.00005	350	400	0.571	0	0.00097	-0.00008	0.00105
							1.42095	7	8	0.571	0	2.55344	-0.20080	1.94510
[TRB	5	1.5%		10	]	0.0126	0.00005	160	160	0.563	0	0.00175	-0.00060	0.00235
							1.68605	16	16	0.563	0	2.51482	-0.87011	2.40450
[TRB	250		2	25	]	0.0115	0.00005	125	125	0.6	0	0.00184	-0.00108	0.00292
							1.95839	5	5	0.6	0	2.66970	-1.80209	3.19810
[TRB	250	0.1%		25	]	0.0115	0.00005	125	125	0.8	0	0.00184	-0.00119	0.00303
							1.95916	5	5	0.8	0	2.67404	-1.95430	3.29853
Panel B: Subperiods, best strategy														
1983-1987														
[MA	20,40				2%]	0.0333	0.00013	398	268	0.827	0	0.00089	-0.00040	0.00128
							1.34254	12	13	0.667	0	2.79888	-0.96585	2.47666
1988-1992														
[FR	0.5%		5	25	]	0.0534	0.00021	307	325	0.593	0	0.00141	-0.00056	0.00197
							1.97336	13	13	0.615	0	3.18590	-1.56473	3.45882
1993-1997														
[MA	30,50			10	]	0.0221	0.00009	130	130	0.615	0	0.00120	-0.00013	0.00132
							1.53693	13	13	0.615	0	2.38807	-0.25821	1.88737

Table 2.6: **Excess returns without transaction costs.** Percentage of trading rules with a strictly positive mean excess return in the case of no transaction costs, when applied to the CSCE and LIFFE continuation series and the Pound-Dollar exchange rate, for the full sample 1983:1-1997:6 and the three subperiods 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6.

	CSCE				**LIFFE**				**BPDO**			
Period	MA	TRB	Filter	All	MA	TRB	Filter	All	MA	TRB	Filter	All
1	16.36	18.72	33.33	19.13	80.64	75.46	69.15	77.47	12.63	14.00	3.65	12.14
2	65.94	45.56	52.74	56.90	71.77	49.22	57.21	61.78	29.57	46.36	51.41	38.32
3	15.82	19.87	36.48	19.63	36.70	36.38	42.79	37.27	2.75	3.91	3.32	3.25
Full	16.72	17.66	33.33	18.92	74.67	63.27	60.03	68.86	5.90	21.73	20.56	13.45

Table 2.7: **Excess returns with 0.1% transaction costs.** Percentage of trading rules with a strictly positive mean excess return in the case of 0.1% transaction costs, when applied to the CSCE and LIFFE continuation series and the Pound-Dollar exchange rate, for the full sample 1983:1-1997:6 and the three subperiods 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6.

	CSCE				**LIFFE**				**BPDo**			
Period	MA	TRB	Filter	All	MA	TRB	Filter	All	MA	TRB	Filter	All
1	11.26	15.35	23.22	14.14	76.76	70.85	64.51	73.25	9.30	11.34	2.65	9.32
2	58.67	41.09	44.78	50.55	63.34	42.10	49.42	53.90	20.85	40.39	44.44	30.81
3	11.80	15.81	28.86	15.19	28.09	28.95	35.66	29.25	1.56	3.01	1.33	2.07
Full	9.19	12.24	25.70	12.18	64.17	52.78	49.59	58.34	2.75	18.57	16.09	10.14

Table 2.8: **Significance: simple t-ratios.** The table shows for all groups of trading rules (MA, TRB, Filter, All) for the full sample and for each of the three subperiods (1, 2, and 3) the percentage for which a significantly positive mean excess return occurs net of 0.1% transaction costs. The table also shows the percentage for which a significantly positive (negative) mean return during buy (sell) days occurs. Further the table shows the percentage of strategies for which the difference in mean return of the data series during buy and sell days is significantly positive. Finally the percentage of strategies for which the data series has a significantly positive mean return during buy days as well as a significantly negative mean return during sell days is given. The table only summarizes the results of one sided tests at the 10% significance level.

		CSCE				**LIFFE**				**BPDo**			
	Period	MA	TRB	Filter	All	MA	TRB	Filter	All	MA	TRB	Filter	All
$t_{Perf} > t_c$	1	0.54	1.05	2.16	0.92	38.11	34.22	18.74	34.52	0.36	0.45	0.00	0.35
	2	2.75	0.40	2.82	1.85	6.99	4.42	9.45	6.31	2.03	8.88	3.81	4.78
	3	0.33	0.45	1.00	0.45	1.23	3.16	2.82	2.13	0.07	0.15	0.00	0.09
	Full	0.22	0.10	1.33	0.30	18.31	8.38	11.44	13.86	0.07	5.22	0.83	2.07
$t_{Buy} > t_c$	1	1.09	1.30	1.99	1.27	25.52	30.41	19.90	26.73	16.36	9.38	4.31	12.42
	2	0.07	1.05	0.66	0.50	0.65	0.50	2.32	0.78	27.72	31.76	31.01	29.63
	3	0.51	0.45	3.81	0.86	2.06	7.58	5.14	4.46	0.65	0.45	0.17	0.52
	Full	0.14	1.15	1.00	0.62	4.56	8.03	13.43	6.86	11.65	16.41	8.46	13.08
$t_{Sell} < -t_c$	1	0.43	0.80	2.16	0.77	50.81	29.65	19.57	39.47	59.03	29.35	25.70	44.29
	2	60.55	26.14	32.17	44.57	67.46	40.04	43.78	54.62	9.81	5.77	4.64	7.73
	3	0.65	0.30	1.00	0.56	1.19	0.50	1.00	0.92	0.69	3.01	4.48	1.98
	Full	6.59	3.46	10.95	5.92	64.82	36.93	29.85	50.53	19.58	15.05	12.60	17.13
$t_{Buy-Sell} > t_c$	1	0.98	1.30	4.15	1.46	53.85	41.60	29.85	46.65	59.54	26.24	12.44	41.90
	2	1.12	1.66	6.80	1.96	8.29	4.77	18.41	8.13	27.36	25.64	21.89	26.13
	3	0.80	0.75	2.49	0.97	2.68	3.76	3.15	3.14	0.72	0.80	0.83	0.77
	Full	1.01	0.50	5.97	1.38	31.52	20.92	22.39	26.58	31.27	27.85	14.93	28.19
$t_{Buy} > t_c \wedge$	1	0.07	0.00	0.00	0.04	18.64	11.99	5.47	14.70	11.91	4.92	4.15	8.44
$t_{Sell} < -t_c$	2	0.00	0.05	0.00	0.02	0.47	0.25	1.33	0.49	5.32	3.11	1.82	4.11
	3	0.00	0.00	0.17	0.02	0.07	0.20	0.33	0.15	0.00	0.20	0.00	0.07
	Full	0.07	0.00	0.17	0.06	3.04	1.66	3.65	2.60	8.83	6.42	0.83	7.04

Table 2.9: **Bad significance: simple t-ratios.** This table shows in contrast to table 2.8 the percentage of strategies for which the mean excess return net of 0.1% transaction costs is significantly negative for all trading rules sets and for all periods. The table also shows the percentage for which a significantly negative (positive) mean return during buy (sell) days occurs. Further the table shows the percentage of strategies for which the difference in mean return of the data series during buy and sell days is significantly negative. Finally the percentage of strategies for which the data series has a significantly negative mean return during buy days as well as a significantly positive mean return during sell days is given. The table only summarizes the results of one sided tests at the 10% significance level.

		CSCE				**LIFFE**				**BPDo**			
	Period	MA	TRB	Filter	All	MA	TRB	Filter	All	MA	TRB	Filter	All
$t_{Perf} < -t_c$	1	21.35	29.65	18.74	24.17	5.90	4.92	9.12	5.87	25.05	24.08	46.60	27.11
	2	5.79	12.74	14.43	9.32	4.74	14.05	10.45	8.80	23.31	9.18	16.92	17.32
	3	33.48	34.47	19.07	32.26	13.14	8.68	11.28	11.28	81.80	51.93	39.97	66.02
	Full	29.64	41.55	26.20	33.72	5.94	7.58	13.76	7.40	80.67	40.89	48.76	62.32
$t_{Buy} < -t_c$	1	5.36	16.41	4.81	9.42	2.75	4.21	4.15	3.46	3.91	6.92	15.59	6.35
	2	28.16	25.99	21.06	26.55	35.90	30.96	17.25	31.96	0.58	0.05	1.33	0.47
	3	6.44	11.74	2.49	7.98	2.17	3.11	0.50	2.34	21.43	15.50	8.96	17.84
	Full	31.81	36.83	17.74	32.13	4.56	4.21	7.79	4.76	0.72	3.01	4.15	1.96
$t_{Sell} > t_c$	1	2.14	10.54	4.98	5.59	3.58	2.91	3.15	3.29	0.33	1.05	2.99	0.90
	2	0.25	2.06	1.00	1.01	0.33	8.28	1.16	3.38	13.03	14.35	10.61	13.26
	3	12.49	18.72	12.60	14.83	5.25	8.83	8.29	6.93	2.06	6.62	5.31	4.13
	Full	0.76	9.03	4.15	4.22	0.80	4.47	2.16	2.32	0.72	4.16	4.15	2.39
$t_{Buy-Sell} < -t_c$	1	9.63	20.17	9.45	13.54	3.08	3.61	3.15	3.29	1.85	2.66	3.48	2.34
	2	4.89	8.68	5.14	6.33	14.15	18.46	7.30	15.00	8.87	9.28	6.47	8.76
	3	19.65	22.93	10.95	19.91	6.84	5.42	3.65	5.96	20.05	13.95	9.78	16.64
	Full	9.59	25.09	7.13	15.09	2.39	2.66	4.81	2.76	1.16	3.81	2.99	2.35
$t_{Buy} < -t_c \wedge$ $t_{Sell} > t_c$	1	0.47	2.61	1.49	1.38	0.87	0.80	0.66	0.82	0.11	0.05	0.50	0.13
	2	0.11	0.50	0.33	0.28	0.14	3.06	0.50	1.27	0.40	0.05	0.83	0.32
	3	3.62	3.31	1.00	3.21	0.47	0.15	0.17	0.32	0.54	2.11	0.50	1.12
	Full	0.29	3.21	0.00	1.35	0.25	0.05	0.00	0.15	0.04	2.06	0.00	0.78

Table 2.11: **Significance after correction for dependence: an estimation based approach.**
Panel A: This table shows for all sets of trading rules applied to the LIFFE cocoa series in the period 1983:1-1987:12 the percentage of trading rules for which the estimated coefficient of the buy (sell) dummy in the regression function of the exponential garch model is significantly positive (negative) at the 10% significance level with a one sided test (second and third column). The fourth column shows the percentage of trading rules for which the coefficient of the buy dummy is significantly positive and the coefficient of the sell dummy is significantly negative.

Rule	$t_{Buy} > t_c$	$t_{Sell} < -t_c$	$t_{Buy} > t_c \wedge t_{Sell} < -t_c$
MA	40.2	32.8	29.6
TRB	41.9	22.7	16.6
Filter	38.7	17.5	9.8
All	40.6	27.4	22.8

Panel B: This table shows for all sets of trading rules applied to the LIFFE cocoa series in the period 1983:1-1987:12 the percentage of trading rules for which the estimated coefficient of the buy (sell) dummy in the regression function of the exponential garch model is significantly negative (positive) at the 10% significance level with a one sided test (second and third column). The fourth column shows the percentage of trading rules for which the coefficient of the buy dummy is significantly negative and the coefficient of the sell dummy is significantly positive.

Rule	$t_{Buy} < -t_c$	$t_{Sell} > t_c$	$t_{Buy} < -t_c \wedge t_{Sell} > t_c$
MA	3.6	4.1	1.5
TRB	5.2	9.6	1.9
Filter	2.1	6.8	0.7
All	4.0	6.4	1.6

Table 2.13: **Significance after correction for dependence: a bootstrap based approach.**
Panel A: Bootstrap results under the null of a random walk, autoregressive, exponential garch model and a model which incorporates the structural change in the data for the LIFFE cocoa futures series in the period 1983:1-1987:12. The table lists the fractions of simulation results which are larger than the results for the original data series. The rows $t_{Perf} > t_c$, $t_{Buy} > t_c$, $t_{Sell} < -t_c$, $t_{Buy-Sell} > t_c$ and $t_{Buy} > t_c \wedge t_{Sell} < -t_c$ show the fraction of the 500 bootstrapped time series for which the percentage of trading strategies with a significantly positive mean excess return, with a significantly positive mean buy return, with a significantly negative mean sell return, with a significantly positive mean buy-sell difference and with a significantly positive mean buy as well as a significantly negative mean sell return is larger than the same percentages when the trading strategies are applied to the original data series.

	RW	AR	EGARCH	Trend
$t_{Perf} > t_c$	0.002	0.038	0.03	0.414
$t_{Buy} > t_c$	0.032	0.074	0.05	0.478
$t_{Sell} < -t_c$	0.14	0.274	0.334	0.528
$t_{Buy-Sell} > t_c$	0	0.012	0.002	0.248
$t_{Buy} > t_c \wedge t_{Sell} < -t_c$	0.006	0.016	0.012	0.426

Panel B: Bootstrap results under the null of a random walk, autoregressive, exponential garch model and a model which incorporates the structural change in the data for the LIFFE cocoa futures series in the period 1983:1-1987:12. The table lists the fractions of simulation results which are larger than the results for the original data series. The rows $t_{Perf} < -t_c$, $t_{Buy} < -t_c$, $t_{Sell} > t_c$, $t_{Buy-Sell} < -t_c$ and $t_{Buy} < -t_c \wedge t_{Sell} > t_c$ show the fraction of the 500 bootstrapped time series for which the percentage of trading strategies with a significantly negative mean excess return, with a significantly negative mean buy return, with a significantly positive mean sell return, with a significantly negative mean buy-sell difference and with a significantly negative mean buy as well as a significantly positive mean sell return is larger than the same percentages when the trading strategies are applied to the original data series.

	RW	AR	EGARCH	Trend
$t_{Perf} < -t_c$	0.964	0.936	0.942	0.96
$t_{Buy} < -t_c$	0.87	0.838	0.902	0.858
$t_{Sell} > t_c$	0.572	0.502	0.428	0.776
$t_{Buy-Sell} < -t_c$	0.968	0.95	0.942	0.952
$t_{Buy} < -t_c \wedge t_{Sell} > t_c$	0.342	0.274	0.278	0.542

Table 2.14: **Cross-correlations.** The cross-correlations between the LIFFE and CSCE continuation cocoa series, and the Pound-Dollar exchange rate for the periods 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6.

83:1-97:6 Corr	LIFFE	CSCE	BPDo	83:1-87:12 Corr	LIFFE	CSCE	BPDo
LIFFE	1			LIFFE	1		
CSCE	0.98	1		CSCE	0.87	1	
BPDO	0.66	0.51	1	BPDO	0.88	0.58	1
88:1-92:12 Corr	**LIFFE**	**CSCE**	**BPDo**	**93:1-97:6 Corr**	**LIFFE**	**CSCE**	**BPDo**
LIFFE	1			LIFFE	1		
CSCE	0.97	1		CSCE	0.93	1	
BPDO	0.08	-0.13	1	BPDO	0.26	0.16	1

Table 2.15: **Excess returns when LIFFE in Dollars and CSCE in Pounds.** Percentage of trading rules with a strictly positive mean excess return in the case of 0.1% transaction costs, when applied to the CSCE continuation series expressed in Pounds and the LIFFE continuation series expressed in Dollars for the full sample 1983:1-1997:6 and the three subperiods 1983:1-1987:12, 1988:1-1992:12 and 1993:1-1997:6.

	CSCE in Pounds				**LIFFE in Dollars**			
Period	MA	TRB	Filter	All	MA	TRB	Filter	All
1	70.03	44.66	45.77	57.93	16.61	33.32	24.54	23.71
2	34.53	27.95	34.83	32.11	77.85	55.59	51.91	66.69
3	9.70	8.38	24.05	10.84	26.75	23.78	33.50	26.40
Full	21.72	13.60	27.20	19.30	34.67	33.07	32.67	33.85

Table 2.16: **Significance when LIFFE in Dollars and CSCE in Pounds: simple t-ratios.** The table shows for all groups of trading rules (MA, TRB, Filter, All) for the full sample period and for each of the three subperiods (1, 2, and 3) the percentage for which a significantly positive mean excess return net of 0.1% transaction costs occurs. The table also shows the percentage for which a significantly positive (negative) mean return during buy (sell) days occurs. Further the table shows the percentage of strategies for which the difference in mean return of the data series during buy and sell days is significantly positive. Finally the percentage of strategies for which the data series has a significantly positive mean return during buy days as well as a significantly negative mean return during sell days is shown. All results reported are for the CSCE futures prices recomputed to Pounds and the LIFFE futures prices recomputed to Dollars. The table only summarizes the results of one sided tests at the 10% significance level.

		CSCE in Pounds				**LIFFE in Dollars**			
	Period	MA	TRB	Filter	All	MA	TRB	Filter	All
$t_{Perf} > t_c$	1	10.39	6.37	5.31	8.33	0.90	1.10	1.33	1.03
	2	1.92	1.56	0.83	1.66	21.17	15.40	16.09	18.44
	3	0.25	0.15	3.15	0.54	1.52	1.40	3.48	1.70
	Full	0.80	0.60	1.16	0.77	1.19	0.95	2.99	1.31
$t_{Buy} > t_c$	1	5.21	5.92	10.95	6.13	1.38	2.16	1.66	1.70
	2	0.62	0.45	1.00	0.60	0.47	3.16	4.64	1.94
	3	0.36	0.40	2.82	0.65	2.79	4.62	7.96	4.05
	Full	0.58	0.45	4.98	1.03	0.87	1.25	4.81	1.46
$t_{Sell} < -t_c$	1	28.95	11.09	5.14	19.65	1.01	1.15	1.99	1.18
	2	22.11	15.40	20.23	19.39	81.58	49.67	47.43	65.91
	3	1.12	0.25	2.49	0.95	0.76	0.10	1.00	0.54
	Full	18.57	8.43	13.60	14.25	32.18	19.47	18.74	25.97
$t_{Buy-Sell} > t_c$	1	26.71	11.89	10.61	19.41	1.88	2.21	2.99	2.13
	2	2.97	2.26	5.97	3.05	14.95	12.09	23.05	14.81
	3	0.76	0.25	5.14	1.06	2.28	2.06	5.64	2.58
	Full	2.82	1.51	6.30	2.73	5.50	3.11	9.78	5.10
$t_{Buy} > t_c \wedge$	1	0.90	0.20	0.17	0.56	0.14	0.00	0.33	0.11
$t_{Sell} < -t_c$	2	0.11	0.05	0.00	0.07	0.07	1.86	0.83	0.82
	3	0.04	0.00	0.50	0.07	0.18	0.00	0.66	0.17
	Full	0.11	0.05	0.17	0.09	0.22	0.25	1.16	0.34

Table 2.17: **Bad significance when LIFFE in Dollars and CSCE in Pounds: simple t-ratios.** This table shows in contrast to table 2.16 the percentage of strategies for which the mean excess return net of 0.1% transaction costs is significantly negative for all trading rules sets and all periods. The table also shows the percentage for which a significantly negative (positive) mean return during buy (sell) days occurs. Further the table shows the percentage of strategies for which the difference in mean return of the data series during buy and sell days is significantly negative. Finally the percentage of strategies for which the data series has a significantly negative mean return during buy days as well as a significantly positive mean return during sell days is shown. All results reported are for the CSCE futures prices recomputed to Pounds and the LIFFE futures prices recomputed to Dollars. The table only summarizes the results of one sided tests at the 10% significance level.

		CSCE in Pounds				**LIFFE in Dollars**			
	Period	MA	TRB	Filter	All	MA	TRB	Filter	All
$t_{Perf} < -t_c$	1	6.01	9.23	13.60	8.07	14.66	8.83	13.43	12.37
	2	11.07	13.45	20.23	12.96	3.08	7.53	14.10	5.94
	3	30.84	39.14	16.09	32.30	13.68	16.86	13.76	14.89
	Full	13.46	28.70	24.71	20.42	8.61	10.59	20.90	10.74
$t_{Buy} < -t_c$	1	3.18	5.22	4.64	4.11	1.38	4.62	1.82	2.63
	2	36.12	24.89	23.38	30.51	26.06	21.78	25.21	24.36
	3	9.48	15.96	3.48	11.23	1.34	1.71	0.66	1.40
	Full	13.54	22.98	15.09	17.24	7.82	7.23	13.60	8.26
$t_{Sell} > t_c$	1	2.46	5.47	6.30	4.02	1.70	1.76	3.32	1.91
	2	0.54	7.43	1.82	3.25	0.25	3.31	0.66	1.44
	3	3.98	11.74	9.45	7.49	9.70	19.92	16.92	14.33
	Full	1.16	4.67	4.98	2.90	0.40	3.66	2.16	1.81
$t_{Buy-Sell} < -t_c$	1	3.66	5.67	4.48	4.50	5.36	3.51	5.64	4.71
	2	16.58	10.89	9.78	13.71	4.42	5.17	7.96	5.10
	3	17.41	26.84	8.46	19.93	7.09	9.48	8.13	8.11
	Full	5.79	13.60	10.12	9.19	1.81	2.81	5.47	2.60
$t_{Buy} < -t_c \wedge$	1	0.58	0.70	0.50	0.62	0.25	0.20	0.17	0.22
$t_{Sell} > t_c$	2	0.14	0.40	0.33	0.26	0.04	0.05	0.00	0.04
	3	2.28	5.17	1.82	3.31	0.22	0.25	0.50	0.26
	Full	0.40	0.75	0.83	0.58	0.07	0.05	0.33	0.09

B. Parameters of technical trading strategies

This appendix presents the values of the parameters of the technical trading strategy set applied in this chapter. Most parameter values are equal to those used by Sullivan et al. (1999). Each basic trading strategy can be extended by a %-band filter (band), time delay filter (delay), fixed holding period (fhp) and a stop-loss (sl). The total set consists of 5353 different trading rules, including the strategies that are always short, neutral or long.

Moving-average rules

n	=number of days over which the price must be averaged
band	=%-band filter
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period
sl	=%-rise (%-fall) from a previous low (high) to liquidate a short (long) position

n	=[1, 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250]
band	=[0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05]
delay	=[2, 3, 4, 5]
fhp	=[5, 10, 25, 50]
sl	=[0.02, 0.03, 0.04, 0.05, 0.075, 0.10]

With the 16 values of n we can construct $\binom{16}{2} = 120$ basic moving-average (MA) trading strategies. We extend these strategies with %-band filters, time delay filters, fixed holding period and a stop-loss. The values chosen above will give us in total:
$120 + 120 * 8 + 120 * 4 + 120 * 4 + 120 * 6 = 2760$ MA strategies.

Trading range break-out rules

n	= length of the period to find local minima (support) and maxima (resistance)
band	=%-band filter
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period
sl	=%-rise (%-fall) from a previous low (high) to liquidate a short (long) position

n	=[5, 10, 15, 20, 25, 50 ,100, 150, 200, 250]
band	=[0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05]
delay	=[2, 3, 4, 5]
fhp	=[5, 10, 25, 50]
sl	=[0.02, 0.03, 0.04, 0.05, 0.075, 0.10]

With the parameters and values given above we construct the following trading range break-out (TRB) strategies:

basic TRB strategies:	10*1	=10
TRB with %-band filter:	10*8	=80
TRB with time delay filter:	10*4	=40
TRB with fixed holding period:	10*4	=40
TRB with stop-loss:	10*6	=60
TRB with %-band and time delay filter:	10*8*4	=320
TRB with %-band and fixed holding:	10*8*4	=320
TRB with %-band and stop-loss:	10*8*6	=480
TRB with time delay and fixed holding:	10*4*4	=160
TRB with time delay and stop-loss:	10*4*6	=240
TRB with fixed holding and stop-loss:	10*4*6	=240

This will give in total 1990 TRB strategies.

Filter rules

filt	= %-rise (%-fall) from a previous low (high) to generate a buy (sell) signal
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period

filt	=[0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, 0.5]
delay	=[2, 3, 4, 5]
fhp	=[5, 10, 25, 50]

With the parameters and values given above we construct the following filter rules (FR):

basic FR:	24*1	=24
FR with time delay:	24*4	=96
FR with fixed holding:	24*4	=96
FR with time delay and fixed holding:	24*4*4	=384

This will give in total 600 filter rules.

Chapter 3

Technical Trading Rule Performance in Dow-Jones Industrial Average Listed Stocks

3.1 Introduction

In 1882 Charles H. Dow, Edward D. Jones and Charles M. Bergstresser started Dow, Jones & Co., publisher of the "Customer's Afternoon Letter". This was the precursor of "The Wall Street Journal", which was founded in 1889. In those early days trading was dominated by pools and prices were subject to spectacular rises and declines. Trading was mainly done on inside information. Stocks were considered to be for gamblers, raiders and speculators. Charles Dow discerned three types of market movements. First there are the daily actions, which reflect speculators' activities, called tertiary or minor trends. Second there are the secondary or intermediate trends, that is short swings of two weeks to a month or more, which reflect the strategies of large investment pools. Charles Dow considered the first two movements to be the result of market manipulations and he advised not to become involved with any kind of speculation, because he believed this was a sure way to lose money. Third, he discerned four-year movements, the primary or major trend, derived from economic forces beyond the control of individuals. Charles Dow thought that expectations for the national economy were translated into market orders that caused stock prices to rise or fall over the long term - usually in advance of actual economic developments. He believed that fundamental economic variables determine prices in the long run. To quantify his theory Charles Dow began to compute averages to measure market movements.

In 1884 Charles Dow started to construct an average of eleven stocks, composed of nine railroad companies and only two non-railroad companies, because in those days railroad companies were the first large national corporations. He recognized that railroad companies presented only a partial picture of the economy and that industrial companies were crucial contributors to America's growth. "*What the industrials make the railroads take*" was his slogan and from this he concluded that two separate measures could act as coconfirmers to detect any broad market trend. This idea led to the birth of the Dow-Jones Railroad Average (DJRA), renamed in 1970 to Dow-Jones Transportation Average, and to the birth of the Dow-Jones Industrial Average (DJIA). The DJIA started on May 26, 1896 at 40.94 points and the DJRA started on September 8, 1896 at 48.55 points.

Initially the DJIA contained 12 stocks. This number was increased to 20 in 1916 and on October 1, 1928 the index was expanded to a 30-stock average, which it still is. The only company permanently present in the index, except for a break between 1898-1907, is General Electric. The first 25 years of its existence the DJIA was not yet known among a wide class of people. In the roaring twenties the DJIA got its popularity, when masses of average citizens began buying stocks. It became a tool by which the general public could measure the overall performance of the US stock market and it gave investors a sense of what was happening in this market. After the crash of 1929 the DJIA made front-page headlines to measure the overall damage in personal investments. The DJIA has been published continuously for more than one hundred years, except for four and a half months at the beginning of World War I when the New York Stock Exchange (NYSE) closed temporarily. Nowadays the DJIA is the oldest and most famous measure of the US stock market.

The DJIA is price weighted rather than market weighted, because of the technology in Charles Dow's days. It is an equally-weighted price average of 30 blue-chip US stocks, each of them representing a particular industry. When stocks split or when the DJIA is revised by excluding and including certain stocks, the divisor is updated to preserve historical continuity. Because the composition of the DJIA is dependent on the decision which stocks to exclude and to include, the index would have a completely different value today, if the DJIA constructors had made different decisions in the past. People criticize the Dow because it is too narrow. It only contains 30 stocks out of thousands of public companies and the calculation is simplistic. However it has been shown that the DJIA tracks other major market indices fairly closely. It follows closely the movement of market-weighted indices such as the NASDAQ composite, NYSE composite, Russell 2000, Standard & Poor's 500 and the Wilshire 5000 (Prestbo, 1999, p.47).

It was William Peter Hamilton in his book "The Stock Market Barometer" (1922) who laid the foundation of "the Dow Theory", the first theory of chart readers. The theory is based on editorials of Charles H. Dow when he was editor of the Wall Street Journal in the period 1889-1902. Robert Rhea popularized the idea in his 1930s market letters and his book "The Dow Theory" (1932). Although the theory bears Charles Dow's name, it is likely that he would deny any allegiance to it. Instead of being a chartist, Charles Dow as a financial reporter advocated to invest on sound fundamental economic variables, that is buying stocks when their prices are well below their fundamental values. His main purpose in developing the averages was to measure market cycles, rather than to use them to generate trading signals.

After the work of Hamilton and Rhea the technical analysis literature was expanded and refined by Richard Schabacker, Robert Edwards and John Magee, and later by Welles Wilder and John Murphy. Technical analysis developed itself into a standard tool used by many to forecast the future price path of all kinds of financial assets such as stocks, bonds, futures and options. Nowadays a lot of technical analysis software packages are sold on the market. Technical analysis newsletters and journals flourish. Every bank employs several chartists who write technical reports spreading around forecasts with all kinds of fancy techniques. Classes (also through the internet) are organized to introduce the home investor in the topic. Technical analysis has become an industry on its own. For example, the questionnaire surveys of Taylor and Allen (1992), Menkhoff (1998) and Cheung and Chinn (1999) show that technical analysis is broadly used in practice. However, despite the fact that chartists have a strong belief in their forecasting ability, for academics it remains the question whether it has any statistically significant forecasting power and whether it can be profitably exploited also after accounting for transaction costs and risk.

Cowles (1933) considered the 26-year forecasting record of Hamilton in the period 1903-1929. He found that Hamilton could not beat a continuous investment in the DJIA or the DJRA after correcting for the effect of brokerage charges, cash dividends and interest earned when not in the market. On 90 occasions Hamilton announced changes in the outlook for the market. It was found that 45 of his changes of position were unsuccessful and that 45 were successful. In a later period, Alexander (1964), and Fama and Blume (1966) found that filter strategies, intended to reveal possible trends in the data, did not yield profits after correcting for transaction costs, when applied to the DJIA and to individual stocks that composed the DJIA. The influential paper of Fama (1970) reviews the theoretical and empirical literature on the efficient markets model until that date and concludes that the evidence in support of the efficient markets model is very extensive, and that contradictory evidence is sparse. From that moment on the efficient markets hypothesis (EMH), which states that it is not possible to forecast the future price movements of a financial asset given any information set, is the central paradigm in financial economics. The impact Fama's (1970) paper was so large, that it took a while before new academic literature on technical trading was published.

The extensive study of Brock, Lakonishok and LeBaron (1992) on technical analysis led to a renewed interest in the topic. They applied 26 simple technical trading strategies, such as moving averages, and support-and-resistance strategies, to the daily closing prices of the DJIA in the period 1897-1986, nearly 90 years of data. They were the first who extended simple standard statistical analysis with parametric bootstrap techniques, inspired by Efron (1979), Freedman and Peters (1984a, 1984b), and Efron and Tibshirani (1986). It was found that the predictive ability of the technical trading rules found was not consistent with a random walk, an AR(1), a GARCH-in-mean model, or an exponential GARCH. The strong results of Brock et al. (1992) were the impetus for many papers published on technical analysis in the 1990s.

Although numerous papers found evidence for economic profitability and statistically significant forecasting power of technical trading rules, they did acknowledge the problem of data snooping. This is the danger that the results of the best forecasting rule may just be generated by chance, instead of truly superior forecasting power over the buy-and-hold benchmark. It could be that the trading rules under consideration were the result of survivorship bias. That is, the best trading rules found by chartists in the past get most attention by academic researchers in the present. Finally White (2000), building on the work of Diebold and Mariano (1995) and West (1996), developed a simple and straightforward procedure, called the Reality Check (RC), for testing the null hypothesis that the best model encountered in a specification search has no predictive superiority over a given benchmark model. Sullivan, Timmermann and White (1999) utilize the RC to evaluate a large set of approximately 7800 simple technical trading strategies on the data set of Brock et al. (1992). They confirm that the results found by Brock et al. (1992) still hold after correcting for data snooping. However in the out-of-sample period 1986-1996 they find no significant forecasting ability for the technical trading strategies anymore. Hansen (2001) shows that the RC is a biased test, which yields inconsistent p-values. Moreover, the test is sensitive to the inclusion of poor and irrelevant models. Further the test has poor power properties, which can be driven to zero. Therefore, within the framework of White (2000), Hansen (2001) derives a test for superior predictive ability (SPA).

In this chapter we test whether objective computerized trend-following technical trading techniques can profitably be exploited after correction for transaction costs when applied to the DJIA and to all stocks listed in the DJIA in the period 1973:1-2001:6.

Furthermore, we test whether the best strategies can beat the buy-and-hold benchmark significantly after correction for data snooping. This chapter may be seen as an empirical application of White's RC and Hansen's SPA-test. In addition we test by recursively optimizing our trading rule set whether technical analysis shows true out-of-sample forecasting power.

In section 3.2 we list the stock price data examined in this chapter and we show the summary statistics. Section 3.3 presents an overview of the technical trading rules applied to the stock price data. Section 3.4 describes which performance measures are used and how they are calculated. In section 3.5 the problem of data snooping is addressed and a short summary of White's RC and Hansen's SPA-test is presented. Section 3.6 shows the empirical results. In section 3.7 we test whether recursively optimizing and updating our technical trading rule set shows genuine out-of-sample forecasting ability. Finally section 3.8 concludes.

3.2 Data and summary statistics

The data series examined in this chapter are the daily closing levels of the Dow-Jones Industrial Average (DJIA) and the daily closing stock prices of 34 companies listed in the DJIA in the period January 2, 1973 through June 29, 2001. Table 3.1 lists the data series. The companies in the DJIA are the largest and most important in their industries. Prices are corrected for dividends, capital changes and stock splits. As a proxy for the risk-free interest rate we use daily data on US 3-month certificates of deposits. Several studies found that technical trading rules show significant forecasting power in the era until 1987 and no forecasting power anymore from then onwards. Therefore we split our data sample in two subperiods. Table 3.2 shows the summary statistics for the period 1973-2001 and the tables 3.3 and 3.4 show the summary statistics for the two subperiods 1973-1986 and 1987-2001. Because the first 260 data points are used for initializing the technical trading strategies, the summary statistics are shown from January 1, 1974. In the tables the first and second column show the names of the data series examined and the number of available data points. The third column shows the mean yearly effective return in percentage/100 terms. The fourth through seventh column show the mean, standard deviation, skewness and kurtosis of the logarithmic daily return. The eight column shows the t-ratio to test whether the mean logarithmic return is significantly different from zero. The ninth column shows the Sharpe ratio, that is the extra return over the risk-free interest rate per extra point of risk, as measured by the standard deviation. The tenth column shows the largest cumulative loss, that is the largest decline from a peak to a through, of the data series in percentage/100 terms. The eleventh column shows the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. The twelfth column shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic testing for autocorrelations in the squared returns.

All data series, except Bethlehem Steel, show in the full sample period a positive mean yearly return which is on average 11.5%. The return distributions are strongly leptokurtic and show signs of negative skewness, especially for the DJIA, Eastman Kodak and Procter & Gamble. The 34 separate stocks are riskier than the index, which is shown by the standard deviation of the returns. On average it is 1.9% for the 34 stocks, while it is 1% for the DJIA. Thus it is clear that firm specific risks are reduced by a diversified index. The Sharpe ratio is negative for 12 stocks, which means that these stocks were not able to beat a continuous risk free investment. Table 3.1 shows that the largest decline of the DJIA is equal to 36% and took place in the period August 26, 1987 until October 19, 1987 that covers the crash of 1987. October 19, 1987 showed the biggest one-day percentage loss in history of the DJIA and brought the index down by 22.61%. October 21, 1987 on its turn showed the largest one-day gain and brought the index up by 9.67%. However the largest decline of each of the 34 separate stocks is larger, on average 61%. For only five stocks (GoodYear Tire, HP, Home Depot, IBM, Wal-Mart) the largest decline started around August 1987. As can be seen in the table, the increasing oil prices during the seventies, caused initially by the oil embargo of the Arab oil exporting countries against countries supporting Israel in "The Yom Kippur War" in 1973, had the largest impact on stock prices. The doubling of oil prices led to a widespread recession and a general crisis of confidence. Bethlehem Steel did not perform very well during the entire 1973-2001 period and declined 97% during the largest part of its sample. AT&T declined 73% within two years: February 4, 1999 until December 28, 2000 which covers the so-called burst of the internet and telecommunications bubble.

If the summary statistics of the two subperiods in tables 3.3 and 3.4 are compared, then some substantial differences can be noticed. The mean yearly return of the DJIA is in the first subperiod 1973-1986 equal to 6.1%, while in the second subperiod 1987-2001 it is equal to 12.1%, almost twice as large. For almost all data series the standard deviation of the returns is higher in the second subperiod than in the first subperiod. The Sharpe ratio is negative for only 5 stocks in the subperiod 1987-2001, while it is negative for 22 stocks and the DJIA in the period 1973-1986, clearly indicating that buy-and-hold stock investments had a hard time in beating a risk free investment particularly in the first subperiod. Also in the second subperiod the return distributions are strongly leptokurtic and negatively skewed, which stands in contrast with the first subperiod, where the kurtosis of the return distributions is much lower and where the skewness is slightly positive for most stocks. Thus, large one-day price changes, especially negative ones, occur more often in the second than in the first subperiod. Higher rewards of holding stocks in the second subperiod come together with higher risks.

We computed autocorrelation functions (ACFs) of the returns and significance is tested with Bartlett (1946) standard errors and Diebold's (1986) heteroskedasticity-consistent standard errors[1]. Under the assumption that the data is white noise with constant variance the standard error for each sample autocorrelation is equal to $\sqrt{1/n}$. However Hsieh (1988) points out that sample autocorrelation may be spurious in the presence of heteroskedasticity, because the standard error of each sample autocorrelation may be underestimated by $\sqrt{1/n}$. Diebold's (1986) heteroskedasticity-consistent estimate of the standard error for the k-th sample autocorrelation, $\hat{\rho}_k$, is calculated as follows:

$$s.e.(\hat{\rho}_k) = \sqrt{1/n\ (1 + \gamma(r^2, k)/\sigma^4)},$$

where $\gamma(r^2, k)$ is the k-th order sample autocorrelation function of the squared returns, and σ is the sample standard deviation of the returns. Moreover Diebold (1986) showed that the adjusted Box-Pierce (1970) Q-statistic

$$\sum_{k=1}^{q} \left(\frac{\hat{\rho}_k}{s.e.(\hat{\rho}_k)} \right)$$

to test that the first q autocorrelations as a whole are not significantly different from zero, is asymptotically χ-squared distributed with q degrees of freedom. Typically autocorrelations of the returns are small with only few lags being significant. It is noteworthy that for most data series the second order autocorrelation is negative in all periods. The first order autocorrelation is negative for only 3 data series in the period 1973-1986, while it is negative for 18 data series in the period 1987-2001. The Ljung-Box (1978) Q-statistics in the second to last columns of tables 3.2, 3.3 and 3.4 reject for all periods for almost all data series the null hypothesis that the first 20 autocorrelations of the returns as a whole are equal to zero. In the first subperiod only for Boeing and HP this null is not rejected, while in the second subperiod the null is not rejected only for GM, HP, IBM and Walt Disney. Hence HP is the only stock which does not show significant autocorrelation in all periods. When looking at the first to last column with Diebold's (1986) heteroskedasticity-consistent Box-Pierce (1970) Q-statistics it appears that heteroskedasticity indeed affects

[1]Separate ACFs of the returns are computed for each data series, but not presented here to save space. The tables are available upon request from the author.

the inferences about serial correlation in the returns. For the full sample period 1973-2001 and the two subperiods 1973-1986 and 1987-2001 for respectively 18, 9 and 19 data series the null hypothesis of no autocorrelation is not rejected by the adjusted Q-statistic, while it is rejected by the Ljung-Box (1978) Q-statistic. The autocorrelation functions of the squared returns show that for all data series and for all periods the autocorrelations are high and significant up to order 20. The Ljung-Box (1978) Q-statistics reject the null of no autocorrelation in the squared returns firmly. Hence, all data series exhibit significant volatility clustering, that is large (small) shocks are likely to be followed by large (small) shocks.

3.3 Technical trading strategies

We refer to section 2.3 for an overview of the technical trading rules applied in this chapter. In this thesis we mainly confine ourselves to objective trend-following technical trading techniques which can be implemented on a computer. In total we test in this chapter a set of 787 technical trading strategies[2]. This set is divided in three different groups: moving-average rules (in total 425), trading range break-out (also called support-and- resistance) rules (in total 170) and filter rules (in total 192). These strategies are also described by Brock, Lakonishok and LeBaron (1992), Levich and Thomas (1993) and Sullivan, Timmermann and White (1999). We use the parameterizations of Sullivan et al. (1999) as a starting point to construct our sets of trading rules. The parameterizations are presented in Appendix B. If a signal is generated at the end of day t, we assume that the corresponding trading position at day $t+1$ is executed against the price at the end of day t. Each trading strategy divides the data set of prices in three subsets. A buy (sell) period is defined as the period after a buy (sell) signal up to the next trading signal. A neutral period is defined as the period after a neutral signal up to the next buy or sell signal. The subsets consisting of buy, sell or neutral periods will be called the set of buy sell or neutral days.

3.4 Trading profits

We superimpose the signals of a technical trading rule on the buy-and-hold benchmark. If a buy signal is generated, then money is borrowed against the risk-free interest rate and a double position in the risky asset is held. On a neutral signal only a long position

[2]The number of technical trading strategies is confined to 787 mainly because of computer power limitations.

in the risky asset is held, while on a sell signal the position in the risky asset is sold and the proceeds are invested against the risk-free interest rate. If a technical trading rule has forecasting power, then it should beat the buy-and-hold strategy consistently and persistently. It should advise to buy when prices rise and it should advise to sell when prices fall. Therefore its performance, i.e. mean return or Sharpe ratio, will be compared to the buy-and-hold performance to examine whether the trading strategy generates valuable signals. The advantage of this procedure is that it circumvents the question whether it is possible to hold an actual short[3] position in an asset. We define P_t as the price of the risky asset, I_t as the investment in the risky asset and S_t as the investment in the risk free asset at the end of period t. The percentage/100 costs of initializing or liquidating a trading position is denoted by c. The real profit during a certain trading position including the costs of initializing and liquidating the trading position is determined as follows:

	I_{t-1}	S_{t-1}	I_t	S_t	*costs*
Initiate a double position					
$Pos_{t-1} \neq 1 \wedge Pos_t = 1$	$2P_{t-1}$	$-P_{t-1}$	$I_{t-1} + 2(P_t - P_{t-1})$	$(1+r^f)S_{t-1}$	cP_{t-1}
Liquidate a double position					
$Pos_t = 1 \wedge Pos_{t+1} \neq 1$			P_t	$(1+r^f)S_{t-1} + P_t$	cP_t
Initiate a risk free position					
$Pos_{t-1} \neq -1 \wedge Pos_t = -1$	0	P_{t-1}	0	$(1+r^f)S_{t-1}$	cP_{t-1}
Liquidate a risk free position					
$Pos_t = -1 \wedge Pos_{t+1} \neq -1$			P_t	$(1+r^f)S_{t-1} - P_t$	cP_t
Initiate a long position					
$Pos_{t-1} \neq 0 \wedge Pos_t = 0$	P_{t-1}	0	$I_{t-1} + (P_t - P_{t-1})$	0	0
Liquidate a long position					
$Pos_t = 0 \wedge Pos_{t+1} \neq 0$			P_t	0	0
Position not changed			$I_{t-1}+$		
$Pos_{t-1} = Pos_t$			$(1+Pos_t)(P_t - P_{t-1})$	$(1+r^f)S_{t-1}$	0

The profit at day t is equal to $(I_t+S_t)-(I_{t-1}+S_{t-1})-costs$. The net return of a technical trading strategy during a trading position is then equal to

$$r_t = \frac{I_t + S_t - costs}{I_{t-1} + S_{t-1}} - 1.$$

Note that because a continuous long position in the risky asset is the benchmark the trading signals are superimposed upon, liquidating the double or risk free position means a return back to the long position. Furthermore, costs are defined to be paid only when a double or risk free position is initialized or liquidated. For example, if a risk free position is held until the end of day t is turned into a double position from the beginning of day

[3] A short position means borrowing an asset and selling it in the market. The proceeds can be invested against the risk-free interest rate, but dividends should be paid. At a later time the asset should be bought back in the market to redeem the loan. A trading strategy intends to buy back at a lower price than the asset is borrowed and sold for.

$t+1$, part of the costs, because of liquidating the risk free position at the end of day t, are at the expense of the profit at day t and part of the costs, because of initializing the long position at the beginning of day $t+1$ against the price at the end of day t, are at the expense of the profit at day $t+1$. In this chapter, 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade are implemented. This wide range of transaction costs captures a range of different trader types. For example, floor traders and large investors, such as mutual funds, can trade against relatively low transaction costs in the range of 0.10 to 0.25%. Home investors face higher costs in the range of 0.25 to 0.75%, depending whether they trade through the internet, by telephone or through their personal account manager. Next, because of the bid-ask spread, extra costs over the transaction costs are faced. By examining a wide range of 0 to 1% costs per trade, we belief that we can capture most of the cost possibilities faced in reality by most of the traders.

3.5 Data snooping

Data snooping is the danger that the performance of the best forecasting model found in a given data set is just the result of chance instead of the result of truly superior forecasting power. The search over many different models should be taken into account before making inferences on the forecasting power of the best model. It is widely acknowledged by empirical researchers that data snooping is a dangerous practice to be avoided. Building on the work of Diebold and Mariano (1995) and West (1996), White (2000) developed a simple and straightforward procedure for testing the null hypothesis that the best model encountered in a specification search has no predictive superiority over a given benchmark model. This procedure is called White's Reality Check (RC) for data snooping. We briefly discuss the method hereafter.

The performance of each technical trading strategy used in this chapter is compared to the benchmark of a buy-and-hold strategy. Predictions are made for M periods, indexed from $J+1$ through $T = J+1+M$, where the first J data points are used to initialize the K technical trading strategies, so that each technical trading strategy starts at least generating signals at time $t = J+1$. The performance of strategy k in excess of the buy-and-hold is defined as f_k. The null hypothesis that the best strategy is not superior to the benchmark of buy-and-hold is given by

$$H_0 : \max_{k=1...K} E(f_k) \leq 0,$$

where $E(.)$ is the expected value. The alternative hypothesis is that the best strategy is superior to the buy-and-hold benchmark. In this chapter we use two performance/selection criteria. Firstly, we use the mean return of the strategy in excess of the mean return of the buy-and-hold (BH) strategy

$$\overline{f}_k = \frac{1}{M}\sum_{t=J+1}^{T} r_{k,t} - \frac{1}{M}\sum_{t=J+1}^{T} r_{BH,t} = \overline{r}_k - \overline{r}_{BH}.$$

Secondly, we use the Sharpe ratio of the strategy in excess of the Sharpe ratio of the buy-and-hold strategy in which case

$$\overline{f}_k = \frac{\overline{r}_k - \overline{r}_f}{s.e.(r_k)} - \frac{\overline{r}_{BH} - \overline{r}_f}{s.e.(r_{BH})} = Sharpe_k - Sharpe_{BH},$$

where $\overline{r}_f$ is the mean risk-free interest rate and $s.e.(.)$ is the standard error of the corresponding return series. The Sharpe ratio measures the excess return of a strategy over the risk-free interest rate per unit of risk, as measured by the standard deviation, of the strategy. The higher the Sharpe ratio, the better the reward attained per unit of risk taken.

The null hypothesis can be evaluated by applying the stationary bootstrap algorithm of Politis and Romano (1994). This algorithm resamples blocks with varying length from the original data series, where the block length follows the geometric distribution[4], to form a bootstrapped data series. The purpose of the stationary bootstrap is to capture and preserve any dependence in the original data series in the bootstrapped data series. The stationary bootstrap algorithm is used to generate B bootstrapped data series. Applying strategy k to the bootstrapped data series yields B bootstrapped values of $\overline{f}_k$, denoted as $\overline{f}^*_{k,b}$, where b indexes the bth bootstrapped sample. Finally the RC p-value is determined by comparing the test statistic

$$\overline{V} = \max_{k=1\ldots K}\{\sqrt{P}\ (\overline{f}_k)\} \tag{3.1}$$

to the quantiles of

$$\overline{V}^*_b = \max_{k=1\ldots K}\{\sqrt{P}\ (\overline{f}^*_{k,b} - \overline{f}_k)\}. \tag{3.2}$$

In formula this is

$$\hat{p} = \sum_{b=1}^{B} \frac{1(\overline{V}^*_b > \overline{V})}{B},$$

[4]Blocks with geometric length are drawn from the original data series by first selecting at random a starting point in the original data series. With probability $1-q$ the block is expanded with the next data point in the original data series and with probability q the resampling is ended and a new starting point for the next block is chosen at random. The mean block length is then equal to $1/q$. We follow Sullivan et al. (1999) by choosing $q = 0.10$.

where 1(.) is an indicator function that takes the value one if and only if the expression within brackets is true. White (2000) applies the Reality Check to a specification search directed toward forecasting the daily returns of the S&P 500 one day in advance in the period May 29, 1988 through May 31, 1994 (the period May 29, 1988 through June 3, 1991 is used as initialization period). In the specification search linear forecasting models that make use of technical indicators, such as momentum, local trend, relative strength indexes and moving averages, are applied to the data set. The mean squared prediction error and directional accuracy are used as prediction measures. White (2000) shows that the Reality Check does not reject the null hypothesis that the best technical indicator model cannot beat the buy-and-hold benchmark. However, if one looks at the p-value of the best strategy not corrected for the specification search, the so called data-mined p-value, the null is not rejected marginally in the case of the mean squared prediction error accuracy, and is rejected in the case of directional accuracy.

Sullivan, Timmermann and White (1999, 2001) utilize the RC to evaluate simple technical trading strategies and calendar effects applied to the Dow-Jones Industrial Average (DJIA) in the period 1897-1996. As performance measures the mean return and the Sharpe ratio are chosen. The benchmark is the buy-and-hold strategy. Sullivan et al. (1999) find for both performance measures that the best technical trading rule has superior forecasting power over the buy-and-hold benchmark in the period 1897-1986 and for several subperiods, while accounting for the effects of data snooping. Thus it is found that the earlier results of Brock et al. (1992) survive the danger of data snooping. However for the period 1986-1996 this result is not repeated. The individual data-mined p-values still reject the null hypothesis, but the RC p-values do not reject the null hypothesis anymore. For the calendar effects (Sullivan et al., 2001) it is found that the individual data-mined p-values do reject the null hypothesis in the period 1897-1996, while the RC, which corrects for the search of the best model, does not reject the null hypothesis of no superior forecasting power of the best model over the buy-and-hold benchmark. Hence Sullivan et al. (1999, 2001) show that if one does not correct for data snooping one can make wrong inferences about the significant forecasting power of the best model.

Hansen (2001) identifies a similarity condition for asymptotic tests of composite hypotheses and shows that this condition is a necessary condition for a test to be unbiased. The similarity condition used is called “asymptotic similarity on the boundary of a null hypothesis” and Hansen (2001) shows that White’s RC does not satisfy this condition. This causes the RC to be a biased test, which yields inconsistent p-values. Further the RC is sensitive to the inclusion of poor and irrelevant models, because the p-value can be increased by including poor models. The RC is therefore a subjective test, because the null hypothesis can finally be rejected by including enough poor models. Also the RC has unnecessary low power, which can be driven to zero by the inclusion of “silly” models. Hansen (2001) concludes that the RC can misguide the researcher to believe that no real forecasting improvement is provided by a class of competing models, even though one of the models indeed is a superior forecasting model. Therefore Hansen (2001) applies within the framework of White (2000) the similarity condition to derive a test for superior predictive ability (SPA), which reduces the influence of poor performing strategies in deriving the critical values. This test is unbiased and is more powerful than the RC. The null hypothesis tested is that none of the alternative models is superior to the benchmark model. The alternative hypothesis is that one or more of the alternative models are superior to the benchmark model. The SPA-test p-value is determined by comparing the test statistic (3.1) to the quantiles of

$$\overline{V}_b^* = \max_{k=1 \ldots K} \{ \sqrt{P} \; (\overline{f}_{k,b}^* - g(\overline{f}_k)) \}, \tag{3.3}$$

where

$$g(\overline{f}_k) = \begin{cases} 0, \text{ if } \overline{f}_k \leq -A_k = -\frac{1}{4} P^{-1/4} \sqrt{\widehat{var}(P^{1/2} \; \overline{f}_k)} \\ \overline{f}_k \end{cases} . \tag{3.4}$$

The correction factor A_k depends on an estimate of $var(P^{1/2} \; \overline{f}_k)$. A simple estimate can be calculated from the bootstrap resamples as

$$\widehat{var}(P^{1/2} \; \overline{f}_k) = \frac{1}{B} \sum_{b=1}^{B} (P^{1/2} \; \overline{f}_{k,b}^* - P^{1/2} \; \overline{f}_k)^2.$$

Equations (3.3) and (3.4) ensure that poor and irrelevant strategies cannot have a large impact on the SPA-test p-value, because (3.4) filters the strategy set for these kind of strategies.

Hansen (2001) uses the RC and the SPA-test to evaluate forecasting models applied to US annual inflation in the period 1952 through 2000. The forecasting models are linear regression models with fundamental variables, such as employment, inventory, interest, fuel and food prices, as the regressors. The benchmark model is a random walk and as performance measure the mean absolute deviation is chosen. Hansen (2001) shows that the null hypothesis is neither rejected by the SPA-test p-value, nor by the RC p-value, but that there is a large difference in magnitude between both p-values, likely to be caused by the inclusion of poor models in the space of forecasting models.

3.6 Empirical results

3.6.1 Results for the mean return criterion

Technical trading rule performance

In section 3.2 we have shown that in the subperiod 1973-1986 most stocks could not even beat a risk free investment, while they boosted in the subperiod 1987-2001. However the larger rewards came with greater risks. One may question whether technical trading strategies can persistently generate higher pay-offs than the buy-and-hold benchmark. In total we apply 787 objective computerized trend-following technical trading techniques with and without transaction costs to the DJIA and to the stocks listed in the DJIA. Tables 3.5 and 3.6 show for the full sample period, 1973:1-2001:6, for each data series some statistics of the best strategy selected by the mean return criterion, if 0% and 0.25% costs per trade are implemented. Column 2 shows the parameters of the best strategy. In the case of a moving-average (MA) strategy these parameters are "[short run MA, long run MA]" plus the refinement parameters "[%-band filter, time delay filter, fixed holding period, stop-loss]". In the case of a trading range break, also called support-and-resistance (SR), strategy, the parameters are "[the number of days over which the local maximum and minimum is computed]" plus the refinement parameters as with the moving averages. In the case of a filter (FR) strategy the parameters are "[the %-filter, time delay filter, fixed holding period]". Columns 3 and 4 show the mean yearly return and excess mean yearly return of the best-selected strategy over the buy-and-hold benchmark, while columns 5 and 6 show the Sharpe ratio and excess Sharpe ratio of the best strategy over the buy-and-hold benchmark. Column 7 shows the maximum loss the best strategy generates. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days profitable trades last. Finally, the last column shows the standard deviation of the returns of the data series during profitable trades divided by the standard deviation of the returns of the data series during non-profitable trades.

To summarize, table 3.7 shows for the full sample period, 1973:1-2001:6, and for the two subperiods, 1973:1-1986:12 and 1987:1-2001:6, for each data series examined, the mean yearly excess return over the buy-and-hold benchmark of the best strategy selected by the mean return criterion, after implementing 0, 0.10, 0.25 and 0.75%[5] costs per trade.

For transaction costs between $0 - 1\%$ it is found for each data series that the excess return of the best strategy over the buy-and-hold is positive in almost all cases; the only exception is Caterpillar in the full sample period if 1% costs per trade are implemented.

[5]Results for the 0.50 and 1% costs per trade cases are not presented here to save space.

Even for Bethlehem Steel, which stock shows considerable losses in all periods, the best strategy generates not only a positive excess return, but also a positive normal return. By this we mean that the best strategy on its own did generate profits. This is important because excess returns can also be positive in the case when a non-profitable strategy loses less than the buy-and-hold benchmark. If transaction costs increase from 0 to 0.75% per trade, then it can be seen in the last row of table 3.7 that on average the excess return by which the best strategy beats the buy-and-hold benchmark decreases; for example from 19 to 5.34% for the full sample period. Further, the technical trading rules yield the best results in the first subperiod 1973-1986, the period during which the stocks performed the worst. On average, in the case of no transaction costs, the mean excess return in this period is equal to 33% yearly, almost twice as large as in the period 1987-2001, when it is equal to 17.3% yearly. In comparison, the DJIA advanced by 6.1% yearly in the 1973-1986 period, while it advanced by 12.1% yearly in the 1987-2001 period. Thus from these results we can conclude that in all sample periods technical trading rules are capable of beating a buy-and-hold benchmark, also after correction for transaction costs.

From table 3.5 (full sample) it can be seen that in the case of zero transaction costs the best-selected strategies are mainly strategies which generate a lot of trading signals. Trading positions are held for only a few days. For example, the best strategy found for the DJIA is a single crossover moving-average strategy with no extra refinements, which generates a signal when the price series crosses a 2-day moving average. The mean yearly return of this strategy is 25%, which corresponds with a mean yearly excess return of 14.4%. The Sharpe ratio is equal to 0.0438 and the excess Sharpe ratio is equal to 0.0385. The maximum loss of the strategy is 25.1%, while the maximum loss of buying and holding the DJIA is equal to 36.1%. The number of trades executed by following the strategy is very large, once every two days, but also the percentage of profitable trades is very large, namely 69.7%. These profitable trades span 80.8% of the total number of trading days. Although the trading rules show economic significance, they all go through periods of heavy losses, well above the 50% for most stocks (table 3.1). Comparable results are found for the other data series and the two subperiods.

If transaction costs are increased to 0.25% per trade, then table 3.6 shows that the best-selected strategies are strategies which generate substantially fewer signals in comparison with the zero transaction costs case. Trading positions are now held for a longer time. For example, for the DJIA the best strategy generates a trade every 2 years and 4 months. Also the percentage of profitable trades and the percentage of days profitable trades last increases for most data series. Similar results are found in the two subperiods.

CAPM

Dooley and Shafer (1983) notice for floating exchange rates that there is some relationship between variability in the returns, as measured by standard deviation and technical trading rule profits. They find that a large increase in the variability is associated with a dramatic increase in the profitability. If no transaction costs are implemented, then from table 3.5, last column, it can be seen that the standard deviations of the returns of the data series themselves during profitable trades are higher than the standard deviations of the returns during non-profitable trades for almost all stocks, except Exxon Mobil, Home Depot and Wal-Mart Stores. However, if 0.25% costs per trade are implemented, then for 18 data series out of 35 the standard deviation ratio is larger than one. According to the EMH it is not possible to exploit a data set with past information to predict future price changes. The good performance of the technical trading rules could therefore be the reward for holding a risky asset needed to attract investors to bear the risk. Since the technical trading rule forecasts only depend on past price history, it seems unlikely that they should result in unusual risk-adjusted profits. To test this hypothesis we regress Sharpe-Lintner capital asset pricing models (CAPMs)

$$r_t^i - r_t^f = \alpha + \beta(r_t^{DJIA} - r_t^f) + \epsilon_t. \tag{3.5}$$

Here r_t^i is the return on day t of the best strategy selected for stock i, r_t^{DJIA} is the return on day t of the price-weighted Dow-Jones Industrial Average, which represents the market portfolio, and r_t^f is the risk-free interest rate. The coefficient β measures the riskiness of the active technical trading strategy relatively to the passive strategy of buying and holding the market portfolio. If β is not significantly different from one, then it is said that the strategy has equal risk as a buying and holding the market portfolio. If $\beta > 1$ ($\beta < 1$), then it is said that the strategy is more risky (less risky) than buying and holding the market portfolio and that it should therefore yield larger (smaller) returns. The coefficient α measures the excess return of the best strategy applied to stock i after correction of bearing risk. If it is not possible to beat a broad market portfolio after correction for risk and hence technical trading rule profits are just the reward for bearing risk, then α should not be significantly different from zero. For the full sample period table 3.8 shows for different transaction cost cases the estimation results, if for each data series the best strategy is selected by the mean return criterion. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. Table 3.9 summarizes the CAPM estimation results for all periods and all transaction cost cases by showing the number of data series for which significant estimates of α or β are found at the 10% significance level.

1973-2001	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	29	14	3	11	3
0.10%	0	17	14	3	5	2
0.25%	0	10	13	5	5	1
0.50%	0	7	14	8	3	2
0.75%	0	7	13	13	2	4
1%	0	8	12	13	2	5
1973-1986						
0%	0	26	5	6	4	6
0.10%	0	16	7	7	4	3
0.25%	0	9	8	7	1	2
0.50%	0	6	10	6	1	2
0.75%	0	6	12	6	1	2
1%	0	5	12	8	1	3
1987-2001						
0%	0	20	19	2	11	2
0.10%	0	11	15	4	3	4
0.25%	0	10	16	3	2	3
0.50%	0	7	16	6	1	4
0.75%	0	7	9	10	1	4
1%	0	7	7	11	1	4

Table 3.9: **Summary: significance CAPM estimates, mean return criterion.** For all periods and for each transaction cost case, the table shows the number of data series for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM (3.5). Columns 1 and 2 show the number of data series for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of data series for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that for the periods 1973-2001, 1973-1986 and 1987-2001, the number of data series analyzed is equal to 35, 30 and 35.

For example, for the best strategy applied to the DJIA in the case of zero transaction costs, the estimate of α is significantly positive at the 1% significance level and is equal to 5.39 basis points per day, that is approximately 13.6% per year. The estimate of β is significantly smaller than one at the 10% significance level, which indicates that although the strategy generates a higher reward than simply buying and holding the index, it is less risky. If transaction costs increase, then the estimate of α decreases to 1.91 basis points per day, 4.8% per year, in the case of 1% transaction costs, but is still significantly positive. The estimate of β is significantly smaller than one for all transaction cost cases at the 10% significance level.

As further can be seen in tables 3.8 and 3.9, if no transaction costs are implemented, then for the full sample period the estimate of α is significantly positive for 28 out of 34 stocks. For none of the data series the estimate of α is significantly negative. Thus, for only six stocks the estimate of α is not significantly different from zero. The estimate of α decreases as costs increase and becomes less significant for more data series. In the 0.50%

and 1% transaction costs cases, only for respectively 7 and 8 data series out of 35 the estimate of α is significantly positive. Further the estimate of β is significantly smaller than one for 14 data series, if zero transaction costs are implemented. Only for three stocks β is significantly larger than one. Further, table 3.9 shows that for all periods and all transaction cost cases the estimate of α is never significantly negative, indicating that the best strategy is never performing significantly worse than the buy-and-hold benchmark. Also for the two subperiods it is found that for more than half of the data series the estimate of α is significantly positive, if no transaction costs are implemented. Moreover, especially for the second subperiod, it is found that the estimate of β is significantly smaller than one for many data series, indicating that the best strategy is less risky than the market portfolio.

From the findings until now we conclude that there are trend-following technical trading techniques which can profitably be exploited, even after correction for transaction costs, when applied to the DJIA and to the stocks listed in the DJIA in the period 1973-2001 and in the two subperiods 1973-1986 and 1987-2001. As transaction costs increase, the best strategies selected are those which trade less frequently. Furthermore, it becomes more difficult for more and more stocks to reject the null hypothesis that the profit of the best strategy is just the reward of bearing risk. However, for transaction costs up to 1% per trade it is found for a group of stocks that the best strategy, selected by the mean return criterion, can statistically significantly beat the buy-and-hold benchmark strategy. Moreover, for many data series it is found that the best strategy, although it does not necessarily beats the buy-and-hold, is less risky than the buy-and-hold strategy.

Data snooping

The question remains open whether the findings in favour of technical trading for particular stocks are the result of chance or of real superior forecasting power. Therefore we apply White's (2000) Reality Check and Hansen's (2001) Superior Predictive Ability test. Because Hansen (2001) showed that the Reality Check is biased in the direction of one, p-values are computed for both tests to investigate whether these tests lead in some cases to different conclusions.

If the best strategy is selected by the mean return criterion, then table 3.10 shows the nominal, RC and SPA-test p-values for the full sample period 1973-2001 in the case of 0 and 0.10% costs per trade, for the first subperiod 1973-1986 in the case of 0 and 0.25% costs per trade and for the second subperiod 1987-2001 only in the case of 0% costs per trade. Table 3.11 summarizes the results for all periods and all transaction cost cases by showing the number of data series for which the corresponding p-value is smaller than

0.10. That is, the number of data series for which the null hypothesis is rejected at the 10% significance level.

period	1973-2001			1973-1986			1987-2001		
costs	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
0%	35	0	8	30	1	13	34	0	1
0.10%	35	0	0	30	0	3	34	0	0
0.25%	35	0	0	30	0	0	34	0	0
0.50%	35	0	0	30	0	0	34	0	0
0.75%	34	0	0	29	0	0	33	0	0
1%	33	0	0	29	0	0	33	0	0

Table 3.11: **Summary: Testing for predictive ability, mean return criterion.** For all periods and for each transaction cost case, the table shows the number of data series for which the nominal (p_n), White's (2000) Reality Check (p_W) or Hansen's (2001) Superior Predictive Ability test (p_H) p-value is smaller than 0.10. Note that for the periods 1973-2001, 1973-1986 and 1987-2001, the number of data series analyzed is equal to 35, 30 and 35.

The nominal p-value, also called data mined p-value, tests the null hypothesis that the *best* strategy *is not* superior to the buy-and-hold benchmark, but *does not* correct for data snooping. From the tables it can be seen that this null hypothesis is rejected for all periods and for all cost cases at the 10% significance level. However, for the full sample period, if we correct for data snooping, then we find, in the case of no transaction costs, that for all of the data series the null hypothesis that the *best* strategy *is not* superior to the benchmark after correcting for data snooping *is not* rejected by the RC. However, for 8 data series the null hypothesis that *none* of the strategies are superior to the benchmark after correcting for data snooping *is* rejected by the SPA-test. In 8 cases the two data snooping tests lead thus to different inferences about predictive ability of technical trading in the 1973-2001 period. For these 8 cases the biased RC misguides by not rejecting the null, even though one of the technical trading strategies is indeed superior, as shown by the SPA-test. However, if we implement as little as 0.10% costs for the full sample period, then both tests do not reject their null anymore for all data series.

For the subperiod 1973-1986 we find that the SPA-test p-value does reject the null for 13 data series, while the RC p-value does reject the null for only 1 data series at the 10% significance level. However, if 0.25% costs are implemented, then both tests do not reject their null for all data series. For the second subperiod 1987-2001 we find that the two tests are in agreement. Even if no transaction costs are implemented, then both tests do not reject the null at the 10% significance level in almost all cases. Hence, we conclude that the best strategy, selected by the mean return criterion, is not capable of beating the buy-and-hold benchmark strategy, after a correction is made for transaction costs and data snooping.

3.6.2 Results for the Sharpe ratio criterion

Technical trading rule performance

Similar to tables 3.5 and 3.6, table 3.12 shows for the full sample period for some data series some statistics of the best strategy selected by the Sharpe ratio criterion, if 0 or 0.25% costs per trade are implemented. Only the results for those data series are presented for which the best strategy selected by the Sharpe ratio criterion differs from the best strategy selected by the mean return criterion. To summarize, table 3.13 shows for all periods and for each data series the Sharpe ratio of the best strategy selected by the Sharpe ratio criterion, after implementing 0, 0.10, 0.25 or 0.75% costs per trade, in excess of the Sharpe ratio of the buy-and-hold benchmark. It is found that the Sharpe ratio of the best-selected strategy in excess of the Sharpe ratio of the buy-and-hold is positive in almost all cases; the only exceptions are Caterpillar in the full sample period and Wal-Mart Stores in the last subperiod, both in the case of 1% transaction costs. If transaction costs increase from 0 to 0.75%, then in the last row of table 3.13 it can be seen that for the full sample period the excess Sharpe ratio declines on average from 0.0258 to 0.0078. For the full sample period table 3.12 shows that the best strategies selected in the case of zero transaction costs are mainly strategies that generate a lot of signals. Trading positions are held for only a short period. Moreover, for most data series the best-selected strategy is the same as in the case that the best strategy is selected by the mean return criterion. If costs are increased to 0.25% per trade, then the best-selected strategies generate fewer signals and trading positions are held for longer periods. Now for 14 data series the best-selected strategy differs from the case when the best strategy is selected by the mean return criterion. For the two subperiods similar results are found. However the excess Sharpe ratios are higher in the period 1973-1986 than in the period 1987-2001.

As for the mean return criterion it is found that for each data series the best strategy, selected by the Sharpe ratio criterion, beats the buy-and-hold benchmark and that this strategy can profitably be exploited, even after correction for transaction costs. The results show that technical trading strategies were most profitable in the period 1973-1986, but also profits are made in the period 1987-2001.

CAPM

The estimation results of the Sharpe-Lintner CAPM in tables 3.14 and 3.15 for the Sharpe ratio selection criterion are similar to the estimation results in tables 3.8 and 3.9 for the mean return selection criterion. In the case of zero transaction costs for most data series the estimate of α is significantly positive, but as costs increase, then we find for fewer data series a significantly positive estimate of α.

1973-2001	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	29	14	1	11	1
0.10%	0	18	19	2	8	1
0.25%	0	13	18	4	6	2
0.50%	0	9	17	6	4	3
0.75%	0	9	14	9	4	4
1%	0	9	14	10	3	4
1973-1986						
0%	0	26	5	6	4	6
0.10%	0	15	8	5	3	3
0.25%	0	8	10	3	0	1
0.50%	0	6	10	4	0	1
0.75%	0	5	11	4	0	1
1%	0	4	12	7	0	1
1987-2001						
0%	0	25	21	1	16	1
0.10%	0	16	20	0	7	0
0.25%	0	11	19	1	3	1
0.50%	0	7	19	2	2	2
0.75%	0	7	18	2	2	2
1%	0	7	12	3	1	3

Table 3.15: **Summary: significance CAPM estimates, Sharpe ratio criterion.** For all periods and for each transaction cost case, the table shows the number of data series for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM (3.5). Columns 1 and 2 show the number of data series for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of data series for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that for the periods 1973-2001, 1973-1986 and 1987-2001, the number of data series analyzed is equal to 35, 30 and 35.

Data snooping

If the best strategy is selected by the Sharpe ratio criterion, then table 3.16 shows the nominal, White's RC and Hansen's SPA-test p-values for all periods and different transaction costs cases. The results are shown for the full sample period 1973-2001 in the case of 0 and 0.10% costs per trade and for the two subperiods 1973-1986 and 1987-2001 in the case of 0 and 0.25% costs per trade. Table 3.17 summarizes the results for all periods and all transaction cost cases by showing the number of data series for which the corresponding p-value is smaller than 0.10.

If the nominal p-value is used to test the null hypothesis that the *best* strategy *is not* superior to the buy-and-hold benchmark, then the null is rejected in all periods for

period	1973-2001			1973-1986			1987-2001		
costs	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
0%	35	4	16	30	10	21	35	0	5
0.10%	35	0	3	30	0	5	35	0	2
0.25%	35	0	0	30	0	0	35	0	1
0.50%	34	0	0	30	0	0	35	0	1
0.75%	30	0	0	30	0	0	34	0	1
1%	29	0	0	28	0	0	34	0	1

Table 3.17: **Summary: Testing for predictive ability, Sharpe ratio criterion.** For all periods and for each transaction cost case, the table shows the number of data series for which the nominal (p_n), White's (2000) Reality Check (p_W) or Hansen's (2001) Superior Predictive Ability test (p_H) p-value is smaller than 0.10. Note that for the periods 1973-2001, 1973-1986 and 1987-2001, the number of data series analyzed is equal to 35, 30 and 35.

most data series at the 5% significance level. For the full sample period, if a correction is made for data snooping, then it is found, in the case of zero transaction costs, that for 4 data series the null hypothesis that the *best* strategy *is not* superior to the benchmark after correcting for data snooping *is* rejected by the RC at the 10% significance level. However, for 16 data series the null hypothesis that *none* of the strategies is superior to the benchmark after correcting for data snooping *is* rejected by the SPA-test. Thus for 12 data series the RC leads to wrong inferences about the forecasting power of the best-selected strategy. However, if we implement as little as 0.10% costs, then these contradictory results only occur for 3 data series (the null is rejected for none of the data series by the RC) and if we increase the costs even further to 0.25%, then for none of the data series either test rejects the null. In the first subperiod 1973-1986, if zero transaction costs are implemented, then the RC p-value rejects the null for 10 data series, while the SPA-test p-value rejects the null for 21 data series. For the second subperiod 1987-2001, if no transaction costs are implemented, then the results of both tests are more in conjunction. The RC rejects the null for none of the data series, while the SPA-test rejects the null for 5 data series. If transaction costs are increased to 0.25%, then for both subperiods both tests do not reject the null for almost all data series. Only for Goodyear Tire, in the last subperiod, the SPA-test does reject the null, even in the 1% costs case. Hence, we conclude that the best strategy, selected by the Sharpe ratio criterion, is *not capable* of beating the benchmark of a buy-and-hold strategy, after a correction is made for transaction costs and data snooping.

3.7 A recursive out-of-sample forecasting approach

Like most academic literature on technical analysis, we investigated the profitability and forecastability of technical trading rules in sample, instead of out of sample. White's (2000) RC and Hansen's (2001) SPA-test, as we applied them, are indeed in-sample test procedures as they test whether the best strategy in a certain trading period has significant forecasting power, after correction for the search for the best strategy in that specific trading period. However, whether a technical trading strategy applied to a financial time series in a certain period shows economically/statistically significant forecasting power does not say much about its future performance. If it shows forecasting power, then profits earned in the past do not necessarily imply that profits can also be made in the future. On the other hand, if the strategy does not show forecasting power, then it could be that during certain subperiods the strategy was actually performing very well due to some characteristics in the data, but the same strategy was loosing during other subperiods, because the characteristics of the data changed. Therefore, only inferences about the forecastability of technical analysis can be made by testing whether strategies that performed well in the past, also perform well in the future. In this section we test the forecasting power of our set of trend-following technical trading techniques by applying a recursive optimizing and testing procedure. For example, recursively at the beginning of each month we investigate which technical trading rule performed the best in the preceding six months (training period) and we select this best strategy to generate trading signals during the coming month (testing period). Sullivan et al. (1999) also apply a recursive out-of-sample forecasting procedure. However, in their procedure, the strategy which performed the best from $t = 0$ is selected to make one step ahead forecasts. We instead use a moving window, as in Lee and Mathur (1995), in which strategies are compared and the best strategy is selected to make forecasts for some period thereafter.

Our approach is similar to the recursive modeling, estimation and forecasting approach of Pesaran and Timmermann (1995, 2000) and Marquering and Verbeek (2000). They use a collection of macro-economic variables as information set to base trading decisions upon. A linear regression model, with a subset of the macro-economic variables as regressors and the excess return of the risky asset over the risk-free interest rate as dependent variable, is estimated recursively with ordinary least squares. The subset of macro-economic variables which yields the best fit to the excess returns is selected to make an out-of-sample forecast of the excess return for the next period. According to a certain trading strategy a position in the market is chosen on the basis of the forecast. They show that historical fundamental information can help in predicting excess returns. We will do essentially the same for technical trading strategies, using only past observations from the financial time series itself.

We define the training period on day t to last from $t - Tr$ until and including $t - 1$, where Tr is the length of the training period. The testing period lasts from t until and including $t + Te - 1$, where Te is the length of the testing period. For each of the 787 strategies the performance during the training period is computed. Then the best technical trading strategy is selected by the mean return or Sharpe ratio criterion and is applied in the testing period to generate trading signals. After the end of the testing period this procedure is repeated again until the end of the data series is reached. For the training and testing periods we use 36 different parameterizations of $[Tr, Te]$ which can be found in Appendix C.

In the case of 0.25% transaction costs tables 3.18 and 3.19 show for the DJIA and for each stock in the DJIA some statistics of the best recursive optimizing and testing procedure, if the best strategy in the training period is selected by the mean return and Sharpe ratio criterion respectively. Because the longest training period is five years, the results are computed for the period 1978:10-2001:6. Table 3.20A, B (i.e. table 3.20 panel A, panel B) summarizes the results for both selection criteria in the case of 0, 0.10 and 0.50% costs per trade. In the second to last row of table 3.20A it can be seen that, if in the training period the best strategy is selected by the mean return criterion, then the excess return over the buy-and-hold of the best recursive optimizing and testing procedure is, on average, 12.3, 6.9, 2.8 and −1.2% yearly in the case of 0, 0.10, 0.25 and 0.50% costs per trade. Thus the excess returns decline on average sharply when implementing as little as 0.10% costs. If the Sharpe ratio criterion is used for selecting the best strategy during the training period, then the Sharpe ratio of the best recursive optimizing and testing procedure in excess of the Sharpe ratio of the buy-and-hold benchmark is on average 0.0145, 0.0077, 0.0031 and −0.0020 in the case of 0, 0.10, 0.25 and 0.50% costs per trade, also declining sharply when low costs are implemented (see second to last row of table 3.20B). Thus in our recursive out-of-sample testing procedures small transaction costs cause forecastability to disappear.

For comparison, the last row in table 3.20A, B shows the average over the results of the best strategies selected by the mean return or Sharpe ratio criterion in sample for each data series tabulated. As can be seen, clearly the results of the best strategies selected in sample are better than the results of the best recursive out-of-sample forecasting procedure.

If the mean return selection criterion is used, then table 3.21A shows for the 0 and 0.10% transaction cost cases[6] for each data series the estimation results of the Sharpe-

[6]Computations are also done for the 0.25 and 0.50% transaction cost cases, but not presented here to

Lintner CAPM (see equation 3.5) where the return of the best recursive optimizing and testing procedure in excess of the risk-free interest rate is regressed against a constant α and the return of the DJIA in excess of the risk-free interest rate. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. Table 3.22 summarizes the CAPM estimation results for all transaction cost cases by showing the number of data series for which significant estimates of α and β are found at the 10% significance level. In the case of zero transaction costs for 12 data series out of 35 the estimate of α is significantly positive at the 10% significance level. This number decreases to 3 (1, 0) if 0.10% (0.25, 0.50%) costs per trade are implemented. Table 3.21B shows the results of the CAPM estimation for the case that the best strategy in the training period is selected by the Sharpe ratio criterion. Now in the case of zero transaction costs for 14 data series it is found that the estimate of α is significantly positive at the 10% significance level. If transaction costs increase to 0.10% (0.25, 0.50%), then only for 7 (6, 1) out of 35 data series the estimate of α is significantly positive. Hence, after correction for transaction costs and risk it can be concluded, independently of the selection criterion used, that the best recursive optimizing and testing procedure shows no statistically significant out-of-sample forecasting power.

	Selection criterion: mean return					
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	12	13	3	5	2
0.10%	0	3	12	5	2	1
0.25%	0	1	8	7	0	1
0.50%	1	0	7	7	0	0
	Selection criterion: Sharpe ratio					
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	14	15	4	7	1
0.10%	0	7	16	3	2	0
0.25%	1	6	14	3	2	1
0.50%	0	1	12	4	0	0

Table 3.22: **Summary: significance CAPM estimates for best out-of-sample testing procedure.** For each transaction cost case, the table shows the number of data series for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM. Columns 1 and 2 show the number of data series for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of data series for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one.

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3.8 Conclusion

In this chapter we apply a set of 787 objective computerized trend-following technical trading techniques to the Dow-Jones Industrial Average (DJIA) and to 34 stocks listed in the DJIA in the period January 1973 through June 2001. For each data series the best technical trading strategy is selected by the mean return or Sharpe ratio criterion. Because numerous research papers found that technical trading rules show some forecasting power in the era until 1987, but not in the period thereafter, we split our sample in two subperiods: 1973-1986 and 1987-2001. We find for all periods and for both selection criteria that for each data series a technical trading strategy can be selected that is capable of beating the buy-and-hold benchmark, even after correction for transaction costs. Although buy-and-hold stock investments had difficulty in beating a continuous risk free investment during the 1973-1986 subsample, the strongest results in favour of technical trading are found for this subperiod. For example, in the full sample period 1973-2001 it is found that the best strategy beats the buy-and-hold benchmark on average with 19, 10, 7.5, 6.1, 5.3 and 4.9% yearly in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% transaction costs, if the best strategy is selected by the mean return criterion. These are quite substantial numbers.

The profits generated by the technical trading strategies could be the reward necessary to attract investors to bear the risk of holding the asset. To test this hypothesis we estimate Sharpe-Lintner CAPMs. For each data series the daily return of the best strategy in excess of the risk-free interest rate is regressed against a constant (α) and the daily return of the DJIA in excess of the risk-free interest rate. The coefficient of the last regression term is called β and measures the riskiness of the strategy relatively to buying and holding the market portfolio. If technical trading rules do not generate excess profits after correction for risk, then α should not be significantly different from zero. If no transaction costs are implemented, then we find for both selection criteria that in all periods for most data series the estimate of α is significantly positive. This means that the best selected technical trading rules show forecasting power after a correction is made for risk. However, if costs are increased, we are less able to reject the null hypothesis that technical trading rule profits are the reward for bearing risk. But still, in numerous cases the estimate of α is significantly positive.

An important question is whether the positive results found in favour of technical trading are due to chance or the fact that the best strategy has genuine superior forecasting power over the buy-and-hold benchmark. This is called the danger of data snooping. We apply White's (2000) Reality Check (RC) and Hansen's (2001) Superior Predictive Ability

(SPA) test, to test the null hypothesis that the best strategy found in a specification search is *not* superior to the benchmark of a buy-and-hold if a correction is made for data snooping. Hansen (2001) showed that the RC is sensitive to the inclusion of poor and irrelevant forecasting rules. Because we compute p-values for both tests, we can investigate whether both test procedures lead to contradictory inferences. If no transaction costs are implemented, then we find for the mean return and the Sharpe ratio criterion that the RC and the SPA-test in some cases lead to different conclusions, especially for the subperiod 1973-1986. The SPA-test finds in numerous cases that the best strategy does beat the buy-and-hold significantly after correction for data snooping and the implementation of bad strategies. Thus the biased RC misguides the researcher in several cases by not rejecting the null. However, if as little as 0.25% costs per trade are implemented, then both tests lead for both selection criteria, for all sample periods and for all data series to the same conclusion: the best strategy is not capable of beating the buy-and-hold benchmark after a correction is made for the specification search that is used to find the best strategy. We therefore finally conclude that the good performance of trend-following technical trading techniques applied to the DJIA and to the individual stocks listed in the DJIA, especially in the 1973-1986 subperiod, is merely the result of chance than of good forecasting power.

Next we apply a recursive optimizing and testing method to test whether the best strategy found in a specification search during a training period shows also forecasting power during a testing period thereafter. For example, every month the best strategy from the last 6 months is selected to generate trading signals during that month. In total we examine 36 different training and testing period combinations. In the case of no transaction costs, the best recursive optimizing and testing procedure yields on average an excess return over the buy-and-hold of 12.3% yearly, if the best strategy in the training period is selected by the mean return criterion. Thus the best strategy found in the past continues to generate good results in the future. However, if as little as 0.25% transaction costs are implemented, then the excess return decreases to 2.8%. Finally, estimation of Sharpe-Lintner CAPMs shows that, after correction for transaction costs and risk, the best recursive optimizing and testing procedure has no statistically significant forecasting power anymore.

Hence, in short, after correcting for transaction costs, risk, data snooping and out-of-sample forecasting, we conclude that objective trend-following technical trading techniques applied to the DJIA and to the stocks listed in the DJIA in the period 1973-2001 are not genuine superior, as suggested by their performances, to the buy-and-hold benchmark.

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Table 3.1: **Data series examined, sample period and largest cumulative loss.** Column 1 shows the names of 34 stocks listed in the DJIA in the period 1973:1-2001:6. Column 2 shows their respective sample periods. Columns 3 and 4 show the largest cumulative loss of the data series in %/100 terms and the period during which this decline occurred.

Data set	Sample period	Max. loss	Period of max. loss
DJIA	12/31/73 - 06/29/01	-0.3613	08/26/87 - 10/19/87
ALCOA	12/31/73 - 06/29/01	-0.4954	04/17/74 - 12/05/74
AMERICAN EXPRESS	12/31/73 - 06/29/01	-0.6313	03/07/74 - 10/03/74
AT&T	12/31/73 - 06/29/01	-0.7326	02/04/99 - 12/28/00
BETHLEHEM STEEL	12/31/73 - 06/29/01	-0.9655	03/11/76 - 12/06/00
BOEING	12/31/73 - 06/29/01	-0.6632	01/31/80 - 06/28/82
CATERPILLAR	12/31/73 - 06/29/01	-0.6064	04/27/81 - 12/13/84
CHEVRON - TEXACO	12/31/73 - 06/29/01	-0.5823	11/27/80 - 08/04/82
CITIGROUP	10/27/87 - 06/29/01	-0.5652	04/07/98 - 10/07/98
COCA - COLA	12/31/73 - 06/29/01	-0.6346	01/04/74 - 10/03/74
E.I. DU PONT DE NEMOURS	12/31/73 - 06/29/01	-0.5347	05/21/98 - 09/26/00
EASTMAN KODAK	12/31/73 - 06/29/01	-0.6551	04/02/76 - 03/06/78
EXXON MOBIL	12/31/73 - 06/29/01	-0.4448	01/04/74 - 10/03/74
GENERAL ELECTRIC	12/31/73 - 06/29/01	-0.5333	01/07/74 - 09/13/74
GENERAL MOTORS	12/31/73 - 06/29/01	-0.5652	01/03/77 - 02/22/82
GOODYEAR TIRE	12/31/73 - 06/29/01	-0.8165	08/12/87 - 11/09/90
HEWLETT - PACKARD	12/31/73 - 06/29/01	-0.6579	10/06/87 - 11/07/90
HOME DEPOT	12/28/84 - 06/29/01	-0.5385	08/12/87 - 10/26/87
HONEYWELL INTL.	09/17/86 - 06/29/01	-0.5123	06/22/99 - 06/27/00
INTEL	12/28/79 - 06/29/01	-0.6978	09/01/00 - 04/04/01
INTL. BUS. MACH.	12/31/73 - 06/29/01	-0.7654	08/21/87 - 08/16/93
INTERNATIONAL PAPER	12/31/73 - 06/29/01	-0.6073	03/11/76 - 04/17/80
J.P. MORGAN CHASE & CO.	12/31/73 - 06/29/01	-0.8165	03/28/86 - 10/31/90
JOHNSON & JOHNSON	12/31/73 - 06/29/01	-0.4758	06/10/74 - 04/25/77
MCDONALDS	12/31/73 - 06/29/01	-0.6667	06/11/74 - 10/04/74
MERCK	12/31/73 - 06/29/01	-0.4957	01/06/92 - 04/15/94
MICROSOFT	03/11/87 - 06/29/01	-0.6516	12/28/99 - 12/20/00
MINNESOTA MNG. & MNFG.	12/31/73 - 06/29/01	-0.4546	01/04/74 - 04/04/78
PHILIP MORRIS	12/31/73 - 06/29/01	-0.6759	11/24/98 - 02/16/00
PROCTER & GAMBLE	12/31/73 - 06/29/01	-0.5445	01/12/00 - 03/10/00
SBC COMMUNICATIONS	11/16/84 - 06/29/01	-0.4045	07/19/99 - 02/23/00
SEARS, ROEBUCK & CO.	12/31/73 - 06/29/01	-0.6746	06/10/74 - 12/11/80
UNITED TECHNOLOGIES	12/31/73 - 06/29/01	-0.5099	01/07/81 - 03/17/82
WAL - MART STORES	12/30/81 - 06/29/01	-0.5047	08/24/87 - 12/03/87
WALT DISNEY	12/31/73 - 06/29/01	-0.6667	03/14/74 - 12/16/74

Table 3.2: **Summary statistics: 1973-2001.** The first column shows the names of the the stocks listed in the DJIA in the period 1973:1-2001:6. Columns 2 to 7 show the number of observations, the mean yearly effective return in %/100 terms, the mean, standard deviation, skewness and kurtosis of the daily logarithmic return. Column 8 shows the t-ratio testing whether the mean daily return is significantly different from zero. Column 9 shows the Sharpe ratio. Column 10 shows the largest cumulative loss in %/100 terms. Column 11 shows the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. Column 12 shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic for testing autocorrelations in the squared returns. Significance level of the (adjusted) Q(20)-test statistic can be evaluated based on the following chi-squared values: a) chi-squared(0.99,20)=37.57, b) chi-squared(0.95,20)=31.41, c) chi-squared(0.90,20)=28.41.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
DJIA	7174	0.0923	0.00035	0.010181	-2.305	63.561	2.91a	0.005243	-0.3613	49.00a	13.01	362.23a
ALCOA	7174	0.0943	0.000358	0.019203	-0.298	12.348	1.58	0.003158	-0.4954	67.11a	30.84c	635.10a
AMERICAN EXPRESS	7174	0.088	0.000335	0.02133	-0.381	11.968	1.33	0.001763	-0.6313	64.77a	30.16c	1650.62a
AT&T	7174	0.0487	0.000189	0.016008	-0.341	17.641	1	-0.006762	-0.7326	43.64a	17.7	1472.98a
BETHLEHEM STEEL	7174	-0.0935	-0.000389	0.027128	-0.309	18.861	-1.22	-0.025299	-0.9655	55.58a	27.76	774.12a
BOEING	7174	0.1882	0.000684	0.019737	-0.036	7.126	2.94a	0.019631	-0.6632	47.48a	37.15b	311.57a
CATERPILLAR	7174	0.0541	0.000209	0.018176	-0.462	12.07	0.97	-0.004834	-0.6064	83.27a	42.37a	722.22a
CHEVRON - TEXACO	7174	0.0855	0.000326	0.016315	-0.058	7.771	1.69c	0.001761	-0.5823	71.30a	48.26a	901.65a
CITIGROUP	3568	0.2742	0.000962	0.021851	0.12	6.162	2.63a	0.033446	-0.5652	39.53a	28.66c	385.97a
COCA - COLA	7174	0.1055	0.000398	0.016902	-0.481	19.144	1.99b	0.005978	-0.6346	67.97a	27.55	1509.56a
E.I. DU PONT DE NEMOURS	7174	0.0615	0.000237	0.016621	-0.207	8.485	1.21	-0.003624	-0.5347	34.18b	24.82	532.20a
EASTMAN KODAK	7174	0.0048	0.000019	0.018006	-1.435	40.483	0.09	-0.015443	-0.6551	42.88a	24.03	460.21a
EXXON MOBIL	7174	0.0994	0.000376	0.01396	-0.672	26.309	2.28b	0.005675	-0.4448	115.49a	45.74a	1359.07a
GENERAL ELECTRIC	7174	0.1355	0.000504	0.015753	-0.188	8.987	2.71a	0.013153	-0.5333	43.32a	21.33	2287.65a
GENERAL MOTORS	7174	0.0471	0.000183	0.017382	-0.204	10.017	0.89	-0.006567	-0.5652	31.61b	22.46	782.11a
GOODYEAR TIRE	7174	0.0467	0.000181	0.018877	-0.593	20.93	0.81	-0.006129	-0.8165	77.94a	38.60a	522.31a
HEWLETT - PACKARD	7174	0.1254	0.000469	0.022922	-0.148	8.719	1.73c	0.0075	-0.6579	23.93	16.28	539.19a
HOME DEPOT	4305	0.3251	0.001117	0.023751	-0.917	19.57	3.09a	0.036954	-0.5385	54.39a	34.95b	122.29a
HONEYWELL INTL.	3857	0.0846	0.000322	0.021072	-0.554	39.883	0.95	0.004262	-0.5123	57.91a	24.53	639.75a
INTEL	5610	0.2199	0.000789	0.028326	-0.249	7.909	2.09b	0.017476	-0.6978	60.98a	37.65a	1090.84a
INTL. BUS. MACH.	7174	0.0725	0.000278	0.01719	-0.347	17.36	1.37	-0.001123	-0.7654	32.99b	18.31	344.98a
INTERNATIONAL PAPER	7174	0.0361	0.000141	0.018256	-0.491	18.143	0.65	-0.008552	-0.6073	61.30a	36.78b	475.13a
J.P. MORGAN CHASE & CO.	7174	0.0721	0.000276	0.019916	-0.468	16.47	1.17	-0.001042	-0.8165	39.65a	20.75	344.59a
JOHNSON & JOHNSON	7174	0.1134	0.000426	0.015839	-0.241	9.105	2.28b	0.008162	-0.4758	87.46a	50.82a	1046.42a
MCDONALDS	7174	0.1094	0.000412	0.01771	-0.432	11.923	1.97b	0.006488	-0.6667	48.44a	25	1384.84a
MERCK	7174	0.1249	0.000467	0.015916	-0.01	6.44	2.49b	0.010692	-0.4957	56.64a	36.36b	930.26a
MICROSOFT	3732	0.3845	0.001291	0.024908	-0.936	18.997	3.17a	0.042494	-0.6516	50.17a	22.16	499.16a
MINNESOTA MNG. & MNFG.	7174	0.0655	0.000252	0.014968	-0.998	28.906	1.42	-0.003025	-0.4546	41.29a	24.22	325.92a
PHILIP MORRIS	7174	0.1406	0.000522	0.017649	-0.537	15.258	2.50b	0.01275	-0.6759	62.53a	42.50a	197.11a

Table 3.2 continued.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
PROCTER & GAMBLE	7174	0.0882	0.000335	0.01567	-2.846	77.504	1.81c	0.002459	-0.5445	65.86a	26.65	193.97a
SBC COMMUNICATIONS	4335	0.1231	0.000461	0.016595	-0.596	21.051	1.83c	0.013299	-0.4045	46.22a	27.58	965.78a
SEARS, ROEBUCK & CO.	7174	0.0371	0.000145	0.018911	-0.161	15.76	0.65	-0.008048	-0.6746	65.60a	27.41	692.74a
UNITED TECHNOLOGIES	7174	0.1469	0.000544	0.016836	-0.075	6.358	2.74a	0.01467	-0.5099	61.04a	41.26a	731.90a
WAL - MART STORES	5087	0.2808	0.000982	0.020218	-0.011	5.566	3.46a	0.03542	-0.5047	55.92a	37.72a	1030.70a
WALT DISNEY	7174	0.1296	0.000484	0.020449	-0.927	21.334	2.00b	0.009125	-0.6667	35.35b	11.95	571.60a

Table 3.3: **Summary statistics: 1973-1986.** The first column shows the names of the the stocks listed in the DJIA in the period 1973:1-1986:12. Columns 2 to 7 show the number of observations, the mean yearly effective return in %/100 terms, the mean, standard deviation, skewness and kurtosis of the daily logarithmic return. Column 8 shows the t-ratio testing whether the mean daily return is significantly different from zero. Column 9 shows the Sharpe ratio. Column 10 shows the largest cumulative loss in %/100 terms. Column 11 shows the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. Column 12 shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic for testing autocorrelations in the squared returns. Significance level of the (adjusted) Q(20)-test statistic can be evaluated based on the following chi-squared values: a) chi-squared(0.99,20)=37.57, b) chi-squared(0.95,20)=31.41, c) chi-squared(0.90,20)=28.41.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
DJIA	3392	0.0613	0.000236	0.009268	0.266	4.718	1.48	-0.014284	-0.3522	64.77a	47.24a	807.23a
ALCOA	3392	0.0251	0.000098	0.018056	-0.06	6.484	0.32	-0.014967	-0.4954	68.61a	46.06a	347.63a
AMERICAN EXPRESS	3392	0.0709	0.000272	0.020474	0.05	5.654	0.77	-0.004728	-0.6313	74.87a	44.34a	1468.10a
AT&T	3392	0.0529	0.000205	0.011221	0.164	6.987	1.06	-0.014608	-0.3076	32.24b	23.36	282.74a
BETHLEHEM STEEL	3392	-0.1163	-0.000491	0.021015	-0.752	17.242	-1.36	-0.040883	-0.8995	76.24a	37.35b	181.61a
BOEING	3392	0.2799	0.000979	0.020775	0.145	4.478	2.75a	0.029395	-0.6632	19.18	16.08	224.74a
CATERPILLAR	3392	-0.008	-0.000032	0.015946	-0.233	8.102	-0.12	-0.025105	-0.6064	97.70a	72.98a	141.18a
CHEVRON - TEXACO	3392	0.0734	0.000281	0.017345	0.289	5.114	0.94	-0.005055	-0.5823	71.72a	53.56a	326.42a
COCA - COLA	3392	0.0441	0.000171	0.015861	-0.063	7.04	0.63	-0.012442	-0.6346	75.94a	41.54a	1223.19a
E.I. DU PONT DE NEMOURS	3392	0.0348	0.000136	0.015226	0.153	5.243	0.52	-0.015284	-0.5171	33.40b	27.21	212.82a
EASTMAN KODAK	3392	-0.0088	-0.000035	0.016197	0.296	6.154	-0.13	-0.024932	-0.6551	38.17a	28.15	631.40a
EXXON MOBIL	3392	0.0846	0.000322	0.012691	0.029	4.334	1.48	-0.003655	-0.4448	50.18a	40.90a	228.64a
GENERAL ELECTRIC	3392	0.0775	0.000296	0.014956	0.135	5.481	1.15	-0.004828	-0.5333	36.78b	21.05	2111.06a
GENERAL MOTORS	3392	0.0302	0.000118	0.015072	0.171	5.658	0.46	-0.016623	-0.5652	39.94a	29.52c	275.71a
GOODYEAR TIRE	3392	0.0779	0.000298	0.016501	0.36	5.811	1.05	-0.004301	-0.5648	29.00c	21.68	311.47a
HEWLETT - PACKARD	3392	0.1113	0.000419	0.019543	0.058	4.91	1.25	0.002576	-0.4795	27.12	22.75	212.75a
INTEL	1828	0.032	0.000125	0.027913	0.068	3.85	0.19	-0.010579	-0.6277	42.82a	37.00b	66.58a
INTL. BUS. MACH.	3392	0.0507	0.000196	0.013597	0.456	5.724	0.84	-0.012678	-0.3937	29.04c	21.23	342.40a

Table 3.3 continued.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
INTERNATIONAL PAPER	3392	0.0277	0.000108	0.016462	0.246	5.347	0.38	-0.015803	-0.6073	76.39a	61.62a	129.18a
J.P. MORGAN CHASE & CO.	3392	0.0635	0.000244	0.016143	0.173	4.846	0.88	-0.007706	-0.4443	32.71b	23.76	389.22a
JOHNSON & JOHNSON	3392	0.0422	0.000164	0.015091	0.093	5.144	0.63	-0.013552	-0.4758	62.21a	40.44a	896.24a
MCDONALDS	3392	0.0997	0.000377	0.018283	-0.521	14.002	1.2	0.000475	-0.6667	66.60a	28.67c	896.54a
MERCK	3392	0.0869	0.000331	0.014654	0.163	6.012	1.31	-0.002578	-0.437	57.45a	34.04b	804.60a
MINNESOTA MNG. & MNFG.	3392	0.0304	0.000119	0.013763	0.305	4.901	0.5	-0.018158	-0.4546	85.93a	61.15a	678.87a
PHILIP MORRIS	3392	0.1269	0.000474	0.015716	0.107	5.412	1.76c	0.006706	-0.4206	67.12a	48.22a	541.40a
PROCTER & GAMBLE	3392	0.0384	0.00015	0.012195	0.173	5.09	0.71	-0.017961	-0.4021	57.27a	39.11a	863.04a
SEARS, ROEBUCK & CO.	3392	-0.0007	-0.000003	0.016463	0.314	5.266	-0.01	-0.022557	-0.6746	56.78a	39.07a	513.68a
UNITED TECHNOLOGIES	3392	0.1645	0.000604	0.016661	0.125	4.444	2.11b	0.014156	-0.5099	33.99b	28.56c	132.37a
WAL - MART STORES	1305	0.5225	0.001668	0.020035	0.107	4.286	3.01a	0.065144	-0.3191	29.04c	24.22	97.21a
WALT DISNEY	3392	0.1083	0.000408	0.020927	-0.596	10.832	1.14	0.001877	-0.6667	39.13a	24.61	214.93a

Table 3.4: **Summary statistics: 1987-2001.** The first column shows the names of the stocks listed in the DJIA in the period 1987:1-2001:6. Columns 2 to 7 show the number of observations, the mean yearly effective return in %/100 terms, the mean, standard deviation, skewness and kurtosis of the daily logarithmic return. Column 8 shows the t-ratio testing whether the mean daily return is significantly different from zero. Column 9 shows the Sharpe ratio. Column 10 shows the largest cumulative loss in %/100 terms. Column 11 shows the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. Column 12 shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic for testing autocorrelations in the squared returns. Significance level of the (adjusted) Q(20)-test statistic can be evaluated based on the following chi-squared values: a) chi-squared(0.99,20)=37.57, b) chi-squared(0.95,20)=31.41, c) chi-squared(0.90,20)=28.41.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
DJIA	3781	0.1209	0.000453	0.010937	-3.681	88.53	2.55b	0.020124	-0.3613	44.74a	10.26	186.47a
ALCOA	3781	0.1604	0.00059	0.02018	-0.456	15.507	1.80c	0.017719	-0.4673	44.13a	22.9	342.83a
AMERICAN EXPRESS	3781	0.1035	0.000391	0.022074	-0.688	16.051	1.09	0.007169	-0.5652	48.82a	19.23	830.77a
AT&T	3781	0.0449	0.000174	0.019322	-0.395	15.058	0.55	-0.003016	-0.7326	31.81b	15.5	653.99a
BETHLEHEM STEEL	3781	-0.0725	-0.000299	0.031628	-0.177	16.356	-0.58	-0.016801	-0.9415	32.68b	19.57	393.34a
BOEING	3781	0.1116	0.00042	0.018759	-0.266	10.499	1.38	0.009988	-0.4853	47.40a	36.79b	139.73a
CATERPILLAR	3781	0.1131	0.000425	0.019968	-0.567	12.788	1.31	0.00964	-0.5397	30.80c	16.33	435.70a
CHEVRON - TEXACO	3781	0.0966	0.000366	0.015336	-0.505	11.389	1.47	0.008688	-0.4308	47.23a	30.39c	645.95a
CITIGROUP	3568	0.2742	0.000962	0.021851	0.12	6.162	2.63a	0.033446	-0.5652	39.53a	28.66c	385.97a
COCA - COLA	3781	0.1637	0.000601	0.017785	-0.75	25.666	2.08b	0.020736	-0.5127	64.68a	23.98	818.69a
E.I. DU PONT DE NEMOURS	3781	0.0859	0.000327	0.017783	-0.41	9.769	1.13	0.005317	-0.5347	36.44b	23.85	282.15a
EASTMAN KODAK	3781	0.0171	0.000067	0.019491	-2.301	53.344	0.21	-0.008479	-0.6134	30.89c	16.75	243.15a

Table 3.4 continued.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
EXXON MOBIL	3781	0.1129	0.000425	0.01501	-1.044	35.377	1.74c	0.01279	-0.3312	134.02a	39.32a	748.31a
GENERAL ELECTRIC	3781	0.1901	0.000691	0.016437	-0.411	11.039	2.58a	0.027863	-0.4117	41.85a	17.67	1042.40a
GENERAL MOTORS	3781	0.0626	0.000241	0.019223	-0.364	10.794	0.77	0.000429	-0.4787	27.99	19.4	424.53a
GOODYEAR TIRE	3781	0.0196	0.000077	0.020783	-0.999	24.937	0.23	-0.007497	-0.8165	71.95a	34.53b	262.80a
HEWLETT - PACKARD	3781	0.1382	0.000514	0.025581	-0.227	9.167	1.23	0.010988	-0.6579	24.62	16.7	221.20a
HOME DEPOT	3781	0.3754	0.001265	0.022779	-1.232	22.137	3.41a	0.04531	-0.5385	68.00a	38.76a	139.68a
HONEYWELL INTL.	3781	0.0868	0.00033	0.021218	-0.553	39.576	0.96	0.00461	-0.5123	57.90a	24.54	626.18a
INTEL	3781	0.3228	0.00111	0.028526	-0.394	9.723	2.39b	0.030756	-0.6978	68.01a	35.49b	889.02a
INTL. BUS. MACH.	3781	0.0924	0.000351	0.019872	-0.563	17.332	1.09	0.005943	-0.7654	24.87	15.83	131.51a
INTERNATIONAL PAPER	3781	0.0437	0.00017	0.019731	-0.867	22.912	0.53	-0.003181	-0.5527	38.80a	23.89	260.81a
J.P. MORGAN CHASE & CO.	3781	0.0799	0.000305	0.02278	-0.651	17.168	0.82	0.003173	-0.7952	28.93c	16.11	132.03a
JOHNSON & JOHNSON	3781	0.1814	0.000661	0.016483	-0.477	11.521	2.47b	0.026017	-0.3838	86.63a	51.54a	497.17a
MCDONALDS	3781	0.1181	0.000443	0.017184	-0.334	9.425	1.58	0.012237	-0.4833	34.80b	21.07	550.76a
MERCK	3781	0.1602	0.000589	0.016972	-0.115	6.46	2.14b	0.021025	-0.4957	46.11a	32.96b	319.04a
MICROSOFT	3732	0.3845	0.001291	0.024908	-0.936	18.997	3.17a	0.042494	-0.6516	50.17a	22.16	499.16a
MINNESOTA MNG. & MNFG.	3781	0.098	0.000371	0.015976	-1.738	39.909	1.43	0.00866	-0.3736	45.38a	21.57	161.36a
PHILIP MORRIS	3781	0.1531	0.000565	0.019223	-0.844	18.412	1.81c	0.017296	-0.6759	48.37a	33.24b	70.86a
PROCTER & GAMBLE	3781	0.1349	0.000502	0.018234	-3.49	79.433	1.69c	0.014789	-0.5445	64.75a	26.14	95.27a
SBC COMMUNICATIONS	3781	0.1018	0.000385	0.017332	-0.567	20.129	1.37	0.008779	-0.4045	44.97a	27.55	833.06a
SEARS, ROEBUCK & CO.	3781	0.0723	0.000277	0.020868	-0.373	18.355	0.82	0.00213	-0.6202	56.42a	21.86	344.34a
UNITED TECHNOLOGIES	3781	0.1314	0.00049	0.016995	-0.243	7.932	1.77c	0.015126	-0.5	49.71a	30.84c	535.93a
WAL - MART STORES	3781	0.2067	0.000746	0.02028	-0.049	5.979	2.26b	0.025299	-0.5047	55.25a	34.79b	938.94a
WALT DISNEY	3781	0.1491	0.000552	0.020017	-1.263	32.498	1.69c	0.01593	-0.4454	23.83	5.3	366.16a

Table 3.5: **Statistics best strategy: 1973-2001, mean return criterion, 0% costs.** Statistics of the best strategy, selected by the mean return criterion, if no costs are implemented, for each data series listed in the first column. Column 2 shows the strategy parameters. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio. Column 7 shows the largest cumulative loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
DJIA	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2491	0.1435	0.0438	0.0385	-0.2507	3531	0.697	0.808	1.3909
ALCOA	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.5131	0.3827	0.0506	0.0474	-0.6360	2885	0.693	0.811	1.2083
AMERICAN EXPRESS	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.3262	0.2190	0.0287	0.0270	-0.8875	3100	0.679	0.793	1.3362

Table 3.5 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
AT&T	[FR: 0.020, 0, 50]	0.1225	0.0704	0.0080	0.0148	-0.6056	232	0.681	0.776	1.2719
BETHLEHEM STEEL	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2104	0.3352	0.0136	0.0389	-0.9926	3247	0.649	0.804	1.2600
BOEING	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4936	0.2570	0.0473	0.0277	-0.7850	2895	0.697	0.808	1.2081
CATERPILLAR	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4904	0.4139	0.0521	0.0569	-0.7815	2895	0.690	0.814	1.1647
CHEVRON - TEXACO	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2746	0.1741	0.0308	0.0290	-0.7196	3466	0.674	0.797	1.3414
CITIGROUP	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.5930	0.2502	0.0540	0.0206	-0.6954	1707	0.689	0.805	1.3224
COCA - COLA	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.2841	0.1616	0.0314	0.0254	-0.6220	2925	0.682	0.793	1.3365
E.I. DU PONT DE NEMOURS	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.2079	0.1379	0.0201	0.0238	-0.5995	3049	0.682	0.800	1.2779
EASTMAN KODAK	[MA: 2, 5, 0.000, 0, 25, 0.000]	0.0776	0.0725	0.0000	0.0154	-0.7019	440	0.634	0.720	1.1390
EXXON MOBIL	[MA: 1, 2, 0.000, 0, 5, 0.000]	0.1754	0.0691	0.0163	0.0106	-0.6480	1472	0.653	0.762	0.8588
GENERAL ELECTRIC	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2388	0.0910	0.0263	0.0132	-0.5838	3417	0.674	0.788	1.3597
GENERAL MOTORS	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.1652	0.1127	0.0132	0.0198	-0.8473	3466	0.670	0.795	1.2530
GOODYEAR TIRE	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2413	0.1859	0.0219	0.0280	-0.8510	3383	0.669	0.794	1.2870
HEWLETT - PACKARD	[MA: 10, 100, 0.000, 0, 50, 0.000]	0.2321	0.0948	0.0211	0.0136	-0.6425	134	0.724	0.704	1.0201
HOME DEPOT	[FR: 0.010, 0, 5,]	0.6428	0.2398	0.0487	0.0118	-0.8918	904	0.667	0.733	0.8617
HONEYWELL INTL.	[MA: 1, 50, 0.000, 0, 50, 0.000]	0.2714	0.1722	0.0332	0.0289	-0.4040	106	0.717	0.824	1.3056
INTEL	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4092	0.1552	0.0278	0.0103	-0.8327	2166	0.696	0.801	1.1638
INTL. BUS. MACH.	[MA: 10, 25, 0.000, 2, 0, 0.000]	0.1727	0.0934	0.0155	0.0166	-0.7380	287	0.714	0.826	1.1015
INTERNATIONAL PAPER	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.2937	0.2486	0.0293	0.0378	-0.9370	3021	0.688	0.808	1.3174
J.P. MORGAN CHASE & CO.	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4459	0.3487	0.0434	0.0444	-0.7045	2907	0.695	0.812	1.3051
JOHNSON & JOHNSON	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.3304	0.1949	0.0397	0.0315	-0.3393	3407	0.687	0.796	1.3344
MCDONALDS	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.2676	0.1427	0.0258	0.0193	-0.7242	2950	0.680	0.792	1.1585
MERCK	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.3409	0.1920	0.0379	0.0272	-0.6204	3369	0.688	0.786	1.2630
MICROSOFT	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.7089	0.2343	0.0590	0.0165	-0.6995	1786	0.680	0.807	1.3912
MINNESOTA MNG. & MNFG.	[FR: 0.005, 0, 10]	0.2485	0.1718	0.0300	0.0330	-0.4865	895	0.683	0.753	1.1536
PHILIP MORRIS	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.2434	0.0901	0.0227	0.0099	-0.8874	2927	0.693	0.810	1.0819
PROCTER & GAMBLE	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2340	0.1339	0.0261	0.0236	-0.5526	3455	0.683	0.785	1.4065
SBC COMMUNICATIONS	[MA: 2, 10, 0.000, 0, 25, 0.000]	0.2837	0.1430	0.0376	0.0243	-0.4012	249	0.743	0.806	1.0756
SEARS, ROEBUCK & CO.	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2411	0.1966	0.0224	0.0305	-0.6622	3474	0.664	0.804	1.3426
UNITED TECHNOLOGIES	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4957	0.3042	0.0561	0.0414	-0.4957	2942	0.697	0.809	1.3119
WAL - MART STORES	[MA: 1, 2, 0.000, 0, 5, 0.000]	0.5028	0.1733	0.0498	0.0144	-0.6527	1055	0.667	0.748	0.9853
WALT DISNEY	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.3978	0.2374	0.0379	0.0288	-0.7506	3329	0.679	0.807	1.2720

Table 3.6: **Statistics best strategy: 1973-2001, mean return criterion, 0.25% costs.** Statistics of the best strategy, selected by the mean return criterion, if 0.25% costs per trade are implemented, for each data series listed in the first column. Column 2 shows the strategy parameters. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio. Column 7 shows the largest cumulative loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
DJIA	[MA: 5, 25, 0.050, 0, 0, 0.000]	0.1480	0.0511	0.0205	0.0153	-0.4619	12	0.833	0.990	0.7946
ALCOA	[MA: 2, 5, 0.050, 0, 0, 0.000]	0.1513	0.0522	0.0094	0.0063	-0.6804	17	0.647	0.990	0.4365
AMERICAN EXPRESS	[FR: 0.020, 0, 50]	0.1790	0.0838	0.0130	0.0113	-0.6908	237	0.679	0.822	0.9709
AT&T	[SR: 150, 0.025, 0, 0, 0.000]	0.1087	0.0573	0.0055	0.0123	-0.5060	9	0.889	0.975	0.6723
BETHLEHEM STEEL	[FR: 0.050, 0, 25]	0.0797	0.1911	0.0002	0.0255	-0.9433	376	0.604	0.670	0.9242
BOEING	[FR: 0.090, 3, 0]	0.2441	0.0471	0.0197	0.0001	-0.7031	174	0.575	0.781	0.8738
CATERPILLAR	[SR: 5, 0.000, 0, 25, 0.000]	0.1109	0.0540	0.0044	0.0093	-0.8183	415	0.593	0.654	0.9245
CHEVRON - TEXACO	[FR: 0.020, 0, 25]	0.1685	0.0766	0.0146	0.0129	-0.7379	426	0.648	0.722	1.0155
CITIGROUP	[FR: 0.200, 3, 0]	0.5070	0.1829	0.0470	0.0136	-0.3511	13	0.846	0.989	0.6553
COCA - COLA	[SR: 250, 0.025, 0, 0, 0.000]	0.1765	0.0643	0.0210	0.0150	-0.5210	6	0.833	0.988	1.1012
E.I. DU PONT DE NEMOURS	[MA: 1, 2, 0.000, 0, 10, 0.000]	0.1003	0.0367	0.0038	0.0075	-0.5472	821	0.404	0.485	1.0763
EASTMAN KODAK	[MA: 10, 100, 0.000, 0, 50, 0.000]	0.0462	0.0414	-0.0058	0.0096	-0.7573	139	0.669	0.641	0.9110
EXXON MOBIL	[SR: 200, 0.000, 4, 0, 0.000]	0.1512	0.0472	0.0128	0.0072	-0.4821	15	0.867	0.941	1.3361
GENERAL ELECTRIC	[MA: 5, 25, 0.050, 0, 0, 0.000]	0.1884	0.0467	0.0172	0.0041	-0.5417	33	0.727	0.879	1.0058
GENERAL MOTORS	[SR: 10, 0.050, 0, 0, 0.000]	0.1443	0.0929	0.0114	0.0179	-0.7442	12	0.917	0.991	0.6222
GOODYEAR TIRE	[SR: 100, 0.050, 0, 0, 0.000]	0.1519	0.1006	0.0104	0.0166	-0.8253	6	0.833	0.996	0.8818
HEWLETT - PACKARD	[MA: 10, 100, 0.000, 0, 50, 0.000]	0.2180	0.0824	0.0193	0.0118	-0.6585	134	0.724	0.704	1.0201
HOME DEPOT	[FR: 0.010, 0, 50]	0.4603	0.1023	0.0374	0.0004	-0.5940	129	0.752	0.855	1.0079
HONEYWELL INTL.	[MA: 1, 50, 0.000, 0, 50, 0.000]	0.2499	0.1526	0.0300	0.0258	-0.4248	106	0.708	0.821	1.2001
INTEL	[MA: 2, 5, 0.000, 0, 50, 0.000]	0.2772	0.0471	0.0166	-0.0009	-0.8191	187	0.615	0.777	0.8705
INTL. BUS. MACH.	[SR: 150, 0.025, 0, 0, 0.000]	0.1199	0.0443	0.0074	0.0085	-0.7342	9	0.778	0.844	1.5333
INTERNATIONAL PAPER	[FR: 0.080, 0, 25]	0.0831	0.0455	0.0010	0.0095	-0.5070	293	0.618	0.652	1.0820
J.P. MORGAN CHASE & CO.	[FR: 0.010, 0, 50]	0.2050	0.1241	0.0149	0.0159	-0.8588	218	0.656	0.813	1.0024
JOHNSON & JOHNSON	[MA: 2, 5, 0.000, 0, 50, 0.000]	0.1674	0.0486	0.0150	0.0069	-0.6904	228	0.711	0.854	1.0281
MCDONALDS	[FR: 0.140, 0, 50]	0.1655	0.0507	0.0173	0.0109	-0.4554	93	0.710	0.743	1.0633
MERCK	[MA: 25, 50, 0.050, 0, 0, 0.000]	0.1847	0.0532	0.0183	0.0076	-0.5552	20	0.750	0.876	0.9966
MICROSOFT	[FR: 0.090, 4, 0]	0.5263	0.1026	0.0422	-0.0003	-0.8167	108	0.472	0.761	0.9004
MINNESOTA MNG. & MNFG.	[FR: 0.005, 0, 10]	0.1443	0.0741	0.0122	0.0153	-0.5572	895	0.439	0.417	1.0209
PHILIP MORRIS	[FR: 0.300, 4, 0]	0.2017	0.0537	0.0168	0.0041	-0.7543	9	0.889	0.989	1.0253
PROCTER & GAMBLE	[MA: 1, 10, 0.000, 0, 50, 0.000]	0.1374	0.0453	0.0088	0.0063	-0.7707	229	0.699	0.795	0.9380
SBC COMMUNICATIONS	[MA: 2, 10, 0.000, 0, 25, 0.000]	0.2367	0.1013	0.0301	0.0169	-0.4101	249	0.675	0.708	1.0608

table 3.6 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
SEARS, ROEBUCK & CO.	[SR: 150, 0.050, 0, 0, 0.000]	0.1307	0.0903	0.0086	0.0166	-0.7156	7	0.857	0.979	1.3855
UNITED TECHNOLOGIES	[SR: 25, 0.000, 0, 50, 0.000]	0.2136	0.0582	0.0261	0.0115	-0.3739	178	0.680	0.792	1.0157
WAL - MART STORES	[FR: 0.180, 4, 0]	0.3694	0.0693	0.0344	-0.0010	-0.6722	32	0.688	0.906	0.9330
WALT DISNEY	[FR: 0.500, 2, 0]	0.1831	0.0475	0.0138	0.0047	-0.7408	2	1.000	1.000	NA

Table 3.7: **Mean return best strategy in excess of mean return buy-and-hold.** Mean return of the best strategy, selected by the mean return criterion after implementing 0, 0.10, 0.25 and 0.75% costs per trade, in excess of the mean return of the buy-and-hold benchmark, for the full sample period 1973:1-2001:6 and the two subperiods 1973:1-1986:12 and 1987:1-2001:6, for each data series listed in the first column.

period	1973:1-2001:6				1973:1-1986:12				1987:1-2001:6			
Data set	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%
DJIA	0.1435	0.0521	0.0511	0.0474	0.1841	0.0883	0.0873	0.0841	0.1255	0.0649	0.0423	0.0298
ALCOA	0.3827	0.1819	0.0522	0.0463	0.5183	0.3403	0.1546	0.0610	0.2757	0.2122	0.1588	0.0391
AMERICAN EXPRESS	0.2190	0.0979	0.0838	0.0441	0.6626	0.4124	0.1906	0.1049	0.1678	0.1501	0.1240	0.1024
AT&T	0.0704	0.0613	0.0573	0.0546	0.1135	0.0651	0.0651	0.0649	0.1047	0.0952	0.0927	0.0845
BETHLEHEM STEEL	0.3352	0.2148	0.1911	0.1152	0.5176	0.3088	0.2135	0.2093	0.2686	0.2545	0.2335	0.1658
BOEING	0.2570	0.0667	0.0471	0.0315	0.4157	0.2253	0.1121	0.1104	0.2032	0.0963	0.0747	0.0287
CATERPILLAR	0.4139	0.2164	0.0540	0.0033	0.6032	0.3787	0.1630	0.0451	0.2633	0.1989	0.1714	0.0840
CHEVRON - TEXACO	0.1741	0.1023	0.0766	0.0276	0.4633	0.2247	0.1549	0.0685	0.1075	0.0988	0.0859	0.0504
CITIGROUP	0.2502	0.1858	0.1829	0.1734					0.2502	0.1858	0.1829	0.1734
COCA - COLA	0.1616	0.0690	0.0643	0.0628	0.2896	0.1422	0.1137	0.1128	0.0874	0.0712	0.0667	0.0655
E.I. DU PONT DE NEMOURS	0.1379	0.0914	0.0367	0.0259	0.2720	0.1473	0.0898	0.0816	0.2225	0.1483	0.0783	0.0387
EASTMAN KODAK	0.0725	0.0552	0.0414	0.0315	0.1639	0.1591	0.1519	0.1283	0.1485	0.1097	0.0743	0.0137
EXXON MOBIL	0.0691	0.0486	0.0472	0.0423	0.1990	0.0954	0.0938	0.0888	0.0751	0.0676	0.0563	0.0355
GENERAL ELECTRIC	0.0910	0.0506	0.0467	0.0369	0.2029	0.1025	0.0898	0.0484	0.0817	0.0788	0.0754	0.0653
GENERAL MOTORS	0.1127	0.0940	0.0929	0.0892	0.2836	0.1510	0.1503	0.1479	0.1721	0.1668	0.1589	0.1329
GOODYEAR TIRE	0.1859	0.1010	0.1006	0.0992	0.2340	0.2143	0.1854	0.0935	0.2220	0.2108	0.1967	0.1939
HEWLETT - PACKARD	0.0948	0.0898	0.0824	0.0578	0.1572	0.0975	0.0851	0.0484	0.1585	0.1298	0.1228	0.0994
HOME DEPOT	0.2398	0.1703	0.1023	0.0870					0.2966	0.1557	0.1249	0.1191
HONEYWELL INTL.	0.1722	0.1643	0.1526	0.1141					0.1639	0.1567	0.1459	0.1105
INTEL	0.1552	0.0608	0.0471	0.0336	0.3187	0.2515	0.2253	0.1746	0.1187	0.1119	0.1063	0.0877
INTL. BUS. MACH.	0.0934	0.0718	0.0443	0.0416	0.0904	0.0821	0.0747	0.0625	0.1541	0.1364	0.1104	0.1017
INTERNATIONAL PAPER	0.2486	0.0817	0.0455	0.0133	0.5821	0.3493	0.0996	0.0366	0.1601	0.1277	0.0980	0.0526
J.P. MORGAN CHASE & CO.	0.3487	0.1513	0.1241	0.0808	0.3981	0.2144	0.1375	0.0960	0.3723	0.1539	0.1453	0.1170
JOHNSON & JOHNSON	0.1949	0.0619	0.0486	0.0207	0.3234	0.1401	0.1258	0.1036	0.0859	0.0832	0.0790	0.0654

Table 3.7 continued.

period	1973:1-2001:6				1973:1-1986:12				1987:1-2001:6			
Data set	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%
MCDONALDS	0.1427	0.0557	0.0507	0.0346	0.3379	0.2068	0.1097	0.0850	0.0892	0.0735	0.0626	0.0499
MERCK	0.1920	0.0759	0.0532	0.0465	0.3521	0.1595	0.0539	0.0517	0.1239	0.0911	0.0770	0.0689
MICROSOFT	0.2343	0.1269	0.1026	0.0643					0.2343	0.1269	0.1026	0.0643
MINNESOTA MNG. & MNFG.	0.1718	0.1317	0.0741	0.0028	0.3252	0.1381	0.1245	0.0803	0.2104	0.1692	0.1099	0.0225
PHILIP MORRIS	0.0901	0.0606	0.0537	0.0507	0.2130	0.1416	0.1288	0.0869	0.1168	0.1118	0.1051	0.0838
PROCTER & GAMBLE	0.1339	0.0587	0.0453	0.0255	0.1804	0.0844	0.0614	0.0581	0.1026	0.0679	0.0558	0.0424
SBC COMMUNICATIONS	0.1430	0.1261	0.1013	0.0464					0.1369	0.1201	0.0953	0.0325
SEARS, ROEBUCK & CO.	0.1966	0.0908	0.0903	0.0885	0.3897	0.1639	0.1219	0.1178	0.1344	0.1261	0.1155	0.0892
UNITED TECHNOLOGIES	0.3042	0.1060	0.0582	0.0282	0.3033	0.1084	0.0988	0.0675	0.3050	0.1043	0.0847	0.0323
WAL - MART STORES	0.1733	0.1024	0.0693	0.0543	0.4780	0.3904	0.2686	0.1880	0.1747	0.1026	0.0546	0.0346
WALT DISNEY	0.2374	0.0560	0.0475	0.0474	0.3354	0.1353	0.0885	0.0883	0.1558	0.1044	0.0974	0.0744
Average	0.1898	0.1009	0.0748	0.0534	0.3303	0.1906	0.1273	0.0932	0.1734	0.1275	0.1076	0.0758

Table 3.8: **Estimation results CAPM: 1973-2001, mean return criterion.** Coefficient estimates of the Sharpe-Lintner CAPM in the period January 1, 1973 through June 29, 2001: $r_t^i - r_t^f = \alpha + \beta(r_t^{DJIA} - r_t^f) + \epsilon_t$. That is, the excess return of the best strategy, selected by the mean return criterion, over the risk-free interest rate is regressed against a constant and the excess return of the DJIA over the risk-free interest rate. Estimation results for the 0, 0.10, 0.25, 0.50 and 0.75% costs per trade cases are shown. a, b, c indicates that the corresponding coefficient is, in the case of α, significantly different from zero, or in the case of β, significantly different from one, at the 1, 5, 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

costs per trade	0%		0.10%		0.25%		0.50%		0.75%	
Data set	α	β	α	β	α	β	α	β	α	β
DJIA	0.000539a	0.872c	0.000210b	0.837	0.000206b	0.837c	0.000199b	0.838c	0.000191c	0.839c
ALCOA	0.001299a	0.887	0.000677b	0.885	0.000199	1.206a	0.000188	1.207a	0.000177	1.207a
AMERICAN EXPRESS	0.000762a	1.150c	0.000352	1.06	0.000301	1.06	0.000215	1.061	0.000144	1.228a
AT&T	0.000125	0.681a	9.18E-05	0.681a	6.59E-05	0.87	6.05E-05	0.87	5.51E-05	0.87
BETHLEHEM STEEL	0.000417	0.829c	3.94E-05	0.869	-3.90E-05	0.868	-0.00017	0.867	-0.000301	0.867
BOEING	0.001248a	0.879	0.000597b	0.878	0.000516	1.017	0.000448	1.271a	0.000442	1.271a
CATERPILLAR	0.001245a	0.781b	0.000648b	0.773a	5.32E-05	1.264	-9.66E-05	1.263	-0.000125	0.942c
CHEVRON - TEXACO	0.000630a	0.667a	0.000376	0.744a	0.000282	0.744a	0.000187	0.672a	0.000101	0.672a
CITIGROUP	0.001320a	1.160b	0.000971a	1.702a	0.000962a	1.701a	0.000947a	1.701a	0.000931a	1.701a
COCA - COLA	0.000651a	0.832b	0.000315	0.955	0.000307c	0.782a	0.000304c	0.783a	0.000301c	0.783a
E.I. DU PONT DE NEMOURS	0.000406c	0.872	0.000238	0.918	3.34E-05	0.918	-1.70E-05	1.108	-1.79E-05	1.108
EASTMAN KODAK	-4.80E-05	0.918	-0.000114	0.918	-0.000169	0.977	-0.000222	1.431c	-0.000232	1.431c

Table 3.8 continued.

costs per trade	0%		0.10%		0.25%		0.50%		0.75%	
Data set	α	β	α	β	α	β	α	β	α	β
EXXON MOBIL	0.00029	1.027	0.000217	0.956	0.000211	0.956	0.000202	0.956	0.000193	0.956
GENERAL ELECTRIC	0.000499b	1.017	0.000345c	1.085	0.000324	1.213	0.000302	1.214	0.000266	1.611a
GENERAL MOTORS	0.000264	0.861	0.000206	0.674a	0.000202	0.674a	0.000195	0.674a	0.000188	0.674a
GOODYEAR TIRE	0.000519c	0.789a	0.000234	0.603a	0.000232	0.604a	0.000229	0.605a	0.000226	0.606a
HEWLETT - PACKARD	0.000474c	1.083	0.000455c	1.083	0.000428c	1.083	0.000382	1.082	0.000336	1.082
HOME DEPOT	0.001311a	1.578c	0.001082b	1.578c	0.001009b	0.969	0.000927b	1.102	0.000815b	1.460a
HONEYWELL INTL.	0.000581c	0.611a	0.000554c	0.611a	0.000513c	0.611a	0.000445	0.611a	0.000377	0.612a
INTEL	0.000896b	1.096	0.000506	1.420a	0.000455	1.420a	0.000462	1.181b	0.000441	1.181b
INTL. BUS. MACH.	0.000294	0.772b	0.000214	0.772b	0.000115	0.704a	0.000109	0.704a	0.000104	0.704a
INTERNATIONAL PAPER	0.000675a	0.932	0.000106	0.927	-2.36E-05	0.83	-0.000118	0.973	-0.000164	1.134
J.P. MORGAN CHASE & CO.	0.001124a	0.792b	0.000496c	0.791b	0.000389	1.027	0.000308	1.028	0.000243	0.819c
JOHNSON & JOHNSON	0.000795a	0.769a	0.000328	0.746b	0.000277	0.746b	0.000193	0.746b	0.000148	1.183a
MCDONALDS	0.000597b	0.893	0.000292	0.711a	0.000273	0.711a	0.000241	0.711a	0.00021	0.730a
MERCK	0.000818a	0.917	0.000412c	0.916	0.000329	0.887b	0.000316	0.888b	0.000303	0.888b
MICROSOFT	0.001735a	0.891	0.001342b	1.025	0.001255b	1.026	0.001036b	1.518b	0.001029b	1.518b
MINNESOTA MNG. & MNFG.	0.000536a	0.896	0.000398b	0.896	0.000191	0.897	-4.32E-06	0.882	-8.65E-05	0.977
PHILIP MORRIS	0.000522c	0.854c	0.000421c	0.709a	0.000372	1.154b	0.000366	1.153b	0.000361	1.153b
PROCTER & GAMBLE	0.000494b	0.821b	0.0002	1.221	0.000149	1.221	0.000115	0.851b	9.42E-05	0.852b
SBC COMMUNICATIONS	0.000602b	0.577a	0.000543b	0.577a	0.000455c	0.577a	0.000308	0.578a	0.00011	1.121
SEARS, ROEBUCK & CO.	0.000513b	0.88	0.000155	0.714a	0.000153	0.715a	0.00015	0.715a	0.000146	0.716a
UNITED TECHNOLOGIES	0.001255a	0.868	0.000600b	0.868	0.000437b	0.648a	0.000375b	0.648a	0.000303c	1.021
WAL - MART STORES	0.001106a	1.119	0.000854a	1.118	0.000714b	1.209	0.000683b	1.21	0.000663b	1.192c
WALT DISNEY	0.000983a	0.93	0.000363	0.742b	0.000302	1.274a	0.000302	1.274a	0.000301	1.274a

Table 3.10: **Testing for predictive ability: mean return criterion.** Nominal (p_n), White's (2000) Reality Check (p_W) and Hansen's (2001) Superior Predictive Ability (p_H) p-values, when strategies are ranked by the mean return criterion, for the period 1973:1-2001:6 in the case of 0 and 0.10% costs per trade, for the period 1973:1-1986:12 in the case of 0 and 0.25% costs per trade and for the period 1987:1-2001:6 only in the case of 0% costs per trade.

period	1973:1-2001:6						1973:1-1986:12						1987:1-2001:6		
costs per trade	0%			0.10%			0%			0.25%			0%		
Data set	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
DJIA	0	0.92	0.06	0	1	0.85	0	0.91	0.03	0	1	0.52	0	0.92	0.1
ALCOA	0	0.86	0	0	0.99	0.45	0	0.82	0.01	0.01	1	0.95	0	0.82	0.2

Table 3.10 continued.

period	1973:1-2001:6						1973:1-1986:12						1987:1-2001:6		
costs per trade	0%			0.10%			0%			0.25%			0%		
Data set	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
AMERICAN EXPRESS	0	0.81	0.54	0	1	0.97	0	0.01	0.01	0	1	0.82	0	1	0.99
AT&T	0	1	0.98	0	1	0.98	0.01	1	0.84	0	1	0.96	0	1	0.96
BETHLEHEM STEEL	0	1	0.73	0	1	0.98	0	1	0.22	0	1	0.98	0	1	1
BOEING	0	0.97	0.01	0.03	1	0.97	0	0.98	0.09	0	1	0.96	0	0.96	0.47
CATERPILLAR	0	0.85	0.44	0	0.98	0.92	0	0.85	0.11	0	1	0.98	0	0.99	0.92
CHEVRON - TEXACO	0	0.96	0.09	0	1	0.65	0	0.92	0	0	1	0.75	0	1	0.77
CITIGROUP	0	1	0.69	0	1	0.87							0	1	0.69
COCA - COLA	0	0.98	0.83	0	1	0.99	0	0.99	0.48	0	1	0.98	0	1	0.99
E.I. DU PONT DE NEMOURS	0	0.99	0.47	0	1	0.87	0	0.92	0.28	0	1	0.99	0	0.78	0.14
EASTMAN KODAK	0	1	0.98	0	1	0.99	0	1	0.44	0	1	0.46	0	1	1
EXXON MOBIL	0	1	0.92	0	1	0.98	0	0.96	0.46	0	1	0.95	0	1	0.69
GENERAL ELECTRIC	0.02	1	0.94	0	1	0.99	0	0.94	0.76	0	1	0.95	0	1	0.96
GENERAL MOTORS	0.01	1	0.98	0	1	0.98	0	0.9	0.82	0	1	0.94	0	1	0.78
GOODYEAR TIRE	0	1	0.8	0	1	0.99	0	0.99	0.35	0	1	0.59	0	1	0.98
HEWLETT - PACKARD	0	1	0.98	0	1	0.96	0	1	0.83	0	1	0.99	0	1	0.98
HOME DEPOT	0	1	0.38	0	1	0.85							0	1	0.27
HONEYWELL INTL.	0	1	0.97	0	1	0.97							0	1	0.97
INTEL	0.02	1	1	0	1	1	0	1	0.99	0	1	1	0.08	1	1
INTL. BUS. MACH.	0	1	0.81	0	1	0.91	0	1	0.96	0	1	0.96	0	1	0.79
INTERNATIONAL PAPER	0	0.75	0.16	0.02	1	1	0	0.66	0	0.02	1	0.99	0	1	0.94
J.P. MORGAN CHASE & CO.	0	1	0	0	1	0.84	0	0.88	0.06	0	1	0.94	0	1	0.77
JOHNSON & JOHNSON	0	0.85	0.06	0	1	0.98	0	0.7	0.27	0	1	0.98	0	1	0.94
MCDONALDS	0.02	1	0.44	0	1	0.99	0	1	0.04	0	1	0.96	0	1	0.96
MERCK	0	0.96	0.04	0	1	0.86	0	0.9	0.01	0	1	1	0	1	0.58
MICROSOFT	0	1	0.97	0	1	1							0	1	0.97
MINNESOTA MNG. & MNFG.	0	0.97	0.12	0	1	0.42	0	1	0.08	0	1	0.93	0	0.76	0.04
PHILIP MORRIS	0.08	1	0.88	0	1	0.96	0	0.81	0.25	0	1	0.71	0	1	0.99
PROCTER & GAMBLE	0	1	0.84	0	1	1	0	1	0.93	0	1	1	0.02	1	1
SBC COMMUNICATIONS	0	0.98	0.54	0	1	0.66							0	1	0.76
SEARS, ROEBUCK & CO.	0	1	0.29	0	1	0.98	0	1	0.01	0	1	0.8	0	1	0.99
UNITED TECHNOLOGIES	0	0.95	0	0	1	0.76	0	0.99	0	0	1	0.8	0	0.38	0.28
WAL - MART STORES	0	0.98	0.34	0	1	0.89	0	0.72	0	0	1	0.22	0	1	0.75
WALT DISNEY	0	1	0.31	0	1	1	0	1	0.76	0	1	1	0.07	1	0.97

Table 3.12: **Statistics best strategy: 1973-2001, Sharpe ratio criterion, 0 and 0.25% costs.** Statistics of the best strategy, selected by the Sharpe ratio criterion, if 0 and 0.25% costs per trade are implemented, for each data series listed in the first column. Column 2 shows the strategy parameters. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio. Column 7 shows the largest cumulative loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades. Results are only shown for those data series for which a different best strategy is selected by the Sharpe ratio criterion than by the mean return criterion.

0% costs per trade										
Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
CITIGROUP	[FR: 0.005, 0, 5]	0.5350	0.2047	0.0542	0.0208	-0.6571	786	0.659	0.749	1.1370
HOME DEPOT	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.5925	0.2019	0.0497	0.0128	-0.7714	1993	0.685	0.787	1.2589
MERCK	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.3381	0.1895	0.0390	0.0283	-0.5995	2877	0.696	0.807	1.2504
PHILIP MORRIS	[FR: 0.080, 0, 50]	0.2094	0.0603	0.0234	0.0107	-0.6697	163	0.755	0.835	0.9455
0.25% costs per trade										
Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
ALCOA	[FR: 0.090, 0, 25]	0.1325	0.0350	0.0100	0.0069	-0.4430	258	0.647	0.688	1.1084
BOEING	[FR: 0.100, 0, 25,]	0.2346	0.0391	0.0242	0.0046	-0.6514	212	0.679	0.718	0.9502
E.I. DU PONT DE NEMOURS	[MA: 25, 50, 0.000, 0, 50, 0.000]	0.0984	0.0348	0.0039	0.0076	-0.5338	165	0.685	0.745	1.0104
EASTMAN KODAK	[MA: 25, 50, 0.050, 0, 0, 0.000]	0.0416	0.0368	-0.0041	0.0114	-0.9162	16	0.688	0.775	1.0509
GENERAL ELECTRIC	[MA: 2, 200, 0.000, 0, 25, 0.000]	0.1607	0.0224	0.0177	0.0046	-0.5022	108	0.685	0.716	0.9953
HOME DEPOT	[MA: 2, 5, 0.050, 0, 0, 0.000]	0.4571	0.0998	0.0398	0.0029	-0.6544	25	0.680	0.941	0.7174
INTEL	[SR: 150, 0.000, 0, 50, 0.000]	0.2737	0.0442	0.0229	0.0055	-0.6109	47	0.723	0.696	0.9037
INTL. BUS. MACH.	[SR: 100, 0.000, 0, 0, 0.050]	0.1138	0.0387	0.0074	0.0086	-0.6570	79	0.519	0.601	0.9881
J.P. MORGAN CHASE & CO.	[MA: 1, 100, 0.000, 0, 50, 0.000]	0.1887	0.1089	0.0166	0.0176	-0.7393	149	0.698	0.725	0.9109
MICROSOFT	[MA: 2, 100, 0.000, 0, 10, 0.000]	0.4528	0.0495	0.0485	0.0060	-0.6099	133	0.481	0.720	0.7916
PHILIP MORRIS	[FR: 0.080, 0, 50]	0.1924	0.0455	0.0206	0.0078	-0.6714	163	0.748	0.833	0.9402
PROCTER & GAMBLE	[FR: 0.120, 0, 50]	0.1238	0.0328	0.0105	0.0081	-0.4245	94	0.734	0.719	1.2723
WAL - MART STORES	[SR: 200, 0.025, 0, 0, 0.000]	0.3531	0.0566	0.0366	0.0012	-0.5933	5	1.000	1.000	NA
WALT DISNEY	[SR: 250, 0.050, 0, 0, 0.000]	0.1595	0.0265	0.0182	0.0091	-0.5259	4	0.750	0.999	0.5323

Table 3.13: **Sharpe ratio best strategy in excess of Sharpe ratio buy-and-hold.** Sharpe ratio of the best strategy, selected by the Sharpe ratio criterion after implementing 0, 0.10, 0.25 and 0.75% costs per trade, in excess of the Sharpe ratio of the buy-and-hold benchmark, for the full sample period 1973:1-2001:6 and the two subperiods 1973:1-1986:12 and 1987:1-2001:6, for each data series listed in the first column.

period	1973:1-2001:6				1973:1-1986:12				1987:1-2001:6			
Data set	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%
DJIA	0.0385	0.0156	0.0153	0.0141	0.0557	0.0317	0.0314	0.0304	0.0279	0.0135	0.0104	0.0096
ALCOA	0.0474	0.0240	0.0069	0.0055	0.0698	0.0513	0.0271	0.0115	0.0302	0.0255	0.0186	0.0032
AMERICAN EXPRESS	0.0270	0.0132	0.0113	0.0059	0.0756	0.0515	0.0277	0.0162	0.0179	0.0159	0.0143	0.0133
AT&T	0.0148	0.0131	0.0123	0.0118	0.0327	0.0201	0.0201	0.0201	0.0179	0.0164	0.0153	0.0140
BETHLEHEM STEEL	0.0389	0.0282	0.0255	0.0187	0.0728	0.0487	0.0372	0.0307	0.0313	0.0298	0.0274	0.0195
BOEING	0.0277	0.0066	0.0046	0.0006	0.0387	0.0188	0.0093	0.0080	0.0259	0.0164	0.0135	0.0037
CATERPILLAR	0.0569	0.0326	0.0093	0.0008	0.0919	0.0646	0.0342	0.0153	0.0320	0.0255	0.0219	0.0100
CHEVRON - TEXACO	0.0290	0.0172	0.0129	0.0046	0.0650	0.0351	0.0250	0.0123	0.0209	0.0192	0.0166	0.0079
CITIGROUP	0.0208	0.0162	0.0136	0.0125					0.0208	0.0162	0.0136	0.0125
COCA - COLA	0.0254	0.0151	0.0150	0.0146	0.0501	0.0289	0.0289	0.0286	0.0120	0.0120	0.0119	0.0117
E.I. DU PONT DE NEMOURS	0.0238	0.0170	0.0076	0.0056	0.0500	0.0309	0.0208	0.0193	0.0341	0.0231	0.0132	0.0062
EASTMAN KODAK	0.0154	0.0127	0.0114	0.0108	0.0347	0.0339	0.0327	0.0286	0.0242	0.0186	0.0138	0.0044
EXXON MOBIL	0.0106	0.0074	0.0072	0.0063	0.0393	0.0205	0.0202	0.0193	0.0175	0.0157	0.0131	0.0042
GENERAL ELECTRIC	0.0132	0.0061	0.0046	0.0021	0.0377	0.0236	0.0208	0.0117	0.0105	0.0102	0.0096	0.0077
GENERAL MOTORS	0.0198	0.0181	0.0179	0.0173	0.0514	0.0388	0.0385	0.0376	0.0277	0.0270	0.0258	0.0218
GOODYEAR TIRE	0.0280	0.0166	0.0166	0.0164	0.0377	0.0349	0.0307	0.0167	0.0401	0.0400	0.0398	0.0392
HEWLETT - PACKARD	0.0136	0.0128	0.0118	0.0082	0.0217	0.0139	0.0122	0.0069	0.0183	0.0177	0.0168	0.0136
HOME DEPOT	0.0128	0.0053	0.0029	0.0011					0.0212	0.0066	0.0054	0.0023
HONEYWELL INTL.	0.0289	0.0277	0.0258	0.0196					0.0265	0.0252	0.0234	0.0171
INTEL	0.0103	0.0059	0.0055	0.0041	0.0366	0.0289	0.0258	0.0215	0.0122	0.0107	0.0086	0.0072
INTL. BUS. MACH.	0.0166	0.0129	0.0086	0.0080	0.0235	0.0212	0.0194	0.0167	0.0217	0.0203	0.0201	0.0196
INTERNATIONAL PAPER	0.0378	0.0149	0.0095	0.0041	0.0831	0.0557	0.0208	0.0090	0.0247	0.0201	0.0139	0.0085
J.P. MORGAN CHASE & CO.	0.0444	0.0210	0.0176	0.0133	0.0622	0.0370	0.0251	0.0185	0.0425	0.0217	0.0206	0.0167
JOHNSON & JOHNSON	0.0315	0.0093	0.0069	0.0023	0.0578	0.0285	0.0261	0.0248	0.0094	0.0062	0.0051	0.0029
MCDONALDS	0.0193	0.0119	0.0109	0.0073	0.0458	0.0294	0.0203	0.0147	0.0137	0.0131	0.0124	0.0098
MERCK	0.0283	0.0094	0.0076	0.0064	0.0591	0.0292	0.0137	0.0134	0.0147	0.0102	0.0097	0.0083
MICROSOFT	0.0165	0.0082	0.0060	0.0028					0.0165	0.0082	0.0060	0.0028
MINNESOTA MNG. & MNFG.	0.0330	0.0259	0.0153	0.0011	0.0637	0.0335	0.0307	0.0215	0.0362	0.0293	0.0190	0.0026
PHILIP MORRIS	0.0107	0.0095	0.0078	0.0065	0.0324	0.0220	0.0200	0.0131	0.0177	0.0152	0.0115	0.0083
PROCTER & GAMBLE	0.0236	0.0098	0.0081	0.0054	0.0439	0.0245	0.0191	0.0183	0.0157	0.0146	0.0129	0.0093
SBC COMMUNICATIONS	0.0243	0.0213	0.0169	0.0029					0.0232	0.0203	0.0160	0.0023
SEARS, ROEBUCK & CO.	0.0305	0.0167	0.0166	0.0164	0.0653	0.0331	0.0264	0.0257	0.0202	0.0185	0.0173	0.0137
UNITED TECHNOLOGIES	0.0414	0.0135	0.0115	0.0046	0.0403	0.0187	0.0161	0.0100	0.0424	0.0182	0.0149	0.0050

Table 3.13 continued.

period	1973:1-2001:6				1973:1-1986:12				1987:1-2001:6			
Data set	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%	0%	0.10%	0.25%	0.75%
WAL - MART STORES	0.0144	0.0052	0.0012	0.0008	0.0476	0.0380	0.0235	0.0064	0.0164	0.0076	0.0052	-0.0009
WALT DISNEY	0.0288	0.0092	0.0091	0.0089	0.0410	0.0183	0.0163	0.0158	0.0182	0.0174	0.0162	0.0123
Average	0.0258	0.0146	0.0112	0.0078	0.0509	0.0322	0.0240	0.0181	0.0229	0.0179	0.0153	0.0100

Table 3.14: **Estimation results CAPM: 1973-2001, Sharpe ratio criterion.** Coefficient estimates of the Sharpe-Lintner CAPM in the period January 1, 1973 through June 29, 2001: $r_t^i - r_t^f = \alpha + \beta(r_t^{DJIA} - r_t^f) + \epsilon_t$. That is, the excess return of the best strategy, selected by the Sharpe ratio criterion, over the risk-free interest rate is regressed against a constant and the excess return of the DJIA over the risk-free interest rate. Estimation results for the 0, 0.10, 0.25, 0.50 and 0.75% costs per trade cases are shown. a, b, c indicates that the corresponding coefficient is, in the case of α, significantly different from zero, or in the case of β, significantly different from one, at the 1, 5, 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

costs per trade	0%		0.10%		0.25%		0.50%		0.75%	
Data set	α	β	α	β	α	β	α	β	α	β
DJIA	0.000539a	0.872c	0.000210b	0.837	0.000206b	0.837c	0.000199b	0.838c	0.000191c	0.839c
ALCOA	0.001299a	0.887	0.000677b	0.885	0.000158	0.738a	0.000188	1.207a	0.000177	1.207a
AMERICAN EXPRESS	0.000762a	1.150c	0.000352	1.06	0.000301	1.06	0.000215	1.061	0.000144	1.228a
AT&T	0.000125	0.681a	9.18E-05	0.681a	6.59E-05	0.87	6.05E-05	0.87	5.51E-05	0.87
BETHLEHEM STEEL	0.000417	0.829c	4.16E-05	0.434a	-3.90E-05	0.868	-0.00017	0.867	-0.000301	0.867
BOEING	0.001248a	0.879	0.000540b	0.83	0.000496b	0.83	0.000422c	0.83	0.000444c	1.215a
CATERPILLAR	0.001245a	0.781b	0.000648b	0.773a	5.32E-05	1.264	-9.66E-05	1.263	-0.000178	1.195
CHEVRON - TEXACO	0.000630a	0.667a	0.000376	0.744a	0.000282	0.744a	0.000187	0.672a	0.000101	0.672a
CITIGROUP	0.001185a	1.114	0.001045a	0.926	0.000962a	1.701a	0.000947a	1.701a	0.000931a	1.701a
COCA - COLA	0.000651a	0.832b	0.000308c	0.782a	0.000307c	0.782a	0.000304c	0.783a	0.000301c	0.783a
E.I. DU PONT DE NEMOURS	0.000406c	0.872	0.000238	0.918	3.17E-05	0.816c	-1.70E-05	1.108	-1.79E-05	1.108
EASTMAN KODAK	-4.80E-05	0.918	-0.000114	0.918	-0.000212	1.431c	-0.000222	1.431c	-0.000232	1.431c
EXXON MOBIL	0.00029	1.027	0.000217	0.956	0.000211	0.956	0.000202	0.956	0.000193	0.956
GENERAL ELECTRIC	0.000499b	1.017	0.000307c	0.790c	0.000242c	0.988	0.000302	1.214	0.00028	1.215
GENERAL MOTORS	0.000264	0.861	0.000206	0.674a	0.000202	0.674a	0.000195	0.674a	0.000188	0.674a
GOODYEAR TIRE	0.000519c	0.789a	0.000234	0.603a	0.000232	0.604a	0.000229	0.605a	0.000226	0.606a
HEWLETT - PACKARD	0.000474c	1.083	0.000455c	1.083	0.000428c	1.083	0.000382	1.082	0.000336	1.082
HOME DEPOT	0.001339a	0.977	0.001082b	1.578c	0.000955b	1.102	0.000927b	1.102	0.000900b	1.103
HONEYWELL INTL.	0.000581c	0.611a	0.000554c	0.611a	0.000513c	0.611a	0.000445	0.611a	0.000377	0.612a
INTEL	0.000896b	1.096	0.000494	1.181b	0.000482	1.181b	0.000462	1.181b	0.000441	1.181b
INTL. BUS. MACH.	0.000294	0.772b	0.000214	0.772b	8.23E-05	0.916	0.000109	0.704a	0.000104	0.704a

Table 3.14 continued.

costs per trade	0%		0.10%		0.25%		0.50%		0.75%	
Data set	α	β	α	β	α	β	α	β	α	β
INTERNATIONAL PAPER	0.000675a	0.932	0.000106	0.927	-2.36E-05	0.83	-0.000118	0.973	-0.000164	1.134
J.P. MORGAN CHASE & CO.	0.001124a	0.792b	0.000496c	0.791b	0.000345	0.819c	0.000294	0.819c	0.000243	0.819c
JOHNSON & JOHNSON	0.000795a	0.769a	0.000328	0.746b	0.000277	0.746b	0.000193	0.746b	0.000148	1.183a
MCDONALDS	0.000597b	0.893	0.000292	0.711a	0.000273	0.711a	0.000241	0.711a	0.000209	0.711a
MERCK	0.000814a	0.848	0.000412c	0.916	0.000329	0.887b	0.000316	0.888b	0.000303	0.888b
MICROSOFT	0.001735a	0.891	0.001111a	1.063	0.001057a	1.062	0.000924a	1.200a	0.000917a	1.201a
MINNESOTA MNG. & MNFG.	0.000536a	0.896	0.000398b	0.896	0.000191	0.897	-4.32E-06	0.882	-8.67E-05	0.882
PHILIP MORRIS	0.000420b	0.702a	0.000398b	0.702a	0.000364c	0.702a	0.000310c	0.915b	0.000308c	0.915b
PROCTER & GAMBLE	0.000494b	0.821b	0.000156	0.617a	0.000133	0.636a	0.0001	0.636a	7.45E-05	0.954
SBC COMMUNICATIONS	0.000602b	0.577a	0.000543b	0.577a	0.000455c	0.577a	0.000308	0.578a	0.00011	1.121
SEARS, ROEBUCK & CO.	0.000513b	0.88	0.000155	0.714a	0.000153	0.715a	0.00015	0.715a	0.000146	0.716a
UNITED TECHNOLOGIES	0.001255a	0.868	0.000474b	0.648a	0.000437b	0.648a	0.000375b	0.648a	0.000314c	0.648a
WAL - MART STORES	0.001106a	1.119	0.000854a	1.118	0.000670b	1.192c	0.000666b	1.192c	0.000663b	1.192c
WALT DISNEY	0.000983a	0.93	0.000253	0.731c	0.000252	0.731c	0.00025	0.731c	0.000248	0.731c

Table 3.16: **Testing for predictive ability: Sharpe ratio criterion.** Nominal (p_n), White's (2000) Reality Check (p_W) and Hansen's (2001) Superior Predictive Ability (p_H) p-values, when strategies are ranked by the Sharpe ratio criterion, for the full sample period 1973:1-2001:6 in the case of 0 and 0.10% costs per trade and for the subperiods 1973:1-1986:12 and 1987:1-2001:6 in the case of 0 and 0.25% costs per trade.

period	1973:1-2001:6						1973:1-1986:12						1987:1-2001:6					
costs per trade	0%			0.10%			0%			0.25%			0%			0.25%		
Data set	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
DJIA	0	0.21	0.06	0.05	1	0.46	0	0.24	0.05	0.01	0.97	0.26	0	0.93	0.28	0.04	1	0.7
ALCOA	0	0.02	0	0	0.86	0.04	0	0.02	0	0	0.98	0.29	0	0.93	0.12	0	1	0.37
AMERICAN EXPRESS	0	0.54	0.06	0	0.99	0.44	0	0.02	0	0	0.99	0.29	0	1	0.56	0	1	0.52
AT&T	0	1	0.47	0	1	0.46	0.02	0.71	0.21	0.05	1	0.41	0	1	0.69	0	1	0.64
BETHLEHEM STEEL	0	0.18	0.05	0	0.55	0.14	0	0.03	0.02	0	0.72	0.35	0	0.82	0.36	0	0.91	0.35
BOEING	0	0.74	0.01	0	1	0.77	0	0.94	0.01	0	1	0.8	0.01	0.99	0.23	0	1	0.68
CATERPILLAR	0	0.04	0.01	0	0.42	0.04	0	0.02	0.01	0	0.88	0.27	0	0.91	0.16	0	1	0.3
CHEVRON - TEXACO	0.01	0.49	0.04	0	0.98	0.17	0	0.02	0	0	0.99	0.25	0	1	0.26	0	1	0.28
CITIGROUP	0	1	0.24	0	1	0.3							0	1	0.24	0	1	0.33
COCA - COLA	0	0.66	0.06	0.02	1	0.22	0	0.36	0.06	0.02	0.97	0.3	0	1	0.81	0	1	0.51
E.I. DU PONT DE NEMOURS	0.01	0.79	0.15	0	0.97	0.27	0	0.24	0.06	0.01	0.99	0.58	0	0.69	0.03	0	1	0.56

Table 3.16 continued.

period	1973:1-2001:6						1973:1-1986:12						1987:1-2001:6					
costs per trade	0%			0.10%			0%			0.25%			0%			0.25%		
Data set	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
EASTMAN KODAK	0	0.98	0.56	0	1	0.66	0	0.64	0.18	0	0.74	0.16	0	0.99	0.39	0	1	0.73
EXXON MOBIL	0.03	1	0.44	0.04	1	0.5	0	0.6	0.08	0.01	1	0.35	0	1	0.17	0	1	0.21
GENERAL ELECTRIC	0.05	1	0.36	0.01	1	0.69	0.01	0.65	0.11	0	1	0.37	0	1	0.76	0	1	0.56
GENERAL MOTORS	0.02	0.96	0.26	0.04	0.98	0.26	0	0.35	0.08	0.02	0.74	0.17	0	0.94	0.19	0	0.96	0.16
GOODYEAR TIRE	0	0.72	0.13	0.05	1	0.52	0	0.75	0.27	0	0.96	0.28	0	0.68	0.05	0	0.68	0.03
HEWLETT - PACKARD	0	1	0.37	0	1	0.3	0	1	0.57	0.01	1	0.77	0	1	0.34	0	1	0.24
HOME DEPOT	0.09	1	0.71	0.07	1	0.92							0.01	1	0.22	0.01	1	0.76
HONEYWELL INTL.	0	0.96	0.12	0	0.98	0.12							0	0.98	0.2	0	1	0.19
INTEL	0.08	1	0.65	0.01	1	0.81	0	0.95	0.22	0	1	0.42	0	1	0.76	0	1	0.72
INTL. BUS. MACH.	0	0.96	0.44	0	0.99	0.57	0	0.98	0.58	0.01	1	0.55	0	0.99	0.58	0	1	0.41
INTERNATIONAL PAPER	0	0.16	0.03	0.02	1	0.49	0	0.02	0.01	0.01	1	0.5	0	0.98	0.36	0	1	0.62
J.P. MORGAN CHASE & CO.	0	0.04	0.01	0	0.88	0.18	0	0.12	0.02	0	0.98	0.42	0	0.42	0.01	0	1	0.4
JOHNSON & JOHNSON	0	0.28	0.03	0	1	0.53	0	0.09	0.04	0	0.92	0.33	0	1	0.86	0.01	1	0.84
MCDONALDS	0.03	0.96	0.27	0	1	0.48	0	0.35	0.08	0	0.99	0.56	0	1	0.76	0	1	0.54
MERCK	0	0.66	0.06	0	1	0.57	0	0.08	0.02	0.07	1	0.77	0	1	0.64	0	1	0.63
MICROSOFT	0.01	1	0.26	0	1	0.74							0.01	1	0.26	0	1	0.77
MINNESOTA MNG. & MNFG.	0	0.3	0.04	0	0.7	0.06	0	0.04	0.02	0	0.88	0.18	0	0.56	0	0	1	0.23
PHILIP MORRIS	0	1	0.66	0	1	0.47	0.01	0.81	0.22	0	1	0.33	0	1	0.53	0	1	0.58
PROCTER & GAMBLE	0	0.74	0.12	0	1	0.66	0.01	0.54	0.1	0	1	0.62	0	1	0.74	0	1	0.65
SBC COMMUNICATIONS	0	0.99	0.15	0	1	0.14							0	1	0.21	0	1	0.27
SEARS, ROEBUCK & CO.	0	0.36	0.05	0.04	0.98	0.39	0	0.03	0.02	0.02	0.99	0.4	0	1	0.5	0	1	0.45
UNITED TECHNOLOGIES	0	0.1	0.01	0	1	0.35	0	0.76	0.09	0	1	0.64	0	0.57	0.03	0	1	0.58
WAL - MART STORES	0	1	0.24	0.02	1	0.72	0	0.95	0.02	0	1	0.29	0	1	0.39	0	1	0.83
WALT DISNEY	0	0.55	0.04	0.04	1	0.81	0.01	0.66	0.18	0.04	1	0.9	0	1	0.59	0	1	0.39

Table 3.18: **Statistics best out-of-sample testing procedure: mean return criterion, 0.25% costs.** Statistics of the best recursively optimizing and testing procedure applied to each data series listed in the first column in the case of 0.25% costs per trade. The best strategy in the optimizing period is selected on the basis of the mean return criterion. Column 2 shows the sample period. Column 3 shows the parameters: [length optimizing period, length testing period]. Columns 4 and 5 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 6 and 7 show the Sharpe and excess Sharpe ratio. Column 8 shows the largest cumulative loss in %/100 terms. Columns 9, 10 and 11 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr > 0$	$\%d > 0$	SDR
DJIA	10/31/78-6/29/01	[1008, 252]	0.1349	0.0198	0.0146	0.0018	-0.4311	164	0.494	0.881	1.0635
ALCOA	10/31/78-6/29/01	[1260, 126]	0.2044	0.0881	0.0172	0.0102	-0.6114	1278	0.292	0.541	1.1771
AMERICAN EXPRESS	10/31/78-6/29/01	[756, 126]	0.1247	0.0011	0.0059	-0.0018	-0.7433	378	0.526	0.693	1.0498
AT&T	10/31/78-6/29/01	[1260, 252]	0.0145	-0.0359	-0.0097	-0.0035	-0.9082	182	0.626	0.738	0.9071
BETHLEHEM STEEL	10/31/78-6/29/01	[1008, 252]	0.1782	0.2726	0.0107	0.0350	-0.7102	917	0.266	0.610	1.1660
BOEING	10/31/78-6/29/01	[126, 10]	0.1240	0.0054	0.0063	-0.0012	-0.6747	678	0.409	0.629	0.9991
CATERPILLAR	10/31/78-6/29/01	[1260, 252]	0.2062	0.1502	0.0168	0.0213	-0.5878	1473	0.249	0.501	1.0641
CHEVRON - TEXACO	10/31/78-6/29/01	[1008, 126]	0.1195	0.0251	0.0070	0.0036	-0.5047	736	0.327	0.641	1.1284
CITIGROUP	8/26/92-6/29/01	[42, 10]	0.4220	0.0727	0.0369	-0.0068	-0.5172	321	0.371	0.541	1.1087
COCA - COLA	10/31/78-6/29/01	[252, 126]	0.1577	0.0080	0.0123	-0.0028	-0.7893	555	0.404	0.658	1.0912
E.I. DU PONT DE NEMOURS	10/31/78-6/29/01	[1260, 126]	0.0293	-0.0563	-0.0081	-0.0096	-0.7602	598	0.426	0.568	0.9584
EASTMAN KODAK	10/31/78-6/29/01	[1260, 252]	0.0055	-0.0297	-0.0130	-0.0039	-0.7596	288	0.462	0.731	0.9212
EXXON MOBIL	10/31/78-6/29/01	[1260, 126]	0.1135	-0.0060	0.0057	-0.0046	-0.6069	219	0.516	0.733	1.1681
GENERAL ELECTRIC	10/31/78-6/29/01	[756, 252]	0.1743	-0.0052	0.0142	-0.0087	-0.6596	187	0.588	0.811	0.8271
GENERAL MOTORS	10/31/78-6/29/01	[504, 252]	0.0700	0.0252	-0.0013	0.0058	-0.6637	353	0.439	0.676	0.8982
GOODYEAR TIRE	10/31/78-6/29/01	[252, 126]	0.1014	0.0463	0.0031	0.0076	-0.8122	503	0.408	0.636	1.0959
HEWLETT - PACKARD	10/31/78-6/29/01	[504, 252]	0.1656	0.0101	0.0096	-0.0019	-0.8086	467	0.493	0.637	1.0680
HOME DEPOT	10/30/89-6/29/01	[126, 42]	0.4145	0.0964	0.0403	0.0002	-0.4604	346	0.376	0.620	0.8692
HONEYWELL INTL.	7/18/91-6/29/01	[1260, 252]	0.1958	0.0609	0.0166	0.0020	-0.6052	87	0.494	0.806	0.6487
INTEL	10/29/84-6/29/01	[252, 126]	0.3172	0.0611	0.0236	0.0001	-0.6988	419	0.372	0.672	1.1498
INTL. BUS. MACH.	10/31/78-6/29/01	[1260, 126]	0.0348	-0.0490	-0.0061	-0.0071	-0.8511	154	0.571	0.753	0.9488
INTERNATIONAL PAPER	10/31/78-6/29/01	[1260, 126]	0.0871	0.0327	0.0011	0.0060	-0.7551	884	0.309	0.561	0.9877
J.P. MORGAN CHASE & CO.	10/31/78-6/29/01	[756, 252]	0.2001	0.1104	0.0145	0.0126	-0.7584	441	0.358	0.673	1.0335
JOHNSON & JOHNSON	10/31/78-6/29/01	[1008, 252]	0.1089	-0.0505	0.0042	-0.0135	-0.6874	291	0.495	0.803	0.9719
MCDONALDS	10/31/78-6/29/01	[252, 126]	0.1173	-0.0246	0.0063	-0.0074	-0.5120	463	0.445	0.630	1.0525
MERCK	10/31/78-6/29/01	[252, 126]	0.1658	-0.0036	0.0136	-0.0065	-0.8547	469	0.458	0.748	0.9708
MICROSOFT	1/09/92-6/29/01	[21, 10]	0.4215	0.1123	0.0385	0.0009	-0.5474	306	0.366	0.538	0.9815
MINNESOTA MNG. & MNFG.	10/31/78-6/29/01	[126, 63]	0.0758	-0.0172	-0.0006	-0.0041	-0.6431	517	0.435	0.600	1.1240
PHILIP MORRIS	10/31/78-6/29/01	[252, 10]	0.1660	0.0026	0.0128	-0.0040	-0.6785	450	0.411	0.661	0.9167
PROCTER & GAMBLE	10/31/78-6/29/01	[756, 126]	0.0629	-0.0491	-0.0027	-0.0101	-0.5250	302	0.520	0.716	0.9495

Table 3.18 continued.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr > 0$	$\%d > 0$	SDR
SBC COMMUNICATIONS	9/18/89-6/29/01	[252, 42]	0.1027	0.0106	0.0071	-0.0007	-0.6655	260	0.442	0.624	0.8597
SEARS, ROEBUCK & CO.	10/31/78-6/29/01	[1008, 252]	0.0683	-0.0066	-0.0014	-0.0006	-0.7466	685	0.236	0.617	1.0365
UNITED TECHNOLOGIES	10/31/78-6/29/01	[1260, 252]	0.1123	-0.0112	0.0054	-0.0042	-0.5593	663	0.330	0.710	0.9482
WAL - MART STORES	10/30/86-6/29/01	[252, 21]	0.2833	0.0778	0.0275	0.0024	-0.7779	315	0.432	0.655	1.0760
WALT DISNEY	10/31/78-6/29/01	[1008, 126]	0.1964	0.0301	0.0163	0.0005	-0.6901	291	0.509	0.786	1.0927

Table 3.19: **Statistics best out-of-sample testing procedure: Sharpe ratio criterion, 0.25% costs.** Statistics of the best recursively optimizing and testing procedure applied to each data series listed in the first column in the case of 0.25% costs per trade. The best strategy in the optimizing period is selected on the basis of the Sharpe ratio criterion. Column 2 shows the sample period. Column 3 shows the parameters: [length optimizing period, length testing period]. Columns 4 and 5 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 6 and 7 show the Sharpe and excess Sharpe ratio. Column 8 shows the largest cumulative loss in %/100 terms. Columns 9, 10 and 11 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr > 0$	$\%d > 0$	SDR
DJIA	10/31/78-6/29/01	[1260, 252]	0.1661	0.0510	0.0252	0.0124	-0.3494	85	0.471	0.854	0.6790
ALCOA	10/31/78-6/29/01	[1008, 252]	0.2202	0.1039	0.0190	0.0120	-0.5396	468	0.177	0.626	1.2539
AMERICAN EXPRESS	10/31/78-6/29/01	[756, 126]	0.1276	0.0040	0.0063	-0.0014	-0.7372	118	0.644	0.702	1.0477
AT&T	10/31/78-6/29/01	[1260, 252]	-0.0243	-0.0747	-0.0156	-0.0094	-0.9082	62	0.790	0.602	1.0126
BETHLEHEM STEEL	10/31/78-6/29/01	[1008, 252]	0.1649	0.2593	0.0092	0.0335	-0.6966	422	0.156	0.587	1.1778
BOEING	10/31/78-6/29/01	[1260, 252]	0.1380	0.0194	0.0079	0.0004	-0.7835	204	0.152	0.664	0.9487
CATERPILLAR	10/31/78-6/29/01	[1260, 252]	0.2547	0.1987	0.0224	0.0269	-0.5878	593	0.132	0.527	1.0262
CHEVRON - TEXACO	10/31/78-6/29/01	[42, 21]	0.1111	0.0167	0.0055	0.0021	-0.6538	235	0.251	0.578	1.1345
CITIGROUP	8/26/92-6/29/01	[504, 126]	0.4496	0.1003	0.0436	-0.0001	-0.6200	66	0.212	0.702	1.0065
COCA - COLA	10/31/78-6/29/01	[504, 126]	0.1230	-0.0267	0.0077	-0.0074	-0.7367	161	0.248	0.620	1.0784
E.I. DU PONT DE NEMOURS	10/31/78-6/29/01	[126, 63]	0.1034	0.0178	0.0041	0.0026	-0.5379	149	0.349	0.613	1.0074
EASTMAN KODAK	10/31/78-6/29/01	[1008, 252]	-0.0010	-0.0362	-0.0129	-0.0038	-0.8146	62	0.629	0.705	0.9497
EXXON MOBIL	10/31/78-6/29/01	[1260, 126]	0.0987	-0.0208	0.0042	-0.0061	-0.4136	57	0.754	0.750	0.8258
GENERAL ELECTRIC	10/31/78-6/29/01	[1260, 252]	0.1691	-0.0104	0.0159	-0.0070	-0.6553	75	0.853	0.834	0.7889
GENERAL MOTORS	10/31/78-6/29/01	[1008, 126]	0.0981	0.0533	0.0029	0.0100	-0.6946	90	0.533	0.745	0.9067
GOODYEAR TIRE	10/31/78-6/29/01	[63, 1]	0.1330	0.0779	0.0082	0.0127	-0.7492	531	0.115	0.477	1.1916
HEWLETT - PACKARD	10/31/78-6/29/01	[504, 252]	0.1818	0.0263	0.0120	0.0005	-0.8192	152	0.296	0.630	0.9360
HOME DEPOT	10/30/89-6/29/01	[252, 42]	0.3923	0.0742	0.0426	0.0025	-0.5015	86	0.267	0.653	1.0607
HONEYWELL INTL.	7/18/91-6/29/01	[756, 126]	0.2393	0.1044	0.0253	0.0107	-0.5554	51	0.314	0.751	0.7963
INTEL	10/29/84-6/29/01	[504, 126]	0.3872	0.1311	0.0317	0.0082	-0.6771	97	0.423	0.742	0.9992

Table 3.19 continued.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr > 0$	$\%d > 0$	SDR
INTL. BUS. MACH.	10/31/78-6/29/01	[252, 126]	0.0766	-0.0072	-0.0004	-0.0014	-0.7582	102	0.539	0.665	1.0053
INTERNATIONAL PAPER	10/31/78-6/29/01	[756, 252]	0.0752	0.0208	-0.0005	0.0044	-0.7404	393	0.176	0.521	1.0723
J.P. MORGAN CHASE & CO.	10/31/78-6/29/01	[252, 10]	0.1552	0.0655	0.0104	0.0085	-0.8088	278	0.252	0.613	1.0458
JOHNSON & JOHNSON	10/31/78-6/29/01	[504, 126]	0.1558	-0.0036	0.0134	-0.0043	-0.5298	154	0.351	0.677	0.8972
MCDONALDS	10/31/78-6/29/01	[756, 126]	0.1543	0.0124	0.0141	0.0004	-0.5308	118	0.576	0.778	0.9448
MERCK	10/31/78-6/29/01	[1260, 126]	0.1291	-0.0403	0.0078	-0.0123	-0.6230	142	0.373	0.716	0.8361
MICROSOFT	1/09/92-6/29/01	[252, 5]	0.3537	0.0445	0.0399	0.0023	-0.4535	68	0.279	0.601	1.0901
MINNESOTA MNG. & MNFG.	10/31/78-6/29/01	[126, 63]	0.0876	-0.0054	0.0018	-0.0017	-0.5439	152	0.441	0.636	1.1148
PHILIP MORRIS	10/31/78-6/29/01	[252, 63]	0.2714	0.1080	0.0294	0.0126	-0.5213	161	0.373	0.736	1.1326
PROCTER & GAMBLE	10/31/78-6/29/01	[1260, 252]	0.0642	-0.0478	-0.0028	-0.0102	-0.5686	76	0.421	0.649	0.8839
SBC COMMUNICATIONS	9/18/89-6/29/01	[252, 126]	0.1133	0.0212	0.0091	0.0013	-0.7219	95	0.274	0.658	0.9916
SEARS, ROEBUCK & CO.	10/31/78-6/29/01	[756, 126]	0.0868	0.0119	0.0012	0.0020	-0.6139	178	0.191	0.656	1.0114
UNITED TECHNOLOGIES	10/31/78-6/29/01	[504, 252]	0.1285	0.0050	0.0083	-0.0013	-0.8343	160	0.344	0.723	0.9601
WAL - MART STORES	10/30/86-6/29/01	[756, 252]	0.2860	0.0805	0.0302	0.0051	-0.4652	72	0.306	0.777	0.8815
WALT DISNEY	10/31/78-6/29/01	[1008, 126]	0.2076	0.0413	0.0186	0.0028	-0.6100	87	0.552	0.700	1.0510

Table 3.20: **Excess performance best out-of-sample testing procedure.** Panel A shows the yearly mean return of the best recursive out-of-sample testing procedure, selected by the mean return criterion, in excess of the yearly mean return of the buy-and-hold. Panel B shows the Sharpe ratio of the best recursive out-of-sample testing procedure, selected by the Sharpe ratio criterion, in excess of the Sharpe ratio of the buy-and-hold. Results are presented for the 0, 0.10 and 0.50% transaction costs per trade cases. The results for the 0.25% transaction costs per trade case can be found in the tables 3.18 and 3.19. The row labeled "Average: out-of-sample" shows the average over the results as presented in the table. The row labeled "Average: in sample" shows the average over the results of the best strategy selected in sample for each data series.

	Panel A			Panel B		
selection criterion	Mean return			Sharpe ratio		
Data set	0%	0.10%	0.50%	0%	0.10%	0.50%
DJIA	0.0775	0.0444	0.0287	0.0189	0.0093	0.0057
ALCOA	0.2881	0.2145	-0.0591	0.0313	0.0187	-0.0045
AMERICAN EXPRESS	0.1020	0.1062	-0.0229	0.0047	0.0052	-0.0024
AT&T	0.0306	-0.0104	-0.0581	0.0038	-0.0027	-0.0048
BETHLEHEM STEEL	0.3270	0.2914	0.1389	0.0472	0.0349	0.0245
BOEING	0.0773	0.0325	-0.0380	0.0125	0.0060	-0.0040
CATERPILLAR	0.3576	0.2667	-0.0567	0.0451	0.0371	0.0043
CHEVRON - TEXACO	0.1262	0.0913	-0.0250	0.0177	0.0111	-0.0038
CITIGROUP	0.1635	0.1384	-0.0176	0.0038	-0.0051	-0.0082
COCA - COLA	0.1576	0.0551	-0.0269	0.0085	0.0041	-0.0117
E.I. DU PONT DE NEMOURS	0.1076	0.0547	-0.0799	0.0174	0.0074	-0.0077
EASTMAN KODAK	0.0529	0.0199	-0.0386	0.0011	0.0021	-0.0041
EXXON MOBIL	0.0200	0.0194	-0.0087	0.0012	-0.0044	-0.0083
GENERAL ELECTRIC	0.0807	0.0295	-0.0407	-0.0028	-0.0071	-0.0028
GENERAL MOTORS	0.0558	0.0286	0.0347	0.0141	0.0109	0.0069
GOODYEAR TIRE	0.1431	0.0982	0.0062	0.0353	0.0261	0.0009
HEWLETT - PACKARD	0.0239	0.0052	0.0078	0.0061	0.0039	-0.0061
HOME DEPOT	0.1915	0.0997	0.0415	0.0009	0.0002	-0.0027
HONEYWELL INTL.	0.2066	0.1337	0.0170	0.0153	0.0118	0.0082
INTEL	0.0660	0.0684	0.0253	0.0137	0.0154	0.0035
INTL. BUS. MACH.	-0.0092	-0.0497	-0.0085	0.0042	-0.0011	-0.0012
INTERNATIONAL PAPER	0.1904	0.0871	-0.0439	0.0203	0.0165	-0.0021
J.P. MORGAN CHASE & CO.	0.2582	0.1492	0.0615	0.0406	0.0226	0.0050
JOHNSON & JOHNSON	0.0269	-0.0398	-0.0678	0.0070	-0.0012	-0.0071
MCDONALDS	0.0585	0.0266	-0.0383	0.0087	0.0022	-0.0034
MERCK	0.0731	0.0216	-0.0398	0.0001	-0.0023	-0.0162
MICROSOFT	0.1420	0.1192	0.0658	0.0149	0.0058	-0.0007
MINNESOTA MNG. & MNFG.	0.0891	0.0139	-0.0400	0.0103	0.0031	-0.0073
PHILIP MORRIS	0.0434	0.0162	-0.0246	0.0133	0.0132	-0.0026
PROCTER & GAMBLE	0.0366	0.0147	-0.0543	0.0018	-0.0083	-0.0015
SBC COMMUNICATIONS	0.1295	0.0176	-0.0379	0.0090	0.0015	-0.0015
SEARS, ROEBUCK & CO.	0.0872	0.0354	-0.0165	0.0132	0.0126	0.0032
UNITED TECHNOLOGIES	0.2242	0.0832	-0.0632	0.0354	0.0110	-0.0055
WAL - MART STORES	0.1074	0.0582	0.0284	0.0065	0.0018	-0.0081
WALT DISNEY	0.1841	0.0599	0.0165	0.0247	0.0061	-0.0025
Average: out-of-sample	0.1228	0.0686	-0.0124	0.0145	0.0077	-0.0020
Average: in sample	0.1616	0.1043	0.0676	0.0220	0.0147	0.0091

Table 3.21: **Estimation results CAPM for best out-of-sample testing procedure.** Coefficient estimates of the Sharpe-Lintner CAPM: $r_t^i - r_t^f = \alpha + \beta(r_t^{DJIA} - r_t^f) + \epsilon_t$. That is, the return of the best recursive optimizing and testing procedure, when selection is done in the optimizing period by the mean return criterion (Panel A) or by the Sharpe ratio criterion (Panel B), in excess of the risk-free interest rate is regressed against a constant and the return of the DJIA in excess of the risk-free interest rate. Estimation results for the 0 and 0.10% costs per trade cases are shown. a, b, c indicates that the corresponding coefficient is, in the case of α, significantly different from zero, or in the case of β, significantly different from one, at the 1, 5, 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.10%		0%		0.10%	
Data set	α	β	α	β	α	β	α	β
DJIA	0.000311a	0.703a	0.000173	0.901	0.000292a	0.851	0.000165	0.832c
ALCOA	0.000955a	0.821c	0.000744a	0.800b	0.000859a	0.847	0.000568c	0.896
AMERICAN EXPRESS	0.000363	1.186	0.000372	1.217	0.000174	1.599a	0.000217	1.126
AT&T	-9.59E-05	0.768b	-0.000249	0.769a	-0.00017	0.838	-0.000295	0.712a
BETHLEHEM STEEL	0.000434	0.796b	0.000317	0.802c	0.00062	0.748a	0.000272	0.772b
BOEING	0.000299	0.862	0.000147	0.863	0.000399	0.901	0.000239	0.932
CATERPILLAR	0.000965a	0.811c	0.000704b	0.792c	0.000943a	0.805c	0.000753b	0.857
CHEVRON - TEXACO	0.000401	0.657a	0.000296	0.585a	0.000376	0.652a	0.000227	0.601a
CITIGROUP	0.000948c	1.614a	0.000874	1.637a	0.000930c	1.540a	0.000675	1.579a
COCA - COLA	0.000658b	0.816	0.000342	0.756b	0.000406	0.756b	0.000315	0.804
E.I. DU PONT DE NEMOURS	0.000281	0.875	9.73E-05	0.904	0.00029	0.905	7.14E-05	0.861
EASTMAN KODAK	-6.32E-05	0.718a	-0.000183	0.699a	-0.000252	0.694a	-0.000246	0.692a
EXXON MOBIL	8.58E-05	1.037	8.49E-05	1.029	0.000113	0.731a	1.34E-05	0.737a
GENERAL ELECTRIC	0.000487b	0.957	0.00032	0.972	0.000276	1.018	0.000174	0.814
GENERAL MOTORS	-6.13E-05	1.039	-0.000171	1.115b	1.68E-05	1.136a	-6.19E-05	1.182a
GOODYEAR TIRE	0.0003	0.869	0.000152	0.844	0.000630b	0.695a	0.000414	0.701a
HEWLETT - PACKARD	0.000191	1.203	0.000131	1.179	0.000383	1.097	0.000315	1.097
HOME DEPOT	0.001074b	1.442a	0.000879b	1.202b	0.000792c	1.085	0.000788c	1.081
HONEYWELL INTL.	0.000681	1.011	0.0005	0.866	0.000516	1.203	0.000415	0.847
INTEL	0.000582	1.11	0.000609	1.003	0.000976b	1.016	0.001036b	0.986
INTL. BUS. MACH.	-0.000115	0.776b	-0.000266	0.763b	9.31E-06	0.859	-0.000109	0.825
INTERNATIONAL PAPER	0.000439	1.022	7.41E-05	1.174a	0.000252	1.198a	0.00015	1.230a
J.P. MORGAN CHASE & CO.	0.000774b	0.809c	0.000441	0.794c	0.000927a	0.754b	0.000507c	0.759b
JOHNSON & JOHNSON	0.00024	1.041	-4.52E-06	1.152c	0.000412c	0.819c	0.000248	0.756b
MCDONALDS	0.000325	0.795b	0.000239	0.637a	0.000372	0.757a	0.000235	0.629a
MERCK	0.000462c	0.827	0.000292	0.841	0.000388	0.963	0.000293	0.749b
MICROSOFT	0.000963c	1.065	0.000892	1.094	0.001068b	0.773b	0.000834c	0.872

Table 3.21 continued.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.10%		0%		0.10%	
Data set	α	β	α	β	α	β	α	β
MINNESOTA MNG. & MNFG.	0.000259	0.841	-4.50E-06	0.855	0.000168	0.915	2.04E-05	0.904
PHILIP MORRIS	0.000343	0.822	0.000254	0.815	0.000580b	0.688a	0.000580b	0.680a
PROCTER & GAMBLE	0.000123	0.982	4.05E-05	1.028	7.88E-05	0.647a	-0.000105	0.658a
SBC COMMUNICATIONS	0.000413	0.682a	2.75E-05	0.701a	0.000226	0.776a	4.89E-05	0.763a
SEARS, ROEBUCK & CO.	0.000183	0.824c	-9.44E-07	0.85	0.000203	0.864	0.000185	0.861
UNITED TECHNOLOGIES	0.000764a	0.897	0.000334	0.834	0.000944a	0.881	0.000334	0.780c
WAL - MART STORES	0.000574	1.307a	0.000496	0.968	0.000633c	0.887	0.000514	0.89
WALT DISNEY	0.000793b	0.723b	0.000403	0.776c	0.000882a	0.814b	0.000416	0.683a

B. Parameters of technical trading strategies

This appendix presents the values of the parameters of the technical trading strategy set applied in this chapter. Most parameter values are equal to those used by Sullivan et al. (1999). Each basic trading strategy can be extended by a %-band filter (band), time delay filter (delay), fixed holding period (fhp) and a stop-loss (sl). The total set consists of 787 different trading rules.

Moving-average rules

n	=number of days over which the price must be averaged
band	=%-band filter
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period
sl	=%-rise (%-fall) from a previous low (high) to liquidate a short (long) position

n	=[1, 2, 5, 10, 25, 50, 100, 200]
band	=[0.001, 0.005, 0.01, 0.025, 0.05]
delay	=[2, 3, 4]
fhp	=[5, 10, 25, 50]
sl	=[0.025, 0.05, 0.075, 0.10]

We combine the short run moving averages $sma = 1, 2, 5, 10, 25$ with the long run moving averages $lma = n : n > sma$. With the 8 values of n we can construct 25 basic MA trading strategies. We extend these strategies with %-band filters, time delay filters, fixed holding period and a stop-loss. The values chosen above will give us in total:
$25 * (1 + 5 + 3 + 4 + 4) = 425$ MA strategies.

Trading range break rules

n	= length of the period to find local minima (support) and maxima (resistance)
band	=%-band filter
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period
sl	=%-rise (%-fall) from a previous low (high) to liquidate a short (long) position

n	=[5, 10, 15, 20, 25, 50 ,100, 150, 200, 250]
band	=[0.001, 0.005, 0.01, 0.025, 0.05]
delay	=[2, 3, 4]
fhp	=[5, 10, 25, 50]
sl	=[0.025, 0.05, 0.075, 0.10]

With the parameters and values given above we construct the following trading range break-out (TRB) strategies:

basic TRB strategies:	10*1	=10
TRB with %-band filter:	10*5	=50
TRB with time delay filter:	10*3	=30
TRB with fixed holding period:	10*4	=40
TRB with stop-loss:	10*4	=40

This will give in total 170 TRB strategies.

Filter rules

filt	= %-rise (%-fall) from a previous low (high) to generate a buy (sell) signal
delay	=number of days a signal must hold if you implement a time delay filter
fhp	=number of days a position is held, ignoring all other signals during this period

filt	=[0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, 0.5]
delay	=[2, 3, 4]
fhp	=[5, 10, 25, 50]

With the parameters and values given above we construct the following filter rules (FR):

basic FR:	24*1	=24
FR with time delay:	24*3	=72
FR with fixed holding:	24*4	=96

This will give in total 192 filter strategies.

C. Parameters of recursive optimizing and testing procedure

This appendix presents the parameter values of the recursive optimizing and testing procedures applied in section 3.7. The two parameters are the length of the training period, TR, and the length of the testing period, Te. The following 36 combinations of training and testing periods, $[Tr,Te]$, are used:

$Train$	$Test$	$Train$	$Test$
5	1	42	21
10	1	63	21
21	1	126	21
42	1	252	21
63	1	63	42
126	1	126	42
252	1	252	42
10	5	126	63
21	5	252	63
42	5	252	126
63	5	504	126
126	5	736	126
252	5	1008	126
21	10	1260	126
42	10	504	252
63	10	736	252
126	10	1008	252
252	10	1260	252

Chapter 4

Technical Trading Rule Performance in Amsterdam Stock Exchange Listed Stocks

4.1 Introduction

In Chapter 3 we have shown that objective computerized trend-following technical trading techniques applied to the Dow-Jones Industrial Average (DJIA) and to stocks listed in the DJIA in the period 1973-2001 are not statistically significantly superior to a buy-and-hold benchmark strategy after correction for data snooping and transaction costs. In this chapter we use a similar approach to test whether technical trading shows statistically significant forecasting power when applied to the Amsterdam Stock Exchange Index (AEX-index) and to stocks listed in the AEX-index in the period 1983-2002.

In section 4.2 we list the stock price data examined in this chapter and we present and discuss the summary statistics. We refer to the sections 3.3, 3.4 and 3.5 of Chapter 3 for the discussions on the set of technical trading rules applied, the computation of the performance measures and finally the problem of data snooping. Section 4.3 presents the empirical results of our study. In section 4.4 we test whether recursively optimizing and updating our technical trading rule set shows genuine out-of-sample forecasting ability. Finally, section 4.5 summarizes and concludes.

4.2 Data and summary statistics

The data series examined in this chapter are the daily closing levels of the Amsterdam Stock Exchange Index (AEX-index) and the daily closing prices of all stocks listed in this index in the period January 3, 1983 through May 31, 2002. The AEX-index is a market-weighted average of the 25 most important stocks traded at the Amsterdam Stock Exchange. These stocks are chosen once a year and their selection is based on the value of trading turnover during the preceding year. At the moment of composition of the index the weights are restricted to be at maximum 10%. Table 4.1 shows an historical overview when and which stocks entered or left the index and in some cases the reason why. For example, Algemene Bank Nederland (ABN) merged with AMRO Bank at August 27, 1990 and the new combination was listed under the new name ABN AMRO Bank. In total we evaluate a set of 50 stocks. All data series are corrected for dividends, capital changes and stock splits. As a proxy for the risk-free interest rate we use daily data on Dutch monthly interbank rates. Table 4.2 shows for each data series the sample period and the largest cumulative loss, that is the largest decline from a peak to a through. Next, table 4.3 shows the summary statistics. Because the first 260 data points are used for initializing the technical trading strategies, the summary statistics are shown from January 1, 1984. The first and second column show the names of the data series examined and the number of available data points. The third column shows the mean yearly effective return in percentage/100 terms. The fourth through seventh column show the mean, standard deviation, skewness and kurtosis of the logarithmic daily return. The eight column shows the t-ratio to test whether the mean logarithmic daily return is significantly different from zero. The ninth column shows the Sharpe ratio, that is the extra return over the risk-free interest rate per extra point of risk, as measured by the standard deviation. The tenth column shows the largest cumulative loss of the stocks in percentage/100 terms. The eleventh column shows the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. The twelfth column shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic testing for autocorrelations in the squared returns.

The mean yearly effective return of the AEX-index during the 1983-2002 period is equal to 10.4% and the yearly standard deviation is approximately equal to 19%. For the AEX-index and 21 stocks the mean logarithmic return is significantly positive, as tested with the simple t-ratios, while for 5 stocks the mean yearly effective return is severely and significantly negative. For example, the business firm Ceteco and truck builder Daf went broke, while the communications and cable networks related companies KPNQWest, UPC and Versatel stopped recently all payments due to their creditors. For the other 4 stocks which show negative returns, plane builder Fokker went broke, software builder Baan was taken over by the British Invensys, while telecommunications firm KPN and temporary employment agency Vedior are nowadays struggling for survival. The return distribution is strongly leptokurtic for all data series, especially for Ceteco, Fokker, Getronics and Nedlloyd, and is negatively skewed for the AEX-index and 32 stocks. On individual basis the stocks are more risky than the market-weighted AEX-index, as can be seen by the standard deviations and the largest cumulative loss numbers. Thus it is clear that firm specific risks are reduced by a diversified index. The Sharpe ratio is negative for 12 stocks, which means that these stocks were not able to beat a risk free investment. Among them are ABN, KLM and the earlier mentioned stocks. The largest cumulative loss of the AEX-index is equal to 47% and took place in the period August 12, 1987 through November 10, 1987. October 19, 1987 showed the biggest one-day percentage loss in history of the AEX-index and brought the index down by 12%. November 11, 1987 on its turn showed the largest one-day gain and brought the index up by 11.8%. For 30 stocks, for which we have data starting before the crash of 1987, only half showed a largest cumulative loss during the year 1987, and their deterioration started well before October 1987, indicating that stock prices were already decaying for a while before the crash actually happened. The financials, for example, lost approximately half of their value during the 1987 period. For the other stocks, for which we have data after the crash of 1987, the periods of largest decline started ten years later in 1997. Baan, Ceteco, Getronics, KPN, KPNQWest, OCE, UPC and Versatel lost almost their total value within two years during the burst of the internet and telecommunications bubble. The summary statistics show no largest declines after the terrorist attack against the US on September 11, 2001[1]. With hindsight, the overall picture is that financials, chemicals and foods produced the best results.

We computed autocorrelation functions (ACFs) of the returns and significance is tested with Bartlett (1946) standard errors and Diebold's (1986) heteroskedasticity-consistent standard errors[2]. Typically autocorrelations of the returns are small with only few lags being significant. Without correcting for heteroskedasticity we find for 36 of the 50 stocks a significant first order autocorrelation, while when corrected for heteroskedasticity we find for 24 stocks a significant first order autocorrelation at the 10% significance level.

[1]At the moment of writing the stock exchanges were reaching new lows, which is not visible in these data until May 2002.

[2]See section 3.2, page 99, for an explanation. Separate ACFs of the returns are computed for each data series, but not presented here to save space. The tables are available upon request from the author.

No severe autocorrelation is found in the AEX-index. It is noteworthy that for most data series the second order autocorrelation is negative, while only in 8 out of 51 cases it is positive. The first order autocorrelation is negative in 10 cases. The Ljung-Box (1978) Q-statistics in the second to last column of table 4.3 reject for almost all data series the null hypothesis that the first 20 autocorrelations of the returns as a whole are equal to zero. For only 10 data series the null is not rejected. When looking at the first to last column with Diebold's (1986) heteroskedasticity-consistent Box-Pierce (1970) Q-statistics it appears that heteroskedasticity indeed seriously affects the inferences about serial correlation in the returns. When a correction is made for heteroskedasticity, then for the AEX-index and 41 stocks the null of no autocorrelation is not rejected. The autocorrelation functions of the squared returns show that for all data series the autocorrelations are high and significant up to order 20. The Ljung-Box (1978) Q-statistics reject the null of no autocorrelation in the squared returns firmly, except for steel manufacturer Corus. Hence, almost all data series exhibit significant volatility clustering, that is large (small) shocks are likely to be followed by large (small) shocks.

4.3 Empirical results

4.3.1 Results for the mean return criterion

Technical trading rule performance

In section 4.2 we have shown that almost no significant autocorrelation in the daily returns can be found after correction for heteroskedasticity. This implies that there is no linear dependence present in the data. One may thus question whether technical trading strategies can persistently beat the buy-and-hold benchmark. However, as noted by Alexander (1961), the dependence in price changes can be of such a complicated nonlinear form that standard linear statistical tools, such as serial correlations, may provide misleading measures of the degree of dependence in the data. Therefore he proposed to use nonlinear technical trading rules to test for dependence. In total we apply 787 objective computerized trend-following technical trading techniques with and without transaction costs to the AEX-index and to 50 stocks listed in the AEX-index (see sections 2.3 and 3.3 and Appendix B of Chapter 3 for the technical trading rule parameterizations). Tables 4.4 and 4.5 show for each data series some statistics of the best strategy selected by the mean return criterion, if 0% and 0.25% costs per trade are implemented. Column 2 shows the parameters of the best strategy. In the case of a moving-average (MA) strategy these parameters are "[short run MA, long run MA]" plus the refinement parameters "[%-band filter, time delay filter, fixed holding period, stop-loss]". In the case of a trading range break, also called support-and-resistance (SR), strategy, the parameters are "[the number of days over which the local maximum and minimum is computed]" plus the refinement parameters as with the moving averages. In the case of a filter (FR) strategy the parameters are "[the %-filter, time delay filter, fixed holding period]". Columns 3 and 4 show the mean yearly return and excess mean yearly return of the best-selected strategy over the buy-and-hold benchmark, while columns 5 and 6 show the Sharpe ratio and excess Sharpe ratio of the best-selected strategy over the buy-and-hold benchmark. Column 7 shows the maximum loss the best strategy generates. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days profitable trades last. Finally, the last column shows the standard deviation of the returns of the data series during profitable trades divided by the standard deviation of the returns of the data series during non-profitable trades.

To summarize, for each data series examined table 4.7A (i.e. table 4.7 panel A) shows the mean yearly excess return over the buy-and-hold benchmark of the best strategy selected by the mean return criterion, after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade. This wide range of costs captures a range of different trader types. For example, floor traders and large investors, such as mutual funds, can trade against relatively low transaction costs in the range of 0.10 to 0.25%. Home investors face higher costs in the range of 0.25 to 0.75%, depending whether they trade through the internet, by telephone or through their personal account manager. Next, because of the bid-ask spread, extra costs over the transaction costs are faced. By examining a wide range of 0 to 1% costs per trade, we belief that we can capture most of the cost possibilities faced in reality by most of the traders.

The results in table 4.7A are astonishing. As can be seen in the last row of the table, on average, the mean yearly excess return of the best strategy over the buy-and-hold benchmark is equal to 152% in the case of zero transaction costs, and it still is 124% in the case of 1% transaction costs. These incredibly good results are mainly caused by the communications and cable network firms KPNQWest, UPC and Versatel. However, subtracting all stocks for which the best strategy generates a return of more than 100% yearly in excess of the buy-and-hold, then, on average, the yearly excess return of the best strategy is equal to 32% in the case of no transaction costs, declining to 15%, if transaction costs increase to 1% per trade. Thus from these results we conclude that technical trading rules are capable of beating a buy-and-hold benchmark even after correction for transaction costs. These results are substantially better than when the same strategy set is applied to the DJIA and to stocks listed in the DJIA. In that case in the period 1987-2001, on average, the mean yearly excess return over the buy-and-hold benchmark declines from 17% to 7%, if transaction costs are increased from 0% to 1% per trade (see section 3.6.1, page 106, and table 3.7, page 128). It is interesting to compare our results to Fama (1965) and Theil and Leenders (1965). It was found by Theil and Leenders (1965) that the proportions of securities advancing and declining today on the Amsterdam Stock Exchange can help in predicting the proportions of securities advancing and declining tomorrow. However, Fama (1965) in contrast found that this is not true for the New York Stock Exchange. In our study we find that this difference in forecastability of both stock markets tends to persists into the 1980s and 1990s.

From table 4.4 it can be seen that in the case of zero transaction costs the best-selected strategies are mainly strategies which generate a lot of signals. Trading positions are held for only a few days. With hindsight, the best strategy for the Fokker and UPC stocks was to never have bought them, earning a risk-free interest rate during the investment period. For the AEX-index, in contrast, the best strategy is a single crossover moving-average rule which generates a signal if the price series crosses a 25-day moving average and where the single refinement is a 10% stop-loss. The mean yearly return is equal to 25%, which corresponds with a mean yearly excess return of 13.2%. The Sharpe ratio is equal to 0.0454 and the excess Sharpe ratio is equal to 0.0307. These excess performance measures are considerably large. The maximum loss of the strategy is 43.9%, slightly less than the maximum loss of buying and holding the AEX-index, which is equal to 46.7% (table 4.2). Once every 12 days the strategy generates a trade and in 65.9% of the trades is profitable. These profitable trades span 85% of the total number of trading days. Although the technical trading rules show economic significance, they all go through periods of heavy losses, well above the 50% for most stocks.

If transaction costs are increased to 0.25%, then table 4.5 shows that the best-selected strategies are strategies which generate substantially fewer signals in comparison with the zero transaction costs case. Trading positions are now held for a longer time. For example, for the AEX-index the best-selected strategy generates a trade every one-and-a-half year. Also the percentage of profitable trades and the percentage of days profitable trades last increases for most data series. Most extremely this is the case for the AEX-index; the 13 trading signals of the best-selected strategy were all profitable.

CAPM

If no transaction costs are implemented, then from the last column in table 4.4 it can be seen that the standard deviations of the returns of the data series themselves during profitable trades are higher than the standard deviations of the returns during non-profitable trades for the AEX-index and almost all stocks, except for Gist Brocades, Stork, TPG and Unilever. However, if 0.25% costs per trade are calculated, then for 22 data series out of 51 the standard deviation ratio is larger than one. According to the efficient markets hypothesis it is not possible to exploit a data set with past information to predict future price changes. The excellent performance of the technical trading rules could therefore be the reward for holding a risky asset needed to attract investors to bear the risk. Since the technical trading rule forecasts only depend on past price history, it seems unlikely that they should result in unusual risk-adjusted profits. To test this hypothesis we regress Sharpe-Lintner capital asset pricing models (CAPMs)

$$r_t^i - r_t^f = \alpha + \beta(r_t^{AEX} - r_t^f) + \epsilon_t. \tag{4.1}$$

Here r_t^i is the return on day t of the best strategy applied to stock i, r_t^{AEX} is the return on day t of the market-weighted AEX-index, which represents the market portfolio, and r_t^f is the risk-free interest rate. The coefficient β measures the riskiness of the active technical trading strategy relatively to the passive strategy of buying and holding the market portfolio. If β is not significantly different from one, then it is said that the strategy has equal risk as a buying and holding the market portfolio. If $\beta > 1$ ($\beta < 1$), then it is said that the strategy is more risky (less risky) than buying and holding the market portfolio and that it therefore should yield larger (smaller) returns. The coefficient α measures the excess return of the best strategy applied to stock i after correction of bearing risk. If it is not possible to beat a broad market portfolio after correction for risk and hence technical trading rule profits are just the reward for bearing risk, then α should not be significantly different from zero. Table 4.8A shows for the 0 and 0.50% transaction costs cases[3] the estimation results if for each data series the best strategy is selected by the mean return criterion. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. Table 4.10 summarizes the CAPM estimation results for all transaction cost cases by showing the number of data series for which significant estimates of α or β are found at the 10% significance level.

For example, for the best strategy applied to the AEX-index in the case of zero transaction costs, the estimate of α is significantly positive at the 1% significance level and is equal to 5.27 basis points per day, that is approximately 13.3% per year. The estimate of β is significantly smaller than one at the 5% significance level, which indicates that although the strategy generates a higher reward than simply buying and holding the index, it is less risky. If transaction costs increase to 1%, then the estimate of α decreases

[3]We also estimated the Sharpe-Lintner CAPMs for the 0.10, 0.25, 0.75 and 1% transaction costs cases. The estimation results for the separate stocks are not presented here to save space.

costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	2	37	39	2	29	2
0.10%	2	37	38	2	29	1
0.25%	3	32	39	3	27	0
0.50%	3	31	38	3	25	0
0.75%	3	26	35	3	19	0
1%	3	24	35	3	17	0

Table 4.10: **Summary: significance CAPM estimates, mean return criterion.** For each transaction cost case, the table shows the number of data series for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM (4.1). Columns 1 and 2 show the number of data series for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of data series for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that the number of data series analyzed is equal to 51 (50 stocks and the AEX-index).

to 3.16 basis points per day, 8% per year, but is still significantly positive. However the estimate of β is not significantly smaller than one anymore if as little as 0.10% costs per trade are charged.

As further can be seen in the tables, if no transaction costs are implemented, then for most of the stocks the estimate of α is also significantly positive at the 10% significance level. Only for 2 stocks the estimate of α is significantly smaller than zero, while it is significantly positive for 36 stocks. Further the estimate of β is significantly smaller than one for 36 stocks (Fokker and UPC excluded). Only for two stocks β is significantly larger than one. The estimate of α decreases as costs increase and becomes less significant in more cases. However in the 0.50% and 1% costs per trade cases for example, still for respectively 31 and 24 data series out of 51 the estimate of α is significantly positive at the 10% significance level. Notice that for a large number of cases it is found that the estimate of α is significantly positive while simultaneously the estimate of β is significantly smaller than one. This means that the best-selected strategy did not only generate a statistically significant excess return over the buy-and-hold benchmark, but is also significantly less risky than the buy-and-hold benchmark.

From the findings until now we conclude that there are trend-following technical trading techniques which can profitably be exploited, also after correction for transaction costs, when applied to the AEX-index and to stocks listed in the AEX-index in the period January 1983 through May 2002. As transaction costs increase, the best strategies selected are those which trade less frequently. Furthermore, if a correction is made for risk by estimating Sharpe-Lintner CAPMs, then it is found that in many cases the best strategy has significant forecasting power, i.e. $\alpha > 0$. It is also even found that in general the best strategy applied to a stock is less risky, i.e. $\beta < 1$, than buying and holding the market portfolio. Hence we *can reject* the null hypothesis that the profits of technical trading are just the reward for bearing risk.

Data snooping

The question remains open whether the findings in favour of technical trading for particular stocks are the result of chance or of real superior forecasting power. Therefore we apply White's (2000) Reality Check (RC) and Hansen's (2001) Superior Predictive Ability (SPA) test. Because Hansen (2001) showed that White's RC is biased in the direction of one, p-values are computed for both tests to investigate whether these tests lead in some cases to different inferences.

In the case of 0 and 0.10% transaction costs table 4.9A shows the nominal, White's (2000) RC and Hansen's (2001) SPA-test p-values, if the best strategy is selected by the mean return criterion. Calculations are also done for the 0.25, 0.50, 0.75 and 1% costs per trade cases, but these yield no remarkably different results compared with the 0.10% costs per trade case. Table 4.11 summarizes the results for all transaction cost cases by showing the number of data series for which the corresponding p-value is smaller than 0.10. That is, the number of data series for which the null hypothesis is rejected at the 10% significance level.

costs	p_n	p_W	p_H
0%	50	2	14
0.10%	51	0	2
0.25%	51	0	2
0.50%	51	0	2
0.75%	51	0	1
1%	51	0	1

Table 4.11: **Summary: Testing for predictive ability, mean return criterion.** For each transaction cost case, the table shows the number of data series for which the nominal (p_n), White's (2000) Reality Check (p_W) or Hansen's (2001) Superior Predictive Ability test (p_H) p-value is smaller than 0.10. Note that the number of data series analyzed is equal to 51 (50 stocks and the AEX-index).

The nominal p-value, also called data mined p-value, tests the null hypothesis that the *best* strategy *is not* superior to the buy-and-hold benchmark, but does not correct for data snooping. From the tables it can be seen that this null hypothesis *is* rejected for most data series in all cost cases at the 10% significance level. Only for the postal company Koninklijke PTT Nederland the null hypothesis is not rejected if no transaction costs are implemented. However, if we correct for data snooping, then we find, in the case of zero transaction costs, that for only two of the data series the null hypothesis that the *best* strategy is not superior to the benchmark after correcting for data snooping *is* rejected by the RC, while for 14 data series the null hypothesis that *none* of the alternative strategies is superior to the buy-and-hold benchmark after correcting for data snooping *is* rejected by the SPA-test. The two data snooping tests thus give contradictory results for 12 data series. However, if we implement as little as 0.10% costs, then both tests do not reject the null anymore for almost all data series. Only for Robeco and UPC the null is still rejected by the SPA-test. Remarkably, for Robeco and UPC the null *is* rejected even if costs are increased to 0.50%, and for UPC only if costs per trade are even higher. Hence, we conclude that the best strategy, selected by the mean return criterion, is not capable of beating the buy-and-hold benchmark strategy, after a correction is made for transaction costs and data snooping.

4.3.2 Results for the Sharpe ratio criterion

Technical trading rule performance

Similar to tables 4.4 and 4.5, table 4.6 shows for some data series some statistics of the best strategy selected by the Sharpe ratio criterion, if 0 or 0.25% costs per trade are implemented. Only the results for those data series are presented for which the best strategy selected by the Sharpe ratio criterion differs from the best strategy selected by the mean return criterion. Further table 4.7B shows for each data series the Sharpe ratio of the best strategy selected by the Sharpe ratio criterion, after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% transaction costs, in excess of the Sharpe ratio of the buy-and-hold benchmark. It is found that the Sharpe ratio of the best-selected strategy in excess of the Sharpe ratio of the buy-and-hold benchmark is positive in all cases. In the last row of table 4.7B it can be seen that the average excess Sharpe ratio declines from 0.0477 to 0.0311 if transaction costs increase from 0 to 1%. For the full sample period table 4.6 shows that the best strategies selected in the case of zero transaction costs are mainly strategies that generate a lot of signals. Trading positions are held for only a short period. Moreover, for most data series, except 13, these best-selected strategies are the same as in the case that the best strategies are selected by the mean return criterion. If transaction costs are increased to 0.25% per trade, then the best strategies generate fewer signals and trading positions are held for longer periods. In that case for the AEX-index and 18 stocks the best-selected strategy differs from the case where strategies are selected by the mean return criterion.

As for the mean return criterion it is found that for each data series the best technical trading strategy, selected by the Sharpe ratio criterion, beats the buy-and-hold benchmark and that this strategy can profitably be exploited, even after correction for transaction costs.

CAPM

The estimation results of the Sharpe-Lintner CAPM in tables 4.8B and 4.12 for the Sharpe ratio criterion are similar to the estimation results in tables 4.8A and 4.10 for the mean return criterion. If zero transaction costs are implemented, then it is found for 39 out of 51 data series that the estimate of α is significantly positive at the 10% significance level. This number decreases to 32 and 25 data series if transaction costs increase to 0.50 and 1% per trade. The estimates of β are in general significantly smaller than one. Thus, after correction for transaction costs and risk, for approximately half of the data series examined it is found that the best technical trading strategy selected by the Sharpe ratio criterion outperforms the strategy of buying and holding the market portfolio and is even less risky.

costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge \beta < 1$	$\alpha > 0 \wedge \beta > 1$
0%	2	39	41	2	32	2
0.10%	2	38	42	1	32	1
0.25%	2	35	42	1	30	0
0.50%	2	32	41	0	26	0
0.75%	2	29	40	0	23	0
1%	3	25	40	0	19	0

Table 4.12: **Summary: significance CAPM estimates, Sharpe ratio criterion.** For each transaction cost case, the table shows the number of data series for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM (4.1). Columns 1 and 2 show the number of data series for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of data series for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that the number of data series analyzed is equal to 51 (50 stocks and the AEX-index).

Data snooping

In the case of 0 and 0.10% transaction costs table 4.9B shows the nominal, White's RC and Hansen's SPA-test p-values, if the best strategy is selected by the Sharpe ratio criterion. Table 4.13 summarizes the results for all transaction cost cases by showing the number of data series for which the corresponding p-value is smaller than 0.10.

The results for the Sharpe ratio selection criterion differ from the mean return selection criterion. If the nominal p-value is used to test the null that the best strategy *is not* superior to the benchmark of buy-and-hold, then the null *is* rejected for most data series at the 10% significance level for all cost cases. If a correction is made for data snooping, then it is found for the no transaction costs case that for 10 data series the null hypothesis that the *best* strategy *is not* superior to the benchmark after correcting for data snooping *is* rejected by the RC. However for 30 data series the null hypothesis that *none* of the alternative strategies is superior to the buy-and-hold benchmark after correcting for data snooping *is* rejected by the SPA-test. The two data snooping tests thus give contradictory results for 20 data series. Even if costs are charged it is found that in a large number of cases the SPA-test rejects the null, while the RC does not. If costs are increased to 0.10 and 1%, then for respectively 17 and 15 data series the null of no superior predictive ability *is* rejected by the SPA-test. Note that these results differ substantially from the mean return selection criterion where in the cases of 0.10 and 1% transaction costs the null was rejected for respectively 2 and 1 data series. Hence, we conclude that the best strategy selected by the Sharpe ratio criterion *is capable* of beating the benchmark of a buy-and-hold strategy for approximately 30% of the stocks analyzed, after a correction is made for transaction costs and data snooping.

costs	p_n	p_W	p_H
0%	50	10	30
0.10%	51	4	17
0.25%	51	4	13
0.50%	51	4	15
0.75%	51	2	15
1%	51	2	15

Table 4.13: **Summary: Testing for predictive ability, Sharpe ratio criterion.** For each transaction cost case, the table shows the number of data series for which the nominal (p_n), White's (2000) Reality Check (p_W) or Hansen's (2001) Superior Predictive Ability test (p_H) p-value is smaller than 0.10. Note that the number of data series analyzed is equal to 51 (50 stocks and the AEX-index).

4.4 A recursive out-of-sample forecasting approach

In section 3.7 we argued to apply a recursive out-of-sample forecasting approach to test whether technical trading rules have true out-of-sample forecasting power. For example, recursively at the beginning of each month it is investigated which technical trading rule performed the best in the preceding six months (training period) and this strategy is used to generate trading signals during the coming month (testing period). In this section we apply the recursive out-of-sample forecasting procedure to the data series examined in this chapter.

We define the training period on day t to last from $t - Tr$ until and including $t - 1$, where Tr is the length of the training period. The testing period lasts from t until and including $t + Te - 1$, where Te is the length of the testing period. At the end of the training period the best strategy is selected by the mean return or Sharpe ratio criterion. Next, the selected technical trading strategy is applied in the testing period to generate trading signals. After the end of the testing period this procedure is repeated again until the end of the data series is reached. For the training and testing periods we use 28 different parameterizations of $[Tr, Te]$ which can be found in Appendix B.

Table 4.14A, B shows the results for both selection criteria in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% transaction costs. Because the longest training period is one year, the results are computed for the period 1984:12-2002:5. In the second to last row of table 4.14A it can be seen that, if in the training period the best strategy is selected by the mean return criterion, then the excess return over the buy-and-hold of the best recursive optimizing and testing procedure is, on average, 32.23, 26.45, 20.85, 15.05, 10.43 and 8.02% yearly in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade. If transaction costs increase, the best recursive optimizing and testing procedure becomes less profitable. However, the excess returns are considerable large. If the Sharpe ratio criterion is used for selecting the best strategy during the training period, then the Sharpe ratio of the best recursive optimizing and testing procedure in excess of the Sharpe ratio of the buy-and-hold benchmark is on average 0.0377, 0.0306, 0.0213, 0.0128, 0.0082 and 0.0044 in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade, also declining if transaction costs increase (see second to last row of table 4.14B).

For comparison, the last row in table 4.14A, B shows the average over the results of the best strategies selected by the mean return or Sharpe ratio criterion in sample for each data series tabulated. As can be seen, clearly the results of the best strategies selected in sample are much better than the results of the best recursive out-of-sample forecasting procedure. Mainly for the network and telecommunications related companies the out-of-sample forecasting procedure performs much worse than the in-sample results.

If the mean return selection criterion is used, then table 4.15A shows for the 0 and 0.50% transaction cost cases for each data series the estimation results of the Sharpe-Lintner CAPM (see equation 4.1) where the return of the best recursive optimizing and testing procedure in excess of the risk-free interest rate is regressed against a constant α and the return of the AEX-index in excess of the risk-free interest rate. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. Table 4.16 summarizes the CAPM estimation results for all transaction cost cases by showing the number of data series for which significant estimates of α and

β are found at the 10% significance level. In the case of zero transaction costs for 31 data series out of 51 the estimate of α is significantly positive at the 10% significance level. This number decreases to 21 (10, 4, 3, 2) if 0.10% (0.25, 0.50, 0.75, 1%) costs per trade are implemented. Table 4.15B shows the results of the CAPM estimation for the case that the best strategy in the training period is selected by the Sharpe ratio criterion. Now in the case of zero transaction costs for 33 data series it is found that the estimate of α is significantly positive at the 10% significance level. If transaction costs increase to 0.10% (0.25, 0.50, 0.75, 1%), then for 24 (11, 2, 2, 2) out of 51 data series the estimate of α is significantly positive. Hence, after correction for 1% transaction costs and risk it can be concluded, independently of the selection criterion used, that the best recursive optimizing and testing procedure shows no statistically significant out-of-sample forecasting power.

	Selection criterion: mean return					
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge \beta < 1$	$\alpha > 0 \wedge \beta > 1$
0%	1	31	35	2	25	0
0.10%	1	21	32	3	15	0
0.25%	1	10	34	4	8	0
0.50%	2	4	31	3	1	0
0.75%	3	3	29	4	1	1
1%	3	2	30	2	1	0
	Selection criterion: Sharpe ratio					
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge \beta < 1$	$\alpha > 0 \wedge \beta > 1$
0%	0	33	42	2	30	1
0.10%	0	24	39	1	21	0
0.25%	0	11	40	2	10	0
0.50%	0	2	36	2	1	0
0.75%	0	2	34	2	1	0
1%	0	2	35	2	1	0

Table 4.16: **Summary: significance CAPM estimates for best out-of-sample testing procedure.** For each transaction cost case, the table shows the number of data series for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM. Columns 1 and 2 show the number of data series for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of data series for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of data series for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that the number of data series analyzed is equal to 51 (50 stocks and the AEX-index).

4.5 Conclusion

In this chapter we apply a set of 787 objective computerized trend-following technical trading techniques to the Amsterdam Stock Exchange Index (AEX-index) and to 50 stocks listed in the AEX-index in the period January 1983 through May 2002. For each data series the best technical trading strategy is selected by the mean return or Sharpe ratio criterion. The advantage of the Sharpe ratio selection criterion over the mean return selection criterion is that it selects the strategy with the highest return/risk pay-off. Although for 12 stocks it is found that they could not even beat a continuous risk free investment, we find for both selection criteria that for each data series a technical trading strategy can be selected that is capable of beating the buy-and-hold benchmark, even after correction for transaction costs. For example, if the best strategy is selected by the mean return criterion, then on average, the best strategy beats the buy-and-hold benchmark with 152, 141, 135, 131, 127 and 124% yearly in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% transaction costs. However these extremely high numbers are mainly caused by IT and telecommunications related companies. If we discard these companies from the calculations, then still on average, the best strategy beats the buy-and-hold benchmark with 32, 22, 19, 17, 16 and 15% for the six different costs cases. These are quite substantial numbers.

The profits generated by the technical trading strategies could be the reward necessary to attract investors to bear the risk of holding the asset. To test this hypothesis we estimate Sharpe-Lintner CAPMs. For each data series the daily return of the best strategy in excess of the risk-free interest rate is regressed against a constant (α) and the daily return of the market-weighted AEX-index in excess of the risk-free interest rate. The coefficient of the last regression term is called β and measures the riskiness of the strategy relatively to buying and holding the market portfolio. If technical trading rules do not generate excess profits after correction for risk, then α should not be significantly different from zero. In the case of zero transaction costs it is found for the mean return as well as the Sharpe ratio criterion that for respectively 37 and 39 data series the estimate of α is significantly positive at the 10% significance level. Even if transaction costs are increased to 1% per trade, then we find for half of the data series that the estimate of α is still significantly positive. Moreover it is found that simultaneously the estimate of β is significantly smaller than one for many data series. Thus for both selection criteria we find for approximately half of the data series that in the presence of transaction costs the best technical trading strategies have forecasting power and even reduce risk.

An important question is whether the positive results found in favour of technical trading are due to chance or the fact that the best strategy has genuine superior forecasting power over the buy-and-hold benchmark. This is called the danger of data snooping. We apply White's (2000) Reality Check (RC) and Hansen's (2001) Superior Predictive Ability (SPA) test, to test the null hypothesis that the best strategy found in a specification search *is not* superior to the benchmark of a buy-and-hold if a correction is made for data snooping. Hansen (2001) showed that White's RC is biased in the direction of one, caused by the inclusion of poor strategies. Because we compute p-values for both tests, we can investigate whether the two test procedures result in different inferences about forecasting ability of technical trading. If zero transaction costs are implemented, then we find for the mean return selection criterion that the RC and the SPA-test in some cases lead to different conclusions. The SPA-test finds in numerous cases that the best strategy does beat the buy-and-hold significantly after correction for data snooping and the inclusion of bad strategies. Thus the biased RC misguides the researcher in several cases by not rejecting the null. However, if as little as 0.10% costs per trade are implemented, then both tests lead for almost all data series to the same conclusion: the best technical trading strategy selected by the mean return criterion is not capable of beating the buy-and-hold benchmark after correcting for the specification search that is used to find the best strategy. In contrast, for the Sharpe ratio selection criterion we find totally different results. Now the SPA-test rejects its null for 30 data series in the case of zero transaction costs, while the RC rejects its null for only 10 data series. If transaction costs are increased further to even 1% per trade, then for approximately one third of the stocks analyzed, the SPA-test *rejects* the null of no superior predictive ability at the 10% significance level, while the RC *rejects* the null for only two data series. We find for the Sharpe ratio selection criterion large differences between the two testing procedures. Thus the inclusion of poor performing strategies for which the SPA-test is correcting, can indeed influence the inferences about the predictive ability of technical trading rules.

The results show that technical trading has forecasting power for a certain group of stocks listed in the AEX-index. Further the best way to select technical trading strategies is on the basis of the Sharpe ratio criterion. However the testing procedures are mainly done in sample. Therefore next we apply a recursive optimizing and testing method to test whether the best strategy found in a specification search during a training period shows also forecasting power during a testing period thereafter. For example, every month the best strategy from the last 6 months is selected to generate trading signals during that month. In total we examine 28 different training and testing period combinations. In the case of zero transaction costs the best recursive optimizing and testing procedure yields on average an excess return over the buy-and-hold of 32.23% yearly, if the best strategy in the training period is selected by the mean return criterion. Thus the best strategy found in the past continues to generate good results in the future. If 0.50% (1%) transaction costs are implemented, then the excess return decreases to 15.05% (8.02%). These are quite substantial numbers. Estimation of Sharpe-Lintner CAPMs shows that, after correction for 0.10% transaction costs and risk, the best recursive optimizing and testing procedure has significant forecasting power for more than 40% of the data series examined. However, if transaction costs increase to 1%, then for almost all data series the best recursive optimizing and testing procedure has no statistically significant forecasting power anymore.

Hence, in short, after correcting for sufficient transaction costs, risk, data snooping and out-of-sample forecasting, we conclude that objective trend-following technical trading techniques applied to the AEX-index and to stocks listed in the AEX-index in the period 1983-2002 are not genuine superior, as suggested by their performances, to the buy-and-hold benchmark. Only for transaction costs below 0.10% technical trading is statistically profitable, if the best strategy is selected by the Sharpe ratio criterion.

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Table 4.1: **Overview of stocks entering and leaving the AEX-index.** Column 1 shows the names of all stocks listed in the AEX-index in the period January 3, 1983 through March 1, 2002. Columns 2 and 3 show the dates when a stock entered or left the index. Column 4 shows the reason. Source: Euronext.

Fund name	In	Out	What happened?
Algemene Bank Nederland (ABN)	01/03/83	08/27/90	Merger with AMRO bank
Ahold (AH)	01/03/83		
Akzo (AKZ)	01/03/83		
Amro (ARB)	01/03/83	08/27/90	Merger with ABN
Koninklijke Gist-Brocades (GIS)	01/03/83	02/20/98	
Heineken (HEI)	01/03/83		
Hoogovens (HO)	01/03/83	10/06/99	Merger with British Steel, name change to Corus Group
KLM	01/03/83	02/18/00	
Royal Dutch (RD)	01/03/83		
Nationale Nederlanden (NN)	01/03/83	03/01/91	Merger with NMB
Philips (PHI)	01/03/83		
Unilever (UNI)	01/03/83		
Koninklijke Nedlloyd (NED) (NDL after Sept 30, 1994)	01/03/83	02/20/98	
Aegon (AGN)	05/29/84		
Robeco (ROB)	01/03/85	09/01/86	
Amev (AMV)	01/03/86	06/20/94	Name change in Fortis Amev
Fortis Amev (FOR) (name change in Fortis (NL) Jan 11, 1999)	06/20/94	12/17/01	Combing of shares Fortis Netherlands and Fortis Belgium
Fortis (FORA)	12/17/01		Result of combining shares Fortis Netherlands and Fortis Belgium
Elsevier (ELS)	09/01/86		
Koninklijke Nederlandse Papierfabrieken (KNP)	09/01/86	03/09/93	Merger with Buhrmann Tettenrode
Buhrmann Tettenrode (BT)	12/01/86	03/09/93	Merger with Koninklijke Nederlandse Papierfabrieken
Nederlandse Middenstands Bank (NMB)	12/01/86	06/20/88	
Nederlandse Middenstands Bank (NMB)	10/05/89	03/01/91	Merger with Nationale Nederlanden
Oce van der Grinten (OCE)	12/01/86	06/20/88	
Oce van der Grinten (OCE)	02/21/97	05/01/97	Name change in OCE
Oce (OCE)	05/01/97	02/18/00	
Van Ommeren Ceteco N.V. (VOC)	06/20/88	02/18/94	
Wessanen N.V. (WES)	06/20/88	04/07/93	Merger with Bols
DAF	10/05/89	02/04/93	
DSM	10/05/89		
Fokker (FOK)	10/05/89	02/17/95	
Verenigd bezit VNU (name change to VNU July 31, 1998)	10/05/89		
ABN AMRO Bank (AAB)	08/27/90		Result of merger ABN and AMRO
Polygram (PLG)	08/27/90	12/08/98	Take over by The Seagram Company Ltd.
Internationale Nederlanden Groep (ING)	03/01/91		Result of merger NMB with NN
Wolters Kluwer (WKL)	04/19/91		
Stork (STO)	02/04/93	02/19/96	

Table 4.1 continued.

Fund name	In	Out	What happened?
KNP BT (KKB) (name change to Buhrmann July 31, 1998)	03/09/93	08/31/98	Result of merger KNP and BT
Buhrmann (BUHR)	08/31/98	02/18/00	
Buhrmann (BUHR)	03/01/01		
Koninklijke BolsWessanen (BSW)	04/07/93	02/20/98	Result of merger Bols and Wessanen
CSM	02/18/94	02/21/97	
Pakhoed (PAK)	02/18/94	02/19/96	
Koninklijke PTT Nederland (KPN)	02/17/95	06/29/98	Split in Koninklijke KPN and TNT Post Group
Hagemeyer (HGM)	02/19/96		
Koninklijke Verenigde Bedrijven Nutricia (NUT)	02/19/96	01/26/98	Name change in Koninklijke Numico
Koninklijke Numico (NUM)	01/26/98		
ASM Lithography (ASML) (name change to ASML Holding NV June 13, 2001)	02/20/98		
Baan Company (BAAN)	02/20/98	08/04/00	Take over by Invensys plc
Vendex International (VI)	02/20/98	06/25/98	Split in Vendex and Vedior
Vendex (VDX)	06/25/98	03/01/01	Result of split Vendex International
Vedior (VDOR)	06/25/98	02/19/99	Result of split Vendex International
Koninklijke KPN (KPN)	06/29/98		Result of split Koninklijke PTT Nederland
TNT Post Group (TPG) (name change to TPG NV August 6, 2001)	06/29/98		Result of split Koninklijke PTT Nederland
Corus Group (CORS)	10/06/99	03/01/01	Result of merger Hoogovens with British Steel
Getronics (GTN)	02/18/00		
United Pan-Europe Communications (UPC)	02/18/00	02/14/02	
Gucci	02/18/00		
KPNQWEST (KQIP)	03/01/01	06/06/02	
Versatel (VERS)	03/01/01	03/01/02	
CMG	03/01/02		
Van der Moolen (MOO)	03/01/02		

Table 4.2: **Data series examined, sample and largest cumulative loss.** Column 1 shows the names of the data series that are examined in this chapter. Column 2 shows their respective sample periods. Columns 3 and 4 show the largest cumulative loss of the data series in %/100 terms and the period during which this decline occurred.

Data set	Sample period	Max. loss	Period of max. loss
AEX	12/30/83 - 05/31/02	-0.4673	08/12/87 - 11/10/87
ABN	12/30/83 - 08/21/90	-0.3977	08/14/86 - 11/10/87
AMRO	12/30/83 - 08/21/90	-0.4824	01/17/86 - 11/30/87
ABN AMRO	08/20/91 - 05/31/02	-0.4821	04/15/98 - 10/05/98
AEGON	12/30/83 - 05/31/02	-0.5748	01/06/86 - 11/10/87
AHOLD	12/30/83 - 05/31/02	-0.4754	08/13/87 - 01/04/88
AKZO NOBEL	12/30/83 - 05/31/02	-0.5646	09/24/87 - 11/08/90
ASML	03/13/96 - 05/31/02	-0.7866	03/13/00 - 09/21/01
BAAN	05/17/96 - 08/03/00	-0.9743	04/22/98 - 05/22/00
BUHRMANN	12/30/83 - 05/31/02	-0.8431	07/25/00 - 09/21/01
CETECO	05/23/95 - 05/31/02	-0.9988	03/30/98 - 07/19/01
CMG	11/29/96 - 05/31/02	-0.928	02/18/00 - 05/30/02
CORUS	10/03/00 - 05/31/02	-0.512	05/23/01 - 09/21/01
CSM	12/30/83 - 05/31/02	-0.343	05/23/86 - 11/10/87
DAF	05/31/90 - 08/31/93	-0.9986	06/27/90 - 08/20/93
DSM	02/02/90 - 05/31/02	-0.4008	05/21/92 - 03/01/93
REED ELSEVIER	12/30/83 - 05/31/02	-0.5169	08/11/87 - 11/10/87
FOKKER	12/30/83 - 03/04/98	-0.9965	06/23/86 - 10/30/97
FORTIS	12/30/83 - 05/31/02	-0.6342	01/17/86 - 12/10/87
GETRONICS	05/23/86 - 05/31/02	-0.9279	03/07/00 - 09/20/01
GIST BROCADES	12/30/83 - 08/27/98	-0.6121	01/06/86 - 12/29/87
GUCCI	10/21/96 - 05/31/02	-0.5938	04/08/97 - 10/08/98
HAGEMEYER	12/30/83 - 05/31/02	-0.7398	07/24/97 - 09/21/01
HEINEKEN	12/30/83 - 05/31/02	-0.4398	08/12/87 - 11/10/87
HOOGOVENS	12/30/83 - 12/09/99	-0.8104	05/23/86 - 11/10/87
ING	02/28/92 - 05/31/02	-0.5442	07/21/98 - 10/05/98
KLM	12/30/83 - 05/31/02	-0.7843	07/16/98 - 09/18/01
KON. PTT NED.	06/09/95 - 06/26/98	-0.1651	07/18/97 - 09/11/97
KPN	06/25/99 - 05/31/02	-0.9692	03/13/00 - 09/05/01
KPNQWEST	11/03/00 - 05/31/02	-0.9929	01/25/01 - 05/29/02
VAN DER MOOLEN	12/15/87 - 05/31/02	-0.6871	07/09/98 - 10/05/98
NAT. NEDERLANDEN	12/30/83 - 04/11/91	-0.4803	05/23/86 - 11/10/87
NEDLLOYD	12/30/83 - 05/31/02	-0.7844	04/18/90 - 10/08/98
NMB POSTBANK	12/30/83 - 03/01/91	-0.5057	01/07/86 - 01/14/88
NUMICO	12/30/83 - 05/31/02	-0.683	11/05/86 - 01/04/88
OCE	12/30/83 - 05/31/02	-0.8189	05/26/98 - 09/21/01
PAKHOED	12/30/83 - 11/03/99	-0.4825	04/23/98 - 10/01/98
PHILIPS	12/30/83 - 05/31/02	-0.6814	09/05/00 - 09/21/01
POLYGRAM	12/13/90 - 12/14/98	-0.3275	08/08/97 - 04/29/98
ROBECO	12/30/83 - 05/31/02	-0.4363	09/13/00 - 09/21/01
ROYAL DUTCH	12/30/83 - 05/31/02	-0.3747	10/13/00 - 09/21/01
STORK	12/30/83 - 05/31/02	-0.7591	10/06/97 - 09/21/01
TPG	06/25/99 - 05/31/02	-0.4174	01/24/00 - 09/14/01
UNILEVER	12/30/83 - 05/31/02	-0.4541	07/07/98 - 03/13/00
UPC	02/10/00 - 05/31/02	-0.999	03/09/00 - 04/16/02
VEDIOR	06/03/98 - 05/31/02	-0.7169	09/10/98 - 02/22/00
VENDEX KBB	05/29/96 - 05/31/02	-0.7781	10/26/99 - 09/21/01
VERSATEL	07/20/00 - 05/31/02	-0.9932	07/26/00 - 05/22/02
VNU	12/30/83 - 05/31/02	-0.6589	02/25/00 - 10/03/01
WESSANEN	12/30/83 - 05/31/02	-0.5711	07/28/97 - 10/05/98
WOLTERS KLUWER	12/30/83 - 05/31/02	-0.5789	01/05/99 - 03/15/00

Table 4.3: **Summary statistics.** The first column shows the names of the data series examined. Columns 2 to 7 show the number of observations, the mean yearly effective return in %/100 terms, the mean, standard deviation, skewness and kurtosis of the daily logarithmic return. Column 8 shows the t-ratio testing whether the mean daily return is significantly different from zero. Column 9 shows the Sharpe ratio. Column 10 shows the largest cumulative loss in %/100 terms. Column 11 shows the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. Column 12 shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic for testing autocorrelations in the squared returns. Significance level of the (adjusted) Q(20)-test statistic can be evaluated based on the following chi-squared values: a) chi-squared(0.99,20)=37.57, b) chi-squared(0.95,20)=31.41, c) chi-squared(0.90,20)=28.41.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
AEX	4805	0.1042	0.000393	0.012051	-0.558	13.195	2.26b	0.014661	-0.4673	70.78a	21.34	4375.57a
ABN	1732	0.0427	0.000166	0.012829	-0.13	8.929	0.54	-0.005931	-0.3977	22.22	9.94	1114.12a
AMRO	1732	0.0679	0.000261	0.014559	-0.276	10.168	0.74	0.001286	-0.4824	27.36	12.57	454.18a
ABN AMRO	2813	0.2012	0.000727	0.016749	-0.336	8.248	2.30b	0.032169	-0.4821	49.55a	23.21	1601.92a
AEGON	4805	0.2033	0.000735	0.017084	-0.239	11.98	2.98a	0.030316	-0.5748	59.60a	20.6	2383.74a
AHOLD	4805	0.1701	0.000624	0.0162	-0.305	12.509	2.67a	0.025118	-0.4754	86.40a	31.45b	3844.46a
AKZO NOBEL	4805	0.1215	0.000455	0.016427	-0.494	11.253	1.92c	0.014513	-0.5646	86.16a	27.63	3432.03a
ASML	1622	0.3809	0.001281	0.041354	0.155	6.225	1.25	0.027639	-0.7866	50.77a	38.62a	89.48a
BAAN	1099	-0.3075	-0.001458	0.048042	1.147	38.714	-1.01	-0.032987	-0.9743	44.12a	18.95	39.16a
BUHRMANN	4805	0.1031	0.000389	0.023772	-1.31	47.813	1.13	0.007261	-0.8431	38.95a	19.78	47.41a
CETECO	1833	-0.5427	-0.003104	0.06784	-3.278	62.774	-1.96c	-0.047808	-0.9988	104.66a	28.09	203.54a
CMG	1435	0.0775	0.000296	0.037376	-0.206	9.389	0.3	0.004156	-0.928	72.96a	48.56a	139.65a
CORUS	433	0.3054	0.001058	0.030171	0.338	4.99	0.73	0.029612	-0.512	27.11	25.17	15.78
CSM	4805	0.1596	0.000587	0.014589	1.327	36.456	2.79a	0.025423	-0.343	60.70a	24.08	812.42a
DAF	848	-0.8565	-0.007703	0.097302	-3.33	36.55	-2.31b	-0.082711	-0.9986	97.94a	13.2	286.71a
DSM	3215	0.1429	0.00053	0.015778	0.198	8.193	1.90c	0.020398	-0.4008	38.75a	22.1	569.54a
REED ELSEVIER	4805	0.192	0.000697	0.018464	0.055	13.556	2.62a	0.026015	-0.5169	82.77a	25.57	2277.49a
FOKKER	3698	-0.2133	-0.000952	0.057443	-3.733	71.209	-1.01	-0.020722	-0.9965	115.12a	24.86	546.71a
FORTIS	4805	0.1473	0.000545	0.017203	0.167	9.926	2.20b	0.019107	-0.6342	34.52b	13.56	2097.37a
GETRONICS	4180	0.0949	0.00036	0.025214	-2.483	60.334	0.92	0.005826	-0.9279	61.16a	17.65	120.88a
GIST BROCADES	3824	0.0695	0.000267	0.017398	-0.39	11.739	0.95	0.001842	-0.6121	47.05a	25.94	499.63a
GUCCI	1464	0.1289	0.000481	0.026198	0.507	10.817	0.7	0.013003	-0.5938	25.72	16.94	177.81a
HAGEMEYER	4805	0.1437	0.000533	0.020354	-0.767	20.041	1.81c	0.015534	-0.7398	48.75a	21.26	924.57a
HEINEKEN	4805	0.1726	0.000632	0.015468	0.067	9.687	2.83a	0.026842	-0.4398	65.52a	27.37	2358.85a
HOOGOVENS	4159	0.1018	0.000385	0.024165	-0.773	17.372	1.03	0.006609	-0.8104	57.43a	28.62c	250.82a
ING	2675	0.2286	0.000817	0.017917	-0.682	11.917	2.36b	0.035597	-0.5442	95.04a	32.78b	1685.41a
KLM	4805	0.0145	0.000057	0.022555	-0.407	13.283	0.18	-0.007074	-0.7843	43.88a	23.15	721.16a

Table 4.3 continued.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
KON. PTT NED.	795	0.3279	0.001125	0.01434	0.287	5.656	2.21b	0.069431	-0.1651	53.09a	35.91b	170.80a
KPN	765	-0.3959	-0.002	0.045616	-0.128	6.22	-1.21	-0.047207	-0.9692	32.65b	22.13	172.90a
KPNQWEST	410	-0.9399	-0.011158	0.087222	-3.346	32.22	-2.59a	-0.129789	-0.9929	54.54a	14.83	108.71a
VAN DER MOOLEN	3773	0.2731	0.000958	0.021531	0.045	12.922	2.73a	0.03462	-0.6871	71.79a	27.05	1177.84a
NAT. NEDERLANDEN	1899	0.1055	0.000398	0.015855	-0.071	17.589	1.09	0.009266	-0.4803	26.94	8.78	1245.69a
NEDLLOYD	4805	0.0786	0.0003	0.023107	1.292	43.435	0.9	0.003627	-0.7844	48.49a	25	127.26a
NMB POSTBANK	1870	0.1135	0.000427	0.015695	-0.111	8.606	1.18	0.011297	-0.5057	22.67	16.29	148.46a
NUMICO	4805	0.1988	0.000719	0.017808	-0.665	24.203	2.80a	0.028239	-0.683	40.15a	20.39	158.90a
OCE	4805	0.0748	0.000286	0.019629	-0.48	18.012	1.01	0.003546	-0.8189	75.60a	26.28	873.42a
PAKHOED	4133	0.1503	0.000556	0.01781	-0.111	10.48	2.01b	0.018523	-0.4825	23.4	14.65	383.09a
PHILIPS	4805	0.1356	0.000505	0.023059	-0.401	9.391	1.52	0.012486	-0.6814	62.15a	28.46c	1386.88a
POLYGRAM	2087	0.1824	0.000665	0.015905	0.267	7.009	1.91c	0.027906	-0.3275	27.46	20.9	116.65a
ROBECO	4805	0.1003	0.000379	0.009457	-0.495	10.909	2.78a	0.017202	-0.4363	56.62a	23.75	1585.92a
ROYAL DUTCH	4805	0.16	0.000589	0.013469	-0.088	7.549	3.03a	0.027653	-0.3747	35.86b	16.22	2875.11a
STORK	4805	0.0823	0.000314	0.020289	-1.356	30.27	1.07	0.004791	-0.7591	52.41a	18.22	702.99a
TPG	765	-0.0129	-0.000052	0.020926	-0.093	5.47	-0.07	-0.009794	-0.4174	23.2	18.63	119.38a
UNILEVER	4805	0.1726	0.000632	0.016744	0.019	11.955	2.62a	0.024806	-0.4541	98.23a	45.94a	731.96a
UPC	601	-0.9212	-0.010084	0.079572	-0.187	6.552	-3.11a	-0.128788	-0.999	33.40b	24.82	109.25a
VEDIOR	1042	-0.1174	-0.000496	0.034184	-0.049	13.428	-0.47	-0.018754	-0.7169	29.83c	25.06	29.96c
VENDEX KBB	1567	0.1287	0.000481	0.023202	-0.035	10.019	0.82	0.014741	-0.7781	38.24a	19.91	227.98a
VERSATEL	486	-0.9173	-0.009892	0.069301	0.629	10.696	-3.15a	-0.145133	-0.9932	19.02	18.61	30.71c
VNU	4805	0.2045	0.000738	0.019594	0.049	11.399	2.61a	0.026633	-0.6589	56.62a	24.11	1379.96a
WESSANEN	4805	0.0656	0.000252	0.016082	-0.351	15.195	1.09	0.002214	-0.5711	82.28a	33.19b	1055.89a
WOLTERS KLUWER	4805	0.2097	0.000755	0.017947	-1.459	29.33	2.92a	0.030022	-0.5789	81.27a	28.16	635.78a

Table 4.4: **Statistics best strategy: mean return criterion, 0% costs.** Statistics of the best strategy, selected by the mean return criterion, if no transaction costs are implemented, for each data series listed in the first column. Column 2 shows the strategy parameters. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio. Column 7 shows the largest cumulative loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
AEX	[MA: 1, 25, 0.000, 0, 0, 0.100]	0.2502	0.1323	0.0454	0.0307	-0.4387	411	0.659	0.849	1.2064

Table 4.4 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
ABN	[MA: 1, 10, 0.010, 0, 0, 0.000]	0.2862	0.2336	0.0467	0.0527	-0.3076	100	0.730	0.842	1.2766
AMRO	[MA: 1, 5, 0.005, 0, 0, 0.000]	0.3874	0.2992	0.0563	0.0550	-0.3216	234	0.718	0.838	1.2825
ABN AMRO	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4982	0.2473	0.0628	0.0307	-0.4880	1114	0.713	0.825	1.1275
AEGON	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.5412	0.2808	0.0637	0.0334	-0.5826	1870	0.718	0.830	1.1375
AHOLD	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.4030	0.1990	0.0490	0.0239	-0.6745	2230	0.686	0.790	1.1167
AKZO NOBEL	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.5598	0.3908	0.0686	0.0541	-0.5888	1834	0.713	0.830	1.1438
ASML	[MA: 2, 50, 0.000, 4, 0, 0.000]	1.3426	0.6965	0.0757	0.0481	-0.5728	29	0.759	0.890	1.4775
BAAN	[FR: 0.005, 0, 0]	0.5678	1.2641	0.0248	0.0577	-0.7490	436	0.706	0.804	1.2107
BUHRMANN	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.5494	0.4047	0.0512	0.0439	-0.5858	2128	0.699	0.810	1.3945
CETECO	[MA: 10, 200, 0.000, 2, 0, 0.000]	0.1616	1.5398	0.0194	0.0672	-0.5315	12	0.750	0.886	2.9653
CMG	[MA: 1, 5, 0.000, 0, 0, 0.075]	1.2144	1.0551	0.0659	0.0618	-0.7236	326	0.709	0.833	1.1708
CORUS	[MA: 1, 25, 0.000, 0, 25, 0.000]	1.2393	0.7154	0.0810	0.0514	-0.3774	21	0.667	0.744	1.1468
CSM	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.2764	0.1008	0.0362	0.0108	-0.5294	1837	0.684	0.802	1.2955
DAF	[MA: 10, 25, 0.025, 0, 0, 0.000]	0.0994	6.6594	0.0005	0.0832	-0.8171	15	0.667	0.779	2.6064
DSM	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.5287	0.3376	0.0693	0.0489	-0.3549	1527	0.692	0.815	1.3443
REED ELSEVIER	[FR: 0.005, 0, 0]	0.3404	0.1245	0.0375	0.0114	-0.6546	1562	0.703	0.824	1.0731
FOKKER	[short]	0.0618	0.3498	0.0000	0.0207	0.0000	1	1.000	1.000	NA
FORTIS	[FR: 0.005, 0, 0]	0.4224	0.2397	0.0508	0.0316	-0.6734	1540	0.708	0.820	1.2021
GETRONICS	[FR: 0.005, 0, 0]	0.6024	0.4634	0.0518	0.0460	-0.8127	1384	0.697	0.815	1.3690
GIST BROCADES	[MA: 1, 25, 0.000, 0, 0, 0.000]	0.2548	0.1733	0.0286	0.0268	-0.4897	332	0.666	0.864	0.9720
GUCCI	[FR: 0.010, 0, 0,]	0.5011	0.3298	0.0414	0.0284	-0.5883	407	0.703	0.829	1.2138
HAGEMEYER	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.6217	0.4180	0.0636	0.0481	-0.6414	1793	0.694	0.810	1.2510
HEINEKEN	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4010	0.1948	0.0527	0.0258	-0.5536	1858	0.700	0.819	1.1882
HOOGOVENS	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4010	0.1948	0.0527	0.0258	-0.5536	1858	0.700	0.819	1.1882
ING	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.8105	0.4736	0.0951	0.0595	-0.5247	994	0.728	0.852	1.3545
KLM	[FR: 0.010, 0, 0]	0.2234	0.2060	0.0199	0.0270	-0.6926	1305	0.707	0.833	1.1918
KON. PTT NED.	[FR: 0.005, 0, 0]	0.5792	0.1892	0.0832	0.0137	-0.2851	247	0.725	0.836	1.2906
KPN	[FR: 0.035, 0, 0]	1.1403	2.5429	0.0538	0.1010	-0.4628	143	0.748	0.865	1.2871
KPNQWEST	[SR 15, 0.025, 0, 0, 0.000]	0.2783	20.2694	0.0176	0.1474	-0.5794	9	0.889	0.988	2.5531
VAN DER MOOLEN	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.8905	0.4850	0.0806	0.0460	-0.5842	1361	0.696	0.809	1.3909
NAT. NEDERLANDEN	[MA: 1, 5, 0.001, 0, 0, 0.000]	0.4646	0.3248	0.0639	0.0546	-0.3051	384	0.688	0.834	1.4260
NEDLLOYD	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.5838	0.4683	0.0489	0.0452	-0.6774	1953	0.683	0.816	1.2050
NMB POSTBANK	[SR 5, 0.000, 0, 0, 0.000]	0.4532	0.3050	0.0590	0.0477	-0.4431	215	0.726	0.865	1.3831
NUMICO	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.5488	0.2920	0.0599	0.0316	-0.8071	1763	0.700	0.820	1.0522
OCE	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.4986	0.3943	0.0506	0.0471	-0.7918	1814	0.695	0.822	1.0832
PAKHOED	[SR 25, 0.000, 0, 0, 0.075]	0.3294	0.1557	0.0389	0.0204	-0.3689	126	0.714	0.831	1.0275

Table 4.4 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
PHILIPS	[FR: 0.005, 0, 0]	0.6646	0.4659	0.0587	0.0462	-0.6383	1639	0.719	0.837	1.1255
POLYGRAM	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.4626	0.2369	0.0571	0.0292	-0.3543	985	0.694	0.790	1.2574
ROBECO	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.3591	0.2352	0.0791	0.0619	-0.3168	1626	0.726	0.839	1.1705
ROYAL DUTCH	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.2841	0.1069	0.0415	0.0138	-0.4719	1926	0.707	0.815	1.1878
STORK	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.3152	0.2152	0.0292	0.0244	-0.8669	2253	0.679	0.802	0.9364
TPG	[FR: 0.025, 0, 25]	0.2077	0.2235	0.0213	0.0311	-0.3973	49	0.633	0.754	0.9465
UNILEVER	[FR: 0.200, 4, 0]	0.2591	0.0737	0.0276	0.0027	-0.5251	15	0.933	0.985	0.8096
UPC	[short]	0.0422	12.2299	0.0000	0.1288	0.0000	1	1.000	1.000	NA
VEDIOR	[MA: 2, 5, 0.000, 0, 25, 0.000]	0.4764	0.6728	0.0332	0.0520	-0.5683	58	0.707	0.844	1.6142
VENDEX KBB	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.6473	0.4594	0.0603	0.0456	-0.7064	634	0.689	0.806	1.4021
VERSATEL	[FR: 0.120, 0, 0,]	0.5762	18.0630	0.0207	0.1658	-0.5642	27	0.704	0.872	1.6760
VNU	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.6397	0.3613	0.0641	0.0375	-0.5945	1874	0.709	0.830	1.1521
WESSANEN	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.3572	0.2736	0.0448	0.0426	-0.5854	1902	0.680	0.815	1.1492
WOLTERS KLUWER	[MA: 1 , 2, 0.001, 0, 0, 0.000]	0.5224	0.2585	0.0609	0.0309	-0.6480	1864	0.697	0.820	1.1813

Table 4.5: **Statistics best strategy: mean return criterion, 0.25% costs.** Statistics of the best strategy, selected by the mean return criterion, if 0.25% costs per trade are implemented, for each data series listed in the first column. Column 2 shows the strategy parameters. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio. Column 7 shows the largest cumulative loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
AEX	[MA: 5, 25, 0.050, 0, 0, 0.000]	0.2060	0.0923	0.0335	0.0188	-0.4148	13	1.000	1.000	NA
ABN	[MA: 5, 10, 0.025, 0, 0, 0.000]	0.2262	0.1764	0.0431	0.0492	-0.2649	11	0.727	0.983	0.6278
AMRO	[MA: 10, 50, 0.025, 0, 0, 0.000]	0.2935	0.2118	0.0463	0.0451	-0.4307	14	0.786	0.925	1.2234
ABN AMRO	[FR: 0.090, 4, 0]	0.3003	0.0828	0.0355	0.0034	-0.6587	53	0.321	0.749	0.6190
AEGON	[MA: 25, 50, 0.050, 0, 0, 0.000]	0.3104	0.0891	0.0407	0.0104	-0.6193	10	0.700	0.884	0.7975
AHOLD	[SR: 10, 0.000, 0, 50, 0.000]	0.3020	0.1129	0.0414	0.0163	-0.6203	145	0.703	0.808	0.9048
AKZO NOBEL	[MA: 1, 10, 0.001, 0, 0, 0.000]	0.2555	0.1196	0.0322	0.0177	-0.4911	611	0.239	0.468	1.0644
ASML	[MA: 2, 50, 0.000, 4, 0, 0.000]	1.2941	0.6620	0.0738	0.0462	-0.5971	29	0.552	0.855	1.2261
BAAN	[FR: 0.045, 0, 25,]	0.5004	1.1679	0.0245	0.0575	-0.6185	65	0.415	0.435	1.1170
BUHRMANN	[MA: 1, 2, 0.050, 0, 0, 0.000]	0.3279	0.2040	0.0395	0.0323	-0.5189	7	1.000	1.000	NA
CETECO	[MA: 10, 200, 0.000, 2, 0, 0.000]	0.1526	1.5211	0.0181	0.0659	-0.5315	12	0.583	0.878	1.9772

Table 4.5 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
CMG	[MA: 25, 50, 0.050, 0, 0, 0.000]	0.9756	0.8343	0.0727	0.0686	-0.6357	8	0.875	0.989	0.7260
CORUS	[MA: 1, 25, 0.000, 0, 25, 0.000]	1.1715	0.6658	0.0777	0.0482	-0.3819	21	0.429	0.455	1.0574
CSM	[MA: 10, 100, 0.050, 0, 0, 0.000]	0.2242	0.0559	0.0286	0.0032	-0.5071	17	0.941	0.959	1.1744
DAF	[short]	0.0908	6.6050	0.0000	0.0827	0.0000	1	1.000	1.000	NA
DSM	[MA: 2, 100, 0.000, 0, 0, 0.100]	0.3218	0.1568	0.0444	0.0241	-0.3954	91	0.407	0.809	0.8567
REED ELSEVIER	[FR: 0.040, 0, 50]	0.2583	0.0558	0.0276	0.0016	-0.7002	133	0.767	0.891	0.6184
FOKKER	[short]	0.0618	0.3500	0.0000	0.0207	0.0000	1	1.000	1.000	NA
FORTIS	[FR: 0.140, 3, 0]	0.2129	0.0573	0.0235	0.0044	-0.7970	46	0.522	0.843	0.6970
GETRONICS	[MA: 5, 100, 0.025, 0, 0, 0.000]	0.3160	0.2021	0.0345	0.0287	-0.5473	40	0.625	0.904	1.2430
GIST BROCADES	[MA: 10, 200, 0.000, 0, 50, 0.000]	0.2053	0.1271	0.0263	0.0245	-0.4796	45	0.733	0.728	0.9605
GUCCI	[SR: 5, 0.000, 0, 50, 0.000]	0.4345	0.2713	0.0388	0.0259	-0.4526	49	0.673	0.867	0.9805
HAGEMEYER	[MA: 25, 100, 0.000, 0, 0, 0.100]	0.2687	0.1094	0.0315	0.0160	-0.6601	75	0.480	0.667	0.8419
HEINEKEN	[MA: 1, 2, 0.000, 0, 50, 0.000]	0.2509	0.0669	0.0363	0.0095	-0.4846	120	0.708	0.893	1.0301
HOOGOVENS	[MA: 1, 2, 0.000, 0, 50, 0.000]	0.2509	0.0669	0.0363	0.0095	-0.4846	120	0.708	0.893	1.0301
ING	[FR: 0.100, 4, 0]	0.4265	0.1613	0.0515	0.0160	-0.4403	42	0.500	0.772	0.9916
KLM	[FR: 0.100, 0, 50]	0.1514	0.1351	0.0147	0.0218	-0.6026	110	0.709	0.821	1.0300
KON. PTT NED.	[MA: 25, 200, 0.000, 3, 0, 0.000]	0.5422	0.1623	0.0673	-0.0019	-0.2701	5	0.800	0.996	1.1393
KPN	[FR: 0.035, 0, 0]	0.7261	1.8596	0.0375	0.0848	-0.5333	143	0.217	0.320	0.8791
KPNQWEST	[SR: 15, 0.025, 0, 0, 0.000]	0.2502	19.8348	0.0157	0.1455	-0.5858	9	0.889	0.988	2.5531
VAN DER MOOLEN	[FR: 0.200, 0, 0]	0.4967	0.1759	0.0508	0.0162	-0.5865	21	0.857	0.937	0.9624
NAT. NEDERLANDEN	[SR: 5, 0.010, 0, 0, 0.000]	0.2544	0.1350	0.0326	0.0234	-0.3684	99	0.434	0.705	1.0256
NEDLLOYD	[MA: 2, 25, 0.000, 0, 0, 0.000]	0.3615	0.2624	0.0341	0.0305	-0.6414	288	0.316	0.695	1.2790
NMB POSTBANK	[SR: 20, 0.000, 0, 0, 0.000]	0.3816	0.2412	0.0480	0.0368	-0.4116	45	0.689	0.866	1.0019
NUMICO	[FR: 0.160, 4, 0,]	0.3788	0.1503	0.0463	0.0181	-0.5632	26	0.808	0.951	0.8727
OCE	[SR: 50, 0.010, 0, 0, 0.000]	0.3427	0.2494	0.0464	0.0429	-0.7001	28	0.786	0.920	1.2531
PAKHOED	[SR: 25, 0.000, 0, 0, 0.075]	0.2954	0.1263	0.0344	0.0159	-0.4018	126	0.540	0.742	1.0265
PHILIPS	[MA: 5, 100, 0.050, 0, 0, 0.000]	0.3584	0.1964	0.0368	0.0244	-0.5935	30	0.833	0.925	1.2026
POLYGRAM	[MA: 1, 2, 0.025, 0, 0, 0.000]	0.3427	0.1359	0.0412	0.0133	-0.4702	12	0.583	0.937	0.6775
ROBECO	[MA: 5, 25, 0.000, 0, 0, 0.075]	0.2036	0.0941	0.0424	0.0252	-0.3751	218	0.353	0.664	0.8953
ROYAL DUTCH	[SR: 100, 0.000, 0, 0, 0.100]	0.2339	0.0639	0.0374	0.0098	-0.3284	40	0.575	0.814	0.7354
STORK	[SR: 20, 0.010, 0, 0, 0.000]	0.2771	0.1801	0.0309	0.0262	-0.5738	83	0.590	0.836	1.0104
TPG	[FR: 0.025, 0, 25]	0.1587	0.1749	0.0155	0.0254	-0.3973	49	0.408	0.395	0.8050
UNILEVER	[FR: 0.200, 4, 0]	0.2543	0.0698	0.0270	0.0022	-0.5298	15	0.800	0.977	0.5217
UPC	[short]	0.0422	12.2439	0.0000	0.1288	0.0000	1	1.000	1.000	NA
VEDIOR	[MA: 2, 5, 0.000, 0, 25, 0.000]	0.4251	0.6157	0.0299	0.0487	-0.5789	58	0.466	0.518	1.0279
VENDEX KBB	[SR: 25, 0.050, 0, 0, 0.000]	0.4469	0.2824	0.0531	0.0384	-0.3155	4	1.000	1.000	NA

Table 4.5 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
VERSATEL	[FR: 0.120, 0, 0]	0.4777	16.8951	0.0174	0.1626	-0.5717	27	0.444	0.730	1.4834
VNU	[MA: 1, 2, 0.050, 0, 0, 0.000]	0.3448	0.1166	0.0420	0.0154	-0.5302	6	0.667	0.995	0.2966
WESSANEN	[MA: 1, 2, 0.025, 0, 0, 0.000]	0.2000	0.1263	0.0254	0.0232	-0.5345	29	0.552	0.963	0.4049
WOLTERS KLUWER	[MA: 2, 5, 0.050, 0, 0, 0.000]	0.2778	0.0564	0.0322	0.0022	-0.6267	13	0.538	0.917	0.5323

Table 4.6: **Statistics best strategy: Sharpe ratio criterion, 0 and 0.25% costs.** Statistics of the best strategy, selected by the Sharpe ratio criterion, if 0 and 0.25% costs per trade are implemented, for each data series listed in the first column. Column 2 shows the strategy parameters. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio. Column 7 shows the largest loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades. Results are only shown for those data series for which a different best strategy is selected by the Sharpe ratio criterion than by the mean return criterion.

0% costs per trade Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
AEX	[MA: 1, 25, 0.000, 0, 0, 0.000]	0.2475	0.1298	0.0454	0.0308	-0.4444	408	0.657	0.849	1.2064
BAAN	[MA: 1, 2, 0.000, 0, 50, 0.000]	0.4911	1.1534	0.0593	0.0923	-0.4425	27	0.741	0.990	1.6964
CMG	[MA: 25, 50, 0.050, 0, 0, 0.000]	0.9886	0.8456	0.0735	0.0693	-0.6322	8	0.875	0.989	0.7260
CORUS	[MA: 1, 2, 0.000, 0, 0, 0.000]	1.1930	0.6799	0.0813	0.0517	-0.4660	176	0.705	0.829	1.5341
DAF	[SR: 20, 0.050, 0, 0, 0.000]	0.0989	6.6563	0.0005	0.0833	-0.5781	9	0.778	0.782	3.8140
GIST BROCADES	[MA: 2, 25, 0.000, 0, 0, 0.000]	0.2547	0.1731	0.0289	0.0270	-0.5015	246	0.711	0.856	1.0282
GUCCI	[FR: 0.200, 0, 50]	0.4060	0.2455	0.0470	0.0340	-0.2944	19	0.842	0.701	1.2907
VAN DER MOOLEN	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.8182	0.4282	0.0808	0.0462	-0.5137	1653	0.674	0.816	1.3728
NMB POSTBANK	[SR: 5, 0.001, 0, 0, 0.000]	0.4489	0.3012	0.0592	0.0479	-0.4275	201	0.731	0.873	1.4092
PAKHOED	[MA: 10, 25, 0.000, 0, 50, 0.000]	0.2739	0.1075	0.0392	0.0207	-0.4607	116	0.690	0.823	1.0159
STORK	[SR: 20, 0.010, 0, 0, 0.000]	0.3046	0.2054	0.0345	0.0297	-0.5606	83	0.819	0.908	0.9992
TPG	[SR: 5, 0.000, 0, 50, 0.000]	0.1531	0.1682	0.0251	0.0349	-0.2260	25	0.760	0.988	1.8030
UNILEVER	[MA: 10, 25, 0.000, 0, 5, 0.000]	0.2134	0.0348	0.0295	0.0047	-0.4496	342	0.705	0.663	0.8162
0.25% costs per trade Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
AEX	[FR: 0.120, 0, 50]	0.1572	0.0482	0.0345	0.0199	-0.2724	42	0.786	0.808	1.3628
ABN AMRO	[SR: 150, 0.000, 0, 0, 0.100]	0.2915	0.0754	0.0457	0.0136	-0.3828	13	0.615	0.924	0.7539
AEGON	[SR: 250, 0.010, 0, 0, 0.000]	0.2914	0.0733	0.0449	0.0146	-0.4530	4	1.000	1.000	NA
BAAN	[MA: 1, 2 0.000, 0, 50, 0.000]	0.4670	1.1197	0.0566	0.0897	-0.4425	27	0.741	0.990	1.6964

Table 4.6 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
CETECO	[SR: 250, 0.025 0, 0, 0.000]	0.1341	1.4806	0.0182	0.0661	-0.4751	3	1.000	1.000	NA
CSM	[SR: 200, 0.000, 0, 50, 0.000]	0.1871	0.0238	0.0321	0.0067	-0.3105	18	0.833	0.873	0.8999
DAF	[SR: 20, 0.050, 0, 0, 0.000]	0.0874	6.5818	-0.0002	0.0825	-0.5823	9	0.778	0.782	3.8140
REED ELSEVIER	[FR: 0.140, 0, 50]	0.2264	0.0290	0.0307	0.0047	-0.5967	45	0.756	0.914	0.8124
FORTIS	[MA: 2, 100, 0.000, 0, 50, 0.000]	0.1978	0.0441	0.0293	0.0102	-0.5023	86	0.733	0.846	0.9443
GETRONICS	[SR: 50, 0.050, 0, 0, 0.000]	0.3134	0.1997	0.0355	0.0297	-0.6535	10	0.900	0.982	0.6250
GUCCI	[FR: 0.200, 0, 50,]	0.3952	0.2364	0.0459	0.0329	-0.2980	19	0.789	0.667	1.3484
ING	[MA: 25, 100, 0.000, 0, 0, 0.100]	0.4013	0.1408	0.0574	0.0219	-0.4027	48	0.583	0.774	0.8523
KON. PTT NED.	[FR: 0.050, 0, 50]	0.4075	0.0608	0.0763	0.0071	-0.1439	19	0.789	0.889	1.1433
PAKHOED	[MA: 10, 25, 0.000, 0, 50, 0.000]	0.2516	0.0883	0.0355	0.0170	-0.4661	116	0.681	0.811	1.0157
POLYGRAM	[FR: 0.050, 0, 25]	0.3190	0.1158	0.0415	0.0137	-0.3669	98	0.561	0.604	0.9687
ROBECO	[SR: 25, 0.025, 0, 0, 0.000]	0.1686	0.0622	0.0435	0.0264	-0.3793	7	0.857	0.968	1.0651
TPG	[FR: 0.035, 0, 50]	0.1581	0.1742	0.0202	0.0302	-0.3420	25	0.680	0.838	1.2569
VENDEX KBB	[FR: 0.400, 2, 0]	0.4458	0.2814	0.0536	0.0389	-0.4861	3	1.000	1.000	NA
WOLTERS KLUWER	[MA: 1, 200 , 0.000, 0, 5, 0.000]	0.2448	0.0292	0.0372	0.0072	-0.3897	106	0.453	0.856	0.5689

Table 4.7: **Performance best strategy in excess of performance buy-and-hold.** Panel A shows the mean return of the best strategy, selected by the mean return criterion after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade, in excess of the mean return of the buy-and-hold benchmark for each data series listed in the first column. Panel B shows the Sharpe ratio of the best strategy, selected by the Sharpe ratio criterion after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade, in excess of the Sharpe ratio of the buy-and-hold benchmark for each data series listed in the first column.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
AEX	0.1323	0.0943	0.0923	0.0889	0.0856	0.0822	0.0308	0.0216	0.0199	0.0180	0.0172	0.0164
ABN	0.2336	0.1988	0.1764	0.1686	0.1608	0.1530	0.0527	0.0504	0.0492	0.0471	0.0451	0.0430
AMRO	0.2992	0.2289	0.2118	0.2003	0.1889	0.1776	0.0550	0.0464	0.0451	0.0429	0.0406	0.0384
ABN AMRO	0.2473	0.1042	0.0828	0.0725	0.0695	0.0666	0.0307	0.0166	0.0136	0.0130	0.0124	0.0118
AEGON	0.2808	0.1117	0.0891	0.0865	0.0840	0.0814	0.0334	0.0147	0.0146	0.0144	0.0143	0.0141
AHOLD	0.1990	0.1256	0.1129	0.0920	0.0803	0.0760	0.0239	0.0185	0.0163	0.0125	0.0096	0.0074
AKZO NOBEL	0.3908	0.2251	0.1196	0.1123	0.1065	0.1008	0.0541	0.0346	0.0177	0.0144	0.0129	0.0114
ASML	0.6965	0.6826	0.6620	0.6281	0.5948	0.5621	0.0481	0.0473	0.0462	0.0442	0.0423	0.0403
BAAN	1.2641	1.2199	1.1679	1.0865	1.0538	1.0215	0.0923	0.0912	0.0897	0.0871	0.0844	0.0818

Table 4.7 continued.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
BUHRMANN	0.4047	0.2050	0.2040	0.2023	0.2006	0.1989	0.0439	0.0324	0.0323	0.0320	0.0318	0.0315
CETECO	1.5398	1.5323	1.5211	1.5025	1.4839	1.4733	0.0672	0.0667	0.0661	0.0658	0.0656	0.0653
CMG	1.0551	0.8963	0.8343	0.8231	0.8118	0.8007	0.0693	0.0690	0.0686	0.0679	0.0671	0.0664
CORUS	0.7154	0.6954	0.6658	0.6176	0.5706	0.5248	0.0517	0.0501	0.0482	0.0451	0.0419	0.0387
CSM	0.1008	0.0586	0.0559	0.0514	0.0470	0.0425	0.0108	0.0071	0.0067	0.0061	0.0054	0.0048
DAF	6.6594	6.6264	6.6050	6.6106	6.6162	6.6218	0.0833	0.0830	0.0825	0.0818	0.0810	0.0828
DSM	0.3376	0.1753	0.1568	0.1317	0.1123	0.0932	0.0489	0.0272	0.0241	0.0188	0.0136	0.0108
REED ELSEVIER	0.1245	0.0670	0.0558	0.0413	0.0407	0.0400	0.0114	0.0055	0.0047	0.0035	0.0024	0.0015
FOKKER	0.3498	0.3499	0.3500	0.3503	0.3505	0.3507	0.0207	0.0207	0.0207	0.0207	0.0208	0.0208
FORTIS	0.2397	0.0969	0.0573	0.0551	0.0547	0.0544	0.0316	0.0118	0.0102	0.0075	0.0054	0.0053
GETRONICS	0.4634	0.3040	0.2021	0.1965	0.1934	0.1902	0.0460	0.0334	0.0297	0.0293	0.0288	0.0283
GIST BROCADES	0.1733	0.1484	0.1271	0.1193	0.1114	0.1036	0.0270	0.0253	0.0245	0.0230	0.0216	0.0201
GUCCI	0.3298	0.2870	0.2713	0.2455	0.2201	0.2096	0.0340	0.0336	0.0329	0.0318	0.0307	0.0295
HAGEMEYER	0.4180	0.2307	0.1094	0.0975	0.0856	0.0739	0.0481	0.0271	0.0160	0.0141	0.0122	0.0103
HEINEKEN	0.1948	0.0784	0.0669	0.0480	0.0340	0.0333	0.0258	0.0118	0.0095	0.0056	0.0022	0.0019
HOOGOVENS	0.1948	0.0784	0.0669	0.0480	0.0340	0.0333	0.0258	0.0118	0.0095	0.0056	0.0022	0.0019
ING	0.4736	0.2656	0.1613	0.1391	0.1173	0.0979	0.0595	0.0326	0.0219	0.0201	0.0185	0.0168
KLM	0.2060	0.1545	0.1351	0.1192	0.1065	0.0992	0.0270	0.0233	0.0218	0.0194	0.0170	0.0146
KON. PTT NED.	0.1892	0.1673	0.1623	0.1541	0.1492	0.1446	0.0137	0.0095	0.0071	0.0035	0.0021	0.0008
KPN	2.5429	2.2521	1.8596	1.6628	1.6541	1.6455	0.1010	0.0945	0.0848	0.0842	0.0839	0.0836
KPNQWEST	20.2694	20.0946	19.8348	19.5219	19.2272	18.9362	0.1474	0.1466	0.1455	0.1440	0.1427	0.1414
VAN DER MOOLEN	0.4850	0.2799	0.1759	0.1686	0.1613	0.1541	0.0462	0.0252	0.0162	0.0153	0.0144	0.0134
NAT. NEDERLANDEN	0.3248	0.2081	0.1350	0.1018	0.0943	0.0869	0.0546	0.0358	0.0234	0.0213	0.0208	0.0203
NEDLLOYD	0.4683	0.3177	0.2624	0.2350	0.2268	0.2186	0.0452	0.0363	0.0305	0.0278	0.0269	0.0259
NMB POSTBANK	0.3050	0.2632	0.2412	0.2052	0.1702	0.1361	0.0479	0.0401	0.0368	0.0313	0.0258	0.0203
NUMICO	0.2920	0.1589	0.1503	0.1429	0.1356	0.1282	0.0316	0.0192	0.0181	0.0170	0.0158	0.0147
OCE	0.3943	0.2546	0.2494	0.2409	0.2325	0.2240	0.0471	0.0437	0.0429	0.0415	0.0401	0.0387
PAKHOED	0.1557	0.1438	0.1263	0.1159	0.1119	0.1079	0.0207	0.0192	0.0170	0.0162	0.0155	0.0148
PHILIPS	0.4659	0.2740	0.1964	0.1879	0.1794	0.1709	0.0462	0.0282	0.0244	0.0233	0.0223	0.0216
POLYGRAM	0.2369	0.1401	0.1359	0.1289	0.1220	0.1151	0.0292	0.0169	0.0137	0.0122	0.0111	0.0100
ROBECO	0.2352	0.1298	0.0941	0.0798	0.0706	0.0613	0.0619	0.0357	0.0264	0.0257	0.0251	0.0245
ROYAL DUTCH	0.1069	0.0674	0.0639	0.0580	0.0554	0.0537	0.0138	0.0106	0.0098	0.0084	0.0071	0.0057
STORK	0.2152	0.1952	0.1801	0.1552	0.1309	0.1106	0.0297	0.0283	0.0262	0.0227	0.0191	0.0182
TPG	0.2235	0.2038	0.1749	0.1527	0.1317	0.1109	0.0349	0.0329	0.0302	0.0268	0.0233	0.0199

Table 4.7 continued.

selection criterion	Panel A Mean return						Panel B Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
UNILEVER	0.0737	0.0721	0.0698	0.0659	0.0619	0.0580	0.0047	0.0025	0.0022	0.0018	0.0017	0.0017
UPC	12.2299	12.2355	12.2439	12.2579	12.2720	12.2862	0.1288	0.1288	0.1288	0.1289	0.1289	0.1290
VEDIOR	0.6728	0.6498	0.6157	0.5604	0.5069	0.4551	0.0520	0.0506	0.0487	0.0454	0.0421	0.0388
VENDEX KBB	0.4594	0.2836	0.2824	0.2803	0.2782	0.2761	0.0456	0.0391	0.0389	0.0387	0.0384	0.0381
VERSATEL	18.0630	17.5873	16.8951	15.7960	14.7618	13.7890	0.1658	0.1646	0.1626	0.1595	0.1563	0.1531
VNU	0.3613	0.1797	0.1166	0.1154	0.1143	0.1131	0.0375	0.0174	0.0154	0.0152	0.0150	0.0148
WESSANEN	0.2736	0.1554	0.1263	0.1184	0.1107	0.1029	0.0426	0.0280	0.0232	0.0218	0.0203	0.0189
WOLTERS KLUWER	0.2585	0.0929	0.0564	0.0531	0.0498	0.0464	0.0309	0.0092	0.0072	0.0041	0.0035	0.0035
Average	1.5103	1.4049	1.3492	1.3038	1.2671	1.2332	0.0477	0.0388	0.0357	0.0339	0.0323	0.0311

Table 4.8: **Estimation results CAPM.** Coefficient estimates of the Sharpe-Lintner CAPM: $r_t^i - r_t^f = \alpha + \beta(r_t^{AEX} - r_t^f) + \epsilon_t$. That is, the return of the best recursive optimizing and testing procedure, when selection is done in the optimizing period by the mean return criterion (Panel A) or by the Sharpe ratio criterion (Panel B), in excess of the risk-free interest rate is regressed against a constant and the return of the AEX-index in excess of the risk-free interest rate. Estimation results for the 0 and 0.50% costs per trade cases are shown. a, b, c indicates that the corresponding coefficient is, in the case of α, significantly different from zero, or in the case of β, significantly different from one, at the 1, 5, 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

selection criterion	Panel A Mean return				Panel B Sharpe ratio			
costs per trade	0%		0.50%		0%		0.50%	
Data set	α	β	α	β	α	β	α	β
AEX	0.000527a	0.809b	0.000340b	0.996	0.000526a	0.767a	0.000340b	0.996
ABN	0.000734b	0.501a	0.000544c	0.372a	0.000734b	0.501a	0.000544c	0.372a
AMRO	0.001014b	0.537a	0.000702c	0.494a	0.001014b	0.537a	0.000702c	0.494a
ABN AMRO	0.001125a	0.954	0.000489c	1.086	0.001125a	0.954	0.000489c	1.086
AEGON	0.001309a	0.934	0.000672b	0.852c	0.001309a	0.934	0.000630a	0.797b
AHOLD	0.000958a	0.875a	0.000618b	0.740a	0.000958a	0.875a	0.000618b	0.740a
AKZO NOBEL	0.001414a	0.759a	0.00047	0.991	0.001414a	0.759a	0.000347	0.621a
ASML	0.002888a	1.158	0.002722a	1.159	0.002888a	1.158	0.002722a	1.159
BAAN	0.000724	1.066	0.00116	0.226a	0.001289c	0.227a	0.00116	0.226a
BUHRMANN	0.001383a	0.744a	0.000820a	0.442a	0.001383a	0.744a	0.000820a	0.442a

Table 4.8 continued.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.50%		0%		0.5%	
Data set	α	β	α	β	α	β	α	β
CETECO	0.000398	0.150a	0.000341	0.151a	0.000398	0.150a	0.000298	0.161a
CMG	0.002793b	0.967	0.002371a	0.702a	0.002417a	0.701a	0.002371a	0.702a
CORUS	0.003574b	0.642b	0.003337c	0.639b	0.003202c	0.383a	0.003337c	0.639b
CSM	0.000673b	0.449a	0.000483c	0.495a	0.000673b	0.449a	0.000386b	0.390a
DAF	6.38E-05	0.448a	-6.00E-08a	4.53E-08a	8.06E-05	0.7	-3.08E-06	0.698
DSM	0.001366a	0.541a	0.000682c	0.633a	0.001366a	0.541a	0.000677b	0.568a
REED ELSEVIER	0.000807b	0.785a	0.000436	1.160a	0.000807b	0.785a	0.000436c	0.762a
FOKKER	-3.15E-08a	6.55E-08a	-3.15E-08a	6.55E-08a	-3.15E-08a	6.55E-08a	-3.15E-08a	6.55E-08a
FORTIS	0.001026a	0.825a	0.000341	1.103	0.001026a	0.825a	0.000335	0.649a
GETRONICS	0.001581a	0.717a	0.000800b	0.565a	0.001581a	0.717a	0.000800b	0.565a
GIST BROCADES	0.000495	0.587a	0.000273	0.740a	0.000495	0.583a	0.000273	0.740a
GUCCI	0.001316	0.599a	0.001018	0.731b	0.001089	0.476a	0.001031	0.476a
HAGEMEYER	0.001593a	0.618a	0.000566c	0.669a	0.001593a	0.618a	0.000566c	0.669a
HEINEKEN	0.001005a	0.660a	0.000516b	0.476a	0.001005a	0.660a	0.000516b	0.476a
HOOGOVENS	0.001565a	1.122c	0.000888b	0.855	0.001565a	1.122c	0.000888b	0.855
ING	0.001886a	1.016	0.000829b	1.144	0.001886a	1.016	0.000651b	0.97
KLM	0.000445	0.784a	0.000173	0.618a	0.000445	0.784a	0.000173	0.618a
KON. PTT NED.	0.000845	0.738a	6.19E-05	1.341a	0.000845	0.738a	0.000128	0.819a
KPN	0.003498b	1.786a	0.002349	1.775a	0.003498b	1.786a	0.001615	1.008
KPNQWEST	0.001679	0.842	0.001611	0.926	0.001679	0.842	0.001611	0.926
VAN DER MOOLEN	0.002127a	0.706a	0.001160b	0.762a	0.001989a	0.642a	0.001160b	0.762a
NAT. NEDERLANDEN	0.001228a	0.577a	0.000494	0.671b	0.001228a	0.577a	0.000365	0.325a
NEDLLOYD	0.001470a	0.782a	0.000805c	0.621a	0.001470a	0.782a	0.000805c	0.621a
NMB POSTBANK	0.001215b	0.531a	0.000901c	0.507a	0.001203b	0.511a	0.000901c	0.507a
NUMICO	0.001427a	0.523a	0.000921a	0.559a	0.001427a	0.523a	0.000921a	0.559a
OCE	0.001257a	0.655a	0.000825a	0.491a	0.001257a	0.655a	0.000825a	0.491a
PAKHOED	0.000721b	0.631a	0.000579c	0.611a	0.000600b	0.455a	0.000579c	0.611a
PHILIPS	0.001616a	1.076	0.000788b	1.031	0.001616a	1.076	0.000788b	1.031
POLYGRAM	0.000932b	0.717a	0.000504	0.837b	0.000932b	0.717a	0.000504	0.837b
ROBECO	0.000921a	0.438a	0.000394b	0.410a	0.000921a	0.438a	0.000350a	0.259a
ROYAL DUTCH	0.000669a	0.571a	0.000474b	0.674a	0.000669a	0.571a	0.000474b	0.674a
STORK	0.0007	0.807	0.000544c	0.558a	0.000712b	0.558a	0.000544c	0.558a
TPG	0.000721	0.291a	0.000412	0.167a	0.000484	0.203a	0.000412	0.167a

Table 4.8 continued.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.50%		0%		0.5%	
Data set	α	β	α	β	α	β	α	β
UNILEVER	0.000606b	0.519a	0.000578b	0.518a	0.000476b	0.427a	0.000451b	0.532a
UPC	-1.37E-08a	1.38E-08a	-1.37E-08a	1.38E-08a	-1.37E-08a	1.38E-08a	-1.37E-08a	1.38E-08a
VEDIOR	0.001478	0.302a	0.001198	0.306a	0.001478	0.302a	0.001198	0.306a
VENDEX KBB	0.001724b	0.426a	0.001172b	0.558a	0.001724b	0.426a	0.001169c	0.560a
VERSATEL	0.002604	1.086	0.00211	1.085	0.002604	1.086	0.00211	1.085
VNU	0.001604a	0.752a	0.000803a	0.838b	0.001604a	0.752a	0.000803a	0.838b
WESSANEN	0.000877a	0.629a	0.000363	0.622a	0.000877a	0.629a	0.000363	0.622a
WOLTERS KLUWER	0.001325a	0.585a	0.000590c	0.747a	0.001325a	0.585a	0.000473b	0.635a

Table 4.9: **Testing for predictive ability.** Nominal (p_n), White's (2000) Reality Check (p_W) and Hansen's (2001) Superior Predictive Ability test (p_H) p-values, if the best strategy is selected by the mean return criterion (Panel A) or if the best strategy is selected by the Sharpe ratio criterion, in the case of 0 and 0.10% costs per trade.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
costs per trade	0%			0.10%			0%			0.10%		
Data set	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
AEX	0	0.93	0.08	0	1	0.28	0	0.77	0.08	0	0.96	0.25
ABN	0	0.65	0.36	0	0.9	0.59	0	0.42	0.13	0	0.52	0.12
AMRO	0	0.99	0.84	0	1	0.94	0	0.78	0.13	0	0.94	0.26
ABN AMRO	0	0.51	0.04	0	1	0.88	0	0.96	0.21	0	1	0.71
AEGON	0	0.26	0.06	0	1	0.94	0	0.77	0.03	0	1	0.45
AHOLD	0	0.47	0.15	0	0.99	0.64	0.01	0.88	0.12	0	0.98	0.19
AKZO NOBEL	0	1	0	0	1	0.4	0	0.01	0	0	0.57	0.02
ASML	0	1	0.96	0	1	0.96	0	0.98	0.02	0	0.98	0.02
BAAN	0.01	1	0.96	0	1	0.97	0	0.06	0.03	0	0.06	0.02
BUHRMANN	0	1	0.39	0	1	0.98	0	0.1	0	0	0.63	0.03
CETECO	0	1	0.51	0	1	0.51	0	0.45	0.01	0	0.46	0.01
CMG	0	1	0.99	0	1	1	0	0.63	0.05	0	0.61	0.03
CORUS	0	1	1	0	1	1	0.04	1	0.82	0	1	0.8
CSM	0.02	1	0.86	0	1	0.98	0.07	1	0.73	0	1	0.7
DAF	0	1	0.27	0	1	0.27	0	0.32	0.29	0	0.36	0.28
DSM	0	0.05	0	0	0.99	0.3	0	0.35	0.01	0	1	0.2
REED ELSEVIER	0.01	1	0.95	0	1	1	0.05	1	0.63	0.01	1	0.88
FOKKER	0.04	1	0.79	0.04	1	0.76	0.04	0.8	0.38	0.04	0.77	0.3
FORTIS	0	0.94	0.92	0	1	0.99	0	0.89	0.03	0	1	0.58
GETRONICS	0	1	0.29	0	1	0.79	0	0.24	0	0	0.78	0.08
GIST BROCADES	0	1	0.92	0	1	0.96	0	0.97	0.22	0	0.99	0.22
GUCCI	0.04	1	0.93	0	1	0.98	0	1	0.36	0	1	0.32
HAGEMEYER	0	1	0.91	0	1	0.96	0	0.22	0	0	0.96	0.04
HEINEKEN	0	0.31	0	0	1	0.78	0	0.7	0.03	0	1	0.43
HOOGOVENS	0	0.31	0	0	1	0.78	0	0.7	0.03	0	1	0.43
ING	0	0.99	0	0	1	0.34	0	0.32	0	0	1	0.12
KLM	0	1	0.98	0	1	0.99	0	0.68	0.22	0	0.84	0.34
KON. PTT NED.	0.15	1	0.84	0	1	0.84	0.44	1	0.97	0.02	1	0.97
KPN	0	1	0.96	0	1	0.98	0	0.23	0.05	0	0.31	0.08
KPNQWEST	0	1	0.3	0	1	0.3	0	0.08	0.08	0	0.08	0.08
VAN DER MOOLEN	0	1	0.07	0	1	0.8	0	0.8	0	0	1	0.33
NAT. NEDERLANDEN	0	0.28	0.11	0	0.99	0.66	0	0.32	0.08	0.01	0.83	0.42
NEDLLOYD	0	1	0.13	0	1	0.65	0	0.16	0	0	0.55	0.02
NMB POSTBANK	0	0.66	0.12	0	0.85	0.24	0	0.71	0.15	0	0.89	0.25
NUMICO	0	1	0.4	0	1	0.95	0	0.88	0.05	0	1	0.32
OCE	0	1	0.38	0	1	0.86	0	0.1	0.01	0	0.17	0
PAKHOED	0	1	0.75	0	1	0.77	0	1	0.21	0	1	0.14
PHILIPS	0	1	0.01	0	1	0.52	0	0.1	0	0	0.87	0.03
POLYGRAM	0	0.86	0.12	0	1	0.58	0.03	0.99	0.39	0	1	0.73
ROBECO	0	0	0	0	0.75	0	0	0.02	0	0	0.74	0.02
ROYAL DUTCH	0.01	0.95	0.36	0	1	0.86	0.05	1	0.45	0	1	0.42
STORK	0.01	1	0.9	0	1	0.94	0	0.83	0.1	0	0.88	0.08
TPG	0	1	1	0	1	1	0	1	0.82	0	1	0.8
UNILEVER	0	1	0.87	0	1	0.82	0	1	0.85	0.04	1	0.92
UPC	0	1	0.1	0	1	0.1	0	0.06	0.02	0	0.06	0.03
VEDIOR	0	1	0.98	0	1	0.98	0	0.92	0.33	0	0.94	0.33
VENDEX KBB	0	1	0.94	0	1	0.99	0	0.94	0.27	0	0.98	0.34
VERSATEL	0	1	0.42	0	1	0.43	0	0.03	0.03	0	0.03	0.03
VNU	0	1	0.01	0	1	0.9	0	0.85	0	0.02	1	0.28
WESSANEN	0	0.96	0.02	0	0.99	0.62	0	0.06	0	0	0.62	0.19
WOLTERS KLUWER	0	1	0.89	0	1	1	0	1	0.03	0	1	0.64

Table 4.14: **Excess performance best out-of-sample testing procedure.** Panel A shows the yearly mean return of the best recursive out-of-sample testing procedure, selected by the mean return criterion, in excess of the yearly mean return of the buy-and-hold. Panel B shows the Sharpe ratio of the best recursive out-of-sample testing procedure, selected by the Sharpe ratio criterion, in excess of the Sharpe ratio of the buy-and-hold. Results are presented for the 0, 0.10, 0.25 and 0.50% transaction costs cases. The row labeled "Average: out-of-sample" shows the average over the results as presented in the table. The row labeled "Average: in sample" shows the average over the results of the best strategy selected in sample for each data series.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
AEX	0.1076	0.0871	0.0171	-0.0107	-0.0352	-0.0515	0.0314	0.0216	0.0136	0.0013	-0.0108	-0.0047
ABN	0.1972	0.1771	0.1186	0.1383	0.0658	0.0179	0.0266	0.0207	0.0210	0.0116	0.0075	0.0068
AMRO	0.3002	0.1491	0.1741	0.1264	0.0717	0.0558	0.0452	0.0373	0.0309	0.0245	0.0163	0.0117
ABN AMRO	0.2317	0.1750	0.1174	0.0595	-0.0095	-0.0285	0.0165	0.0115	-0.0021	-0.0047	-0.0017	-0.0066
AEGON	0.2579	0.2387	0.1866	0.1315	0.1033	0.0975	0.0303	0.0170	0.0076	0.0049	0.0016	-0.0005
AHOLD	0.2115	0.1758	0.1583	0.1218	0.0990	0.1005	0.0187	0.0152	0.0122	0.0000	0.0018	-0.0074
AKZO NOBEL	0.4165	0.3126	0.1861	0.0107	-0.0376	-0.0479	0.0455	0.0356	0.0227	0.0095	-0.0008	-0.0115
ASML	0.0997	0.2644	0.3582	0.5279	0.2838	0.3105	-0.0009	0.0051	0.0026	-0.0116	-0.0038	-0.0006
BAAN	0.2921	0.3498	0.4187	0.2578	0.2401	0.1432	0.0582	0.0550	0.0505	0.0423	0.0377	0.0399
BUHRMANN	0.2906	0.2232	0.1459	0.0737	-0.0374	-0.0020	0.0263	0.0145	0.0074	0.0030	0.0029	-0.0077
CETECO	0.5496	0.3833	0.3638	0.3601	0.2866	0.2533	0.0539	0.0443	0.0380	0.0355	0.0304	0.0304
CMG	1.2489	1.1705	1.0928	0.7014	0.4715	0.3412	0.0818	0.0724	0.0628	0.0407	0.0179	0.0312
CORUS	1.4040	1.2349	1.0419	0.8183	0.6792	0.5440	0.0039	-0.0023	-0.0090	-0.0140	-0.0182	-0.0053
CSM	0.0723	0.0287	-0.0231	-0.0577	-0.0822	-0.0948	0.0085	0.0004	-0.0029	-0.0076	-0.0175	-0.0218
DAF	0.2506	0.2016	0.1937	0.1595	0.1768	0.1745	0.0775	0.0879	0.0873	0.0831	0.0861	0.0785
DSM	0.2766	0.1723	0.1690	0.0134	0.0024	-0.0069	0.0370	0.0221	0.0029	-0.0103	-0.0088	-0.0057
REED ELSEVIER	0.1636	0.1153	0.0256	-0.0815	-0.0725	-0.0743	0.0021	0.0045	-0.0009	-0.0160	-0.0200	-0.0261
FOKKER	0.1708	0.1059	0.0537	-0.0234	-0.0495	-0.0200	0.0082	0.0082	0.0082	0.0083	0.0083	0.0083
FORTIS	0.1929	0.0948	0.0509	-0.0469	-0.0914	-0.1267	0.0163	0.0071	-0.0007	-0.0117	-0.0181	-0.0264
GETRONICS	0.3375	0.2511	0.1869	0.1444	-0.0070	-0.0373	0.0388	0.0322	0.0251	0.0226	0.0229	0.0177
GIST BROCADES	0.0856	0.0508	0.0424	-0.0051	0.0089	-0.0695	0.0225	0.0190	0.0131	0.0029	-0.0036	0.0024
GUCCI	0.3182	0.2343	0.2869	0.4464	0.2923	0.2365	0.0373	0.0337	0.0315	0.0289	0.0158	0.0209
HAGEMEYER	0.2593	0.1657	0.0707	0.0353	0.0128	0.0056	0.0348	0.0258	0.0036	-0.0039	-0.0086	-0.0129
HEINEKEN	0.1277	0.0950	0.0196	-0.0685	-0.1205	-0.1161	0.0326	0.0044	-0.0077	-0.0259	-0.0299	-0.0284
HOOGOVENS	0.4009	0.3061	0.2213	0.1763	0.0450	-0.0246	0.0440	0.0313	0.0251	0.0133	0.0018	-0.0058
ING	0.2090	0.1260	0.1028	-0.0142	-0.0632	-0.0732	0.0220	0.0137	0.0009	-0.0101	-0.0151	-0.0278
KLM	0.1803	0.1128	0.0896	0.0630	0.0024	0.0114	0.0319	0.0180	0.0130	0.0071	0.0036	0.0001

Table 4.14 continued.

selection criterion	Panel A						Panel B					
	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
KON. PTT NED.	0.1292	0.1599	0.1350	0.0943	0.1270	0.0800	0.0086	-0.0056	-0.0269	-0.0373	-0.0482	-0.0484
KPN	1.0787	0.9829	0.9163	0.8445	0.5666	0.5991	0.1425	0.1185	0.1015	0.1068	0.0992	0.0841
KPNQWEST	0.4183	0.4129	0.4049	0.3920	0.6060	0.5880	0.1640	0.1622	0.1596	0.1550	0.1506	0.1221
VAN DER MOOLEN	0.3970	0.3502	0.2888	0.1832	0.1401	0.0841	0.0297	0.0193	0.0100	-0.0044	-0.0079	-0.0123
NAT. NEDERLANDEN	0.2439	0.2009	0.1045	0.0048	-0.0163	-0.0339	0.0567	0.0436	0.0289	0.0193	0.0014	-0.0036
NEDLLOYD	0.4392	0.3444	0.2632	0.0531	0.0285	-0.0165	0.0383	0.0321	0.0175	0.0093	0.0062	0.0002
NMB POSTBANK	0.4363	0.3660	0.1964	0.1044	0.1101	0.0271	0.0346	0.0330	0.0273	0.0213	0.0062	-0.0057
NUMICO	0.2212	0.1330	0.0904	0.0561	-0.0047	-0.0645	0.0275	0.0139	0.0036	-0.0032	-0.0078	-0.0159
OCE	0.3564	0.2763	0.1655	0.1684	0.0872	0.0875	0.0605	0.0434	0.0252	0.0054	0.0069	0.0046
PAKHOED	0.1123	0.0757	0.0582	0.0341	0.0176	-0.0403	0.0188	0.0109	0.0023	-0.0099	-0.0100	-0.0170
PHILIPS	0.3218	0.1933	0.1035	-0.0149	-0.0481	-0.0986	0.0166	0.0167	-0.0001	0.0001	-0.0056	-0.0113
POLYGRAM	0.2305	0.1006	-0.0283	-0.1426	-0.1913	-0.1345	0.0023	0.0061	0.0035	-0.0156	-0.0225	-0.0254
ROBECO	0.1745	0.0954	0.0293	0.0040	0.0043	-0.0169	0.0517	0.0301	0.0000	-0.0114	-0.0178	-0.0235
ROYAL DUTCH	0.0240	0.0118	-0.0237	-0.0225	-0.0615	-0.0810	0.0060	-0.0044	-0.0073	-0.0157	-0.0167	-0.0263
STORK	0.1774	0.1206	0.1702	-0.0440	-0.0074	-0.0077	0.0264	0.0224	0.0071	-0.0086	-0.0085	-0.0071
TPG	0.3160	0.3458	0.1942	0.0607	0.0126	-0.0601	0.0474	0.0419	0.0344	0.0239	0.0139	0.0169
UNILEVER	-0.0213	-0.0429	-0.0775	-0.1083	-0.1045	-0.1347	-0.0076	-0.0108	-0.0212	-0.0239	-0.0296	-0.0341
UPC	0.5227	0.5098	0.4911	1.0538	1.0499	1.0460	0.1255	0.1421	0.1295	0.1165	0.1414	0.1312
VEDIOR	-0.1383	-0.1671	-0.1786	-0.2218	-0.1493	-0.1302	0.0078	0.0074	0.0096	0.0073	0.0036	0.0093
VENDEX KBB	0.2894	0.2136	0.0585	0.0427	-0.0590	-0.0659	0.0346	0.0284	0.0210	0.0216	0.0113	0.0094
VERSATEL	1.2925	1.2756	1.2508	1.2103	1.1710	1.1329	0.1079	0.1071	0.1122	0.1060	0.1044	0.1029
VNU	0.3450	0.2892	0.1556	0.0298	-0.0018	0.0161	0.0232	0.0153	-0.0012	-0.0097	-0.0117	-0.0224
WESSANEN	0.2391	0.1542	0.0414	-0.0364	-0.0675	-0.0965	0.0333	0.0211	0.0048	0.0014	-0.0082	-0.0188
WOLTERS KLUWER	0.1809	0.0842	-0.0472	-0.1254	-0.1280	-0.1059	0.0170	0.0101	-0.0110	-0.0271	-0.0306	-0.0319
Average: out-of-sample	0.3223	0.2645	0.2085	0.1505	0.1043	0.0802	0.0377	0.0306	0.0213	0.0128	0.0082	0.0044
Average: in sample	6.8571	6.7184	6.6225	6.5136	6.4123	6.3151	0.0522	0.0431	0.0402	0.0380	0.0363	0.0350

Table 4.15: **Estimation results CAPM for best out-of-sample testing procedure.** Coefficient estimates of the Sharpe-Lintner CAPM: $r_t^i - r_t^f = \alpha + \beta(r_t^{AEX} - r_t^f) + \epsilon_t$. That is, the return of the best recursive optimizing and testing procedure, when selection is done in the optimizing period by the mean return criterion (Panel A) or by the Sharpe ratio criterion (Panel B), in excess of the risk-free interest rate is regressed against a constant and the return of the AEX-index in excess of the risk-free interest rate. Estimation results for the 0 and 0.50% costs per trade cases are shown. a, b, c indicates that the corresponding coefficient is, in the case of α, significantly different from zero, or in the case of β, significantly different from one, at the 1, 5, 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.50%		0%		0.50%	
Data set	α	β	α	β	α	β	α	β
AEX	0.000371b	0.99	-5.39E-05	1.082	0.000493a	0.730a	7.98E-05	0.846c
ABN	0.000663c	0.662b	0.000467	0.637b	0.000366	0.546a	0.00014	0.651b
AMRO	0.001047b	0.525a	0.0005	0.522a	0.000736c	0.412a	0.000467	0.523a
ABN AMRO	0.000935b	0.879c	0.00036	1.074	0.000627c	0.898c	0.000242	0.949
AEGON	0.001116a	1.005	0.000746b	1.062	0.001038a	0.687a	0.000602b	0.866
AHOLD	0.000972a	0.816b	0.000699b	0.876	0.000789a	0.610a	0.00044	0.696a
AKZO NOBEL	0.001397a	0.624a	0.000168	0.728a	0.001022a	0.558a	0.000432	0.768a
ASML	0.001011	1.556a	0.002076	1.489a	0.000959	1.497a	0.000337	1.431b
BAAN	-0.00158	0.958	-0.00172	0.909	-6.01E-05	0.685b	-0.001048	0.693b
BUHRMANN	0.000956b	0.831b	0.000248	1.045	0.000759b	0.621a	0.000157	0.856b
CETECO	-0.000523	0.259a	-0.001442	0.291a	-0.000159	0.290a	-0.001581	0.094a
CMG	0.002969b	1.181	0.001839	1.176	0.003175b	0.919	0.001406	0.921
CORUS	0.004795c	0.616c	0.004226	0.560c	0.005136c	0.626c	0.004563	0.635
CSM	0.000537b	0.360a	8.29E-05	0.441a	0.000593b	0.355a	0.000248	0.387a
DAF	-0.005082c	1.422	-0.006421b	1.497	-0.002042	1.373	-0.001437	1.566
DSM	0.001089a	0.524a	0.00029	0.522a	0.000981a	0.464a	0.000113	0.607a
REED ELSEVIER	0.000846a	0.722a	7.95E-06	0.964	0.000466	0.816a	3.84E-05	1.091
FORTIS	0.000785a	0.764a	-3.76E-05	0.97	0.000564b	0.699a	-2.84E-05	0.911c
GETRONICS	0.001028b	0.678a	0.000432	0.739b	0.001171a	0.708a	0.000665	0.965
GIST BROCADES	0.00016	0.714a	-0.00016	0.697a	0.000365	0.645a	-5.60E-05	0.656a
GUCCI	0.001627	0.570a	0.001947c	0.838	0.002076b	0.473a	0.001732c	0.488a
HAGEMEYER	0.001091a	0.726a	0.000434	0.617a	0.001156a	0.553a	0.000326	0.607a
HEINEKEN	0.000728a	0.615a	6.66E-05	0.689a	0.000966a	0.527a	-6.22E-05	0.551a
HOOGOVENS	0.001074b	0.943	0.000437	0.89	0.001159a	0.818c	0.000258	0.779a
ING	0.000900b	1.01	0.000143	1.236c	0.000820b	0.881c	0.000193	0.954

Table 4.15 continued.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.50%		0%		0.50%	
Data set	α	β	α	β	α	β	α	β
KLM	0.000336	0.746a	-0.000104	0.904	0.000493	0.713a	-0.000205	0.935
KON. PTT NED.	0.000539	0.843	0.000164	1.074	0.00084	0.751b	-2.57E-05	0.638a
KPN	0.00245	1.706b	0.0023	2.244a	0.003785c	1.731b	0.001819	1.705c
KPNQWEST	-0.00421	1.182	-0.004448	1.174	-0.000803	0.647	-0.001073	0.636
VAN DER MOOLEN	0.001618a	0.811b	0.001064c	0.837c	0.001406a	0.662a	0.000632	0.810b
NAT. NEDERLANDEN	0.000818c	0.639a	1.36E-05	0.549a	0.000929b	0.506a	0.000358	0.577a
NEDLLOYD	0.001282a	0.639a	9.88E-05	0.647a	0.001015b	0.578a	0.000175	0.622a
NMB POSTBANK	0.001547a	0.491a	0.000611	0.529a	0.000880b	0.481a	0.00072	0.417a
NUMICO	0.001061a	0.504a	0.000558	0.558a	0.001020a	0.450a	0.000436	0.484a
OCE	0.001104a	0.553a	0.000521	0.679a	0.001301a	0.533a	8.51E-05	0.630a
PAKHOED	0.000508	0.540a	0.000243	0.569a	0.000617c	0.538a	-5.79E-05	0.771b
PHILIPS	0.001068a	1.025	-1.57E-05	1.203	0.000580c	0.94	0.00014	1.083
POLYGRAM	0.000849c	0.495a	-0.000475	0.657a	0.000219	0.766a	-0.000175	0.694a
ROBECO	0.000681a	0.413a	0.000106	0.470a	0.000670a	0.369a	5.77E-06	0.415a
ROYAL DUTCH	0.00035	0.493a	0.000184	0.528a	0.000452b	0.484a	9.14E-05	0.532a
STORK	0.000525	0.834	-0.000206	0.568a	0.000550c	0.580a	-0.000235	0.490a
TPG	0.001137	0.450a	0.000209	0.568a	0.001019	0.571a	0.000232	0.374a
UNILEVER	0.000264	0.370a	-5.50E-05	0.402a	0.000269	0.403a	-7.37E-05	0.399a
UPC	-0.001767	0.736	0.000276	0.071a	-0.001142	1.158	-0.00182	0.301a
VEDIOR	-0.000718	0.467a	-0.001119	0.548a	0.00023	0.689c	0.000203	0.703c
VENDEX KBB	0.000876	0.464a	2.81E-05	0.632a	0.000891	0.363a	0.000519	0.480a
VERSATEL	0.00177	0.598	0.001552	0.594	0.000621	0.485	0.000526	0.579
VNU	0.001359a	0.700a	0.000422	0.846c	0.001129a	0.825b	0.000225	0.795a
WESSANEN	0.000706b	0.602a	-0.000231	0.520a	0.000541c	0.546a	-6.58E-05	0.552a
WOLTERS KLUWER	0.000978a	0.542a	-6.04E-05	0.799c	0.000873a	0.507a	-7.49E-05	0.602a

B. Parameters of recursive optimizing and testing procedure

This appendix presents the parameter values of the recursive optimizing and testing procedures applied in section 4.4. The two parameters are the length of the training period, TR, and the length of the testing period, Te. The following 28 combinations of training and testing periods, [Tr,Te], are used:

$Train$	$Test$	$Train$	$Test$
5	1	42	10
10	1	63	10
21	1	126	10
42	1	252	10
63	1	42	21
126	1	63	21
252	1	126	21
10	5	252	21
21	5	63	42
42	5	126	42
63	5	252	42
126	5	126	63
252	5	252	63
21	10	252	126

Chapter 5

Technical Trading Rule Performance in Local Main Stock Market Indices

5.1 Introduction

Brock, Lakonishok and LeBaron (1992) found that technical trading rules show forecasting power when applied to the Dow-Jones Industrial Average (DJIA) in the period 1896-1986. Sullivan, Timmermann and White (1999) confirmed their results for the same period, after they made a correction for data snooping. However they noticed that the forecasting power seems to disappear in the period after 1986. Next, Bessembinder and Chan (1998) found that break even transaction costs, that is costs for which trading rule profits disappear, are lower than real transaction costs in the period 1926-1991 and that therefore the technical trading rules examined by Brock et al. (1992) are not economically significant when applied to the DJIA. The trading rule set of Brock et al. (1992) has been applied to many other local main stock market indices. For example, to Asian stock markets by Bessembinder and Chan (1995), to the UK stock market by Hudson, Dempsey and Keasey (1996) and Mills (1997), to the Spanish stock market by Fernández-Rodríguez, Sosvilla-Rivero, and Andrada-Félix (2001), to Latin-American stock markets by Ratner and Leal (1999) and to the Hong Kong stock market by Coutts and Cheung (2000).

In this chapter we test whether objective computerized trend-following technical trading techniques can profitably be exploited after correction for risk and transaction costs when applied to the local main stock market indices of 50 countries and the MSCI World Index. Firstly, we do as if we are a local trader and we apply the technical trading rules to the indices in local currency and we compute the profits in local currency. However these profits could be spurious if the local currencies weakened against other currencies. Therefore, secondly, we do as if we are an US-based trader and we calculate the profits that could be made by technical trading rules in US Dollars. For this second case we generate technical trading signals in two different ways. Firstly by using the local main stock market index in local currency and secondly by using the local main stock market index recomputed in US Dollars. Observed technical trading rule profits could be the reward for risk. Therefore we test by estimating a Sharpe-Lintner capital asset pricing model (CAPM) whether the best technical trading rule selected for each stock market index is also profitable after correction for risk. Both the local index and the MSCI World Index are used as the benchmark market portfolio in the CAPM estimation equation. If the technical trading rules show economically significant forecasting power after correction for risk and transaction costs, then further it is tested whether the best strategy found for each local main stock market index is indeed superior to the buy-and-hold benchmark after correction for data snooping. This chapter may therefore be seen as an empirical application of White's (2000) Reality Check and Peter Hansen's (2001) test for superior predictive ability. Further we test by recursively optimizing our technical trading rule set whether technical analysis shows true out-of-sample forecasting power.

In section 5.2 we list the local main stock market indices examined in this chapter and we show the summary statistics. We refer to the sections 3.3, 3.4 and 3.5 for the discussions on the set of technical trading rules applied, the computation of the performance measures and finally the problem of data snooping. Section 5.3 presents the empirical results of our study. In section 5.4 we test whether recursively optimizing and updating our technical trading rule set shows genuine out-of-sample forecasting ability. Finally, section 5.5 summarizes and concludes.

5.2 Data and summary statistics

The data series examined in this chapter are the daily closing levels of local main stock market indices in Africa, the Americas, Asia, Europe, the Middle East and the Pacific in the period January 2, 1981 through June 28, 2002. Local main stock market indices are intended to show a representative picture of the local economy by including the most important or most traded stocks in the index. The MSCI[1] World Index is a market capitalization index that is designed to measure global developed market equity performance. In this chapter we analyze in total 51 indices. Column 1 of table 5.1 shows for each country which local main stock market index is chosen. Further for each country data is collected on the exchange rate against the US Dollar. As a proxy for the risk-free

[1]Morgan Stanley Capital International. MSCI indices are the most widely used benchmarks by global portfolio managers.

interest rate we use for most countries daily data on 1-month interbank interest rates when available or otherwise rates on 1-month certificates of deposits. Table 5.1 shows the summary statistics of the stock market indices expressed in local currency, while table 5.2 shows the summary statistics if the stock market indices are expressed in US Dollars. Hence in table 5.2 it can be seen whether the behavior of the exchange rates of the local currencies against the US Dollar alters the features of the local main stock market data. Because the first 260 data points are used for initializing the technical trading strategies, the summary statistics are shown from January 1, 1982. In the tables the first and second column show the names of the indices examined and the number of available data points. The third column shows the mean yearly effective return in percentage/100 terms. The fourth through seventh column show the mean, standard deviation, skewness and kurtosis of the logarithmic daily return. The eight column shows the t-ratio to test whether the mean daily logarithmic return is significantly different from zero. The ninth column shows the Sharpe ratio, that is the extra return over the risk-free interest rate per extra point of risk. The tenth column shows the largest cumulative loss, that is the largest decline from a peak to a through, of the indices in percentage/100 terms. The eleventh column shows for each stock market index the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. The twelfth column shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic testing for autocorrelations in the squared returns.

The mean yearly effective return of the MSCI World Index during the 1982-2002 period is equal to 8.38% and the yearly standard deviation of the returns is approximately equal to 12%. Measured in local currency 7 indices show a negative mean yearly effective return, although not significantly. These are stock market indices mainly in Asia, Eastern Europe and Latin America. For 17 indices a significantly positive mean return is found, mainly for the West European and US indices, but also for the Egyptian CMA and the Israeli TA100 index. If measured in US Dollars, then the number of indices which show a negative mean return more than doubles and increases to 16, while the number of indices which show a significantly positive mean return declines from 17 to 10. Especially for the Asian and Latin American stock market indices the results in US Dollars are worse than in local currency. For example, in the Latin American stock markets the Brazilian Bovespa shows a considerable positive mean yearly return of 13.85% if measured in Brazilian Reals, while it shows a negative mean yearly return of −2.48% if measured in US Dollars. In the Asian stock markets it is remarkable that the results for the Chinese Shanghai Composite, the Hong Kong Hang Seng and the Singapore Straits Times are not affected by a recomputation in US Dollars, despite the Asian crises. The separate indices are more risky than the MSCI World Index, as can be seen by the standard deviations and the largest cumulative loss numbers. Thus it is clear that country specific risks are reduced by the broad diversified world index. The return distribution is strongly leptokurtic for all indices and is negatively skewed for a majority of the indices. Thus large negative shocks occur more frequently than large positive shocks. The local interest rates are used for computing the Sharpe ratio (i.e. the extra return over the risk-free interest rate per extra point of risk as measured by the standard deviation) in local currency, while the rates on 1-month US certificates of deposits are used for computing the Sharpe ratio in US Dollars. The Sharpe ratio is negative for 23 indices, if expressed in local currency or in US Dollars, indicating that these indices were not able to beat a continuous risk free investment. Only the European and US stock market indices as well as the Egyptian and Israeli stock market indices were able in generating a positive excess return over the risk-free interest rate. For more than half of the indices the largest cumulative loss is larger than 50% if expressed in local currency or US Dollars. For example, during the Argentine economic crises the Merval lost 77% of its value in local currency and 91% of its value in US Dollars. The Russian Moscow Times lost 94% of its value in US Dollars in a short period of approximately one year between August 1997 and October 1998. The largest decline of the MSCI World Index is equal to 39% and occurred in the period March 27, 2000 through September 21, 2001. Of the 14 indices for which we have data preceding the year 1987, only for 4 indices, namely the DJIA, the NYSE Composite, the Australian ASX and the Dutch AEX, the largest cumulative loss, when measured in local currency, occurred preceding and during the crash of 1987. If measured in US Dollars, only the largest decline for the Dutch AEX changes and took place in the period January 4, 2000 through September 21, 2001. Remarkably for most indices the largest decline started well before the terrorist attack against the US on September 11, 2001, but stopped only 10 days after it[2]. With hindsight, the overall picture is that the European and US stock markets performed the best, but also the Egyptian and Israeli stock markets show remarkably good results.

We computed autocorrelation functions (ACFs) of the returns and significance is tested with Bartlett (1946) standard errors and Diebold's (1986) heteroskedasticity-consistent standard errors[3]. Typically autocorrelations of the returns are small with only few lags

[2]At the moment of writing the stock markets are reaching new lows.

[3]See section 3.2, page 99, for an explanation. Separate ACFs of the returns are computed for each stock market index, but not presented here to save space. The tables are available upon request from the author.

being significant. Without correcting for heteroskedasticity we find for 35 of the 51 indices a significant first order autocorrelation both in local and US currency, while when corrected for heteroskedasticity we find for 30 (23) indices measured in local (US) currency a significant first order autocorrelation at the 10% significance level. It is noteworthy that for more than half of the indices the second order autocorrelation is negative. In contrast, the first order autocorrelation is negative for only 5 (10) indices in local (US) currency. The Ljung-Box (1978) Q-statistics in the second to last columns of tables 5.1 and 5.2 reject for almost all indices the null hypothesis that the first 20 autocorrelations of the returns as a whole are equal to zero. For only 3 (5) indices the null is not rejected in the local (US) currency case, see for example New Zealand's NZSE30 and the Finnish HEX. When looking at the first to last column with Diebold's (1986) heteroskedasticity-consistent Box-Pierce (1970) Q-statistics it appears that heteroskedasticity indeed seriously affects the inferences about serial correlation in the returns. Now for 26 (34) indices the null of no autocorrelation is not rejected in the local (US) currency case. The autocorrelation functions of the squared returns show that for all indices the autocorrelations are high and significant up to order 20. The Ljung-Box (1978) statistics reject the null of no autocorrelation in the squared returns firmly, except for the Venezuela Industrial if expressed in US Dollars. Hence, almost all indices exhibit significant volatility clustering, that is large (small) shocks are likely to be followed by large (small) shocks.

5.3 Empirical results

5.3.1 Results for the mean return criterion

Technical trading rule performance

In section 5.2 we showed that almost half of the local main stock market indices could not even beat a continuous risk free investment. Further we showed that for half of the indices no significant autocorrelation in the daily returns can be found after correction for heteroskedasticity. This implies that there is no linear dependence present in the data. One may thus question whether technical trading strategies can persistently beat the buy-and-hold benchmark. However as noted by Alexander (1961), the dependence in price changes can be of such a complicated nonlinear form that standard linear statistical tools, such as serial correlations, may provide misleading measures of the degree of dependence in the data. Therefore he proposed to use nonlinear technical trading rules to test for dependence. If technical trading rules can capture dependence, which they can profitably trade upon, the question remains whether the profits disappear after implementing transaction costs. Furthermore, it is necessary to test whether the profits are just the compensation for bearing the risk of holding the risky asset during certain periods.

In total we apply 787 objective computerized trend-following technical trading techniques with and without transaction costs to the 51 market indices (see sections 2.3 and 3.3 and Appendix B of Chapter 3 for the technical trading rule parameterizations). We consider three different trading cases. First we do as if we are a local trader and we apply our technical trading rule set to the indices expressed in local currency and we compute the profits expressed in local currency. If no trading position in the stock market index is held, then the local risk-free interest rate is earned. Due to depreciation however, it is possible that profits in local currencies disappear when recomputed in US Dollars. Therefore we also consider the problem from the perspective of an US-based trader. Trading signals are then generated in two different ways: firstly on the indices expressed in local currency and secondly on the indices recomputed in US Dollars. Recomputation of local indices in US Dollars is done to correct for possible trends in the levels of stock market indices caused by a declining or advancing exchange rate of the local currency against the US Dollar. If the US-based trader holds no trading position in the stock market index, then the US risk-free interest rate is earned. Summarized we examine the following trading cases:

	Trader	Index in	Profits in
Trading case 1	local trader	local currency	local currency
Trading case 2	US trader	local currency	US Dollars
Trading case 3	US trader	US Dollars	US Dollars

We refer to section 3.4 for a discussion on how the technical trading rule profits are computed. If 0 and 0.25% costs per trade are implemented, then for trading case 3 tables 5.3 and 5.4 show for each local main stock market index some statistics of the best strategy selected by the mean return criterion. Column 2 shows the parameters of the best strategy. In the case of a moving-average (MA) strategy these parameters are "[short run MA, long run MA]" plus the refinement parameters "[%-band filter, time delay filter, fixed holding period, stop-loss]". In the case of a trading range break, also called support-and-resistance (SR), strategy, the parameters are "[the number of days over which the local maximum and minimum is computed]" plus the refinement parameters as with the moving averages. In the case of a filter (FR) strategy the parameters are "[the %-filter, time delay filter, fixed holding period]". Columns 3 and 4 show the mean yearly return and excess mean yearly return of the best-selected strategy over the buy-and-hold benchmark, while columns 5 and 6 show the Sharpe ratio and excess Sharpe ratio of the best-selected strategy over the buy-and-hold benchmark. Column 7 shows the maximum cumulative loss the best strategy generates. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days profitable trades last. Finally, the last column shows the standard deviation of the returns of the indices during profitable trades divided by the standard deviation of the returns of the indices during non-profitable trades.

To summarize, for trading case 3 table 5.6A (i.e. table 5.6 panel A) shows for each index the mean yearly excess return over the buy-and-hold benchmark of the best strategy selected by the mean return criterion, after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade. This wide range of costs captures a range of different trader types. For example, floor traders and large investors, such as mutual funds, can trade against relatively low transaction costs in the range of 0.10 to 0.25%. Home investors face higher costs in the range of 0.25 to 0.75%, depending whether they trade through the internet, by telephone or through their personal account manager. Next, because of the bid-ask spread, extra costs over the transaction costs are faced. By examining a wide range of 0 to 1% costs per trade, we belief that we can capture most of the cost possibilities faced in reality by most of the traders. At the bottom of table 5.6A, the row labeled "Average 3" shows for each transaction cost case the average over the results for trading case 3 as presented in the table. For comparison with the other two trading cases the row labeled "Average 1" shows the average over the results if trading case 1 is examined and the row labeled "Average 2" shows the average over the results if trading case 2 is examined.

Table 5.6A clearly shows that for each stock market index the best technical trading strategy selected by the mean return criterion is capable of beating the buy-and-hold benchmark, even after correction for transaction costs. If transaction costs increase from 0 to 1% per trade, then it can be seen that the excess returns decline on average from 49.14 to 17.22%. However, even in the large 1% costs per trade case, the best technical trading strategy is superior to the buy-and-hold strategy. The lowest excess returns are found for the West European stock market indices, while the highest excess returns are found for the Asian and Latin American stock market indices. No large differences are found between the three trading cases. The results, as summarized by the averages in the bottom rows of table 5.6A, are similar.

From table 5.3 it can be seen that in the case of zero transaction costs the best-selected strategies are mainly strategies that generate a lot of signals. Trading positions are held for only a few days. For example, the best technical trading strategy found for the MSCI World Index is a single crossover moving-average rule, with no extra refinements, which generates a signal when the price series crosses a 2-day moving average. The mean yearly return is equal to 52%, which corresponds with a mean yearly excess return of 40%. The Sharpe ratio is equal to 0.1461 and the excess Sharpe ratio is equal to 0.1349. These excess performance measures are considerably large. The maximum loss of the strategy is 18.7%, half less than the maximum loss of buying and holding the MSCI World Index, which is equal to 38.7%. The number of trades is very large, once every 2.4 days, but also the percentage of profitable trades is very large, namely 74.8%. These profitable trades span 86% of the total number of trading days. Similar good results are also found for the other stock market indices. For 42 of the 51 indices the maximum loss of the best strategy is less than the largest cumulative loss of the buy-and-hold strategy. For most indices the percentage of profitable trades is larger than 70% and these profitable trades span more than 80% of the total number of trading days. Although the Sharpe ratio of the buy-and-hold was negative for 23 indices, indicating that these indices were not able in beating a continuous risk free investment, it is found for all indices that the best-selected strategy shows a positive Sharpe ratio.

If transaction costs are increased to 0.25% per trade, then table 5.4 shows that the best-selected strategies are strategies which generate substantially fewer signals in comparison with the zero transaction costs case. Trading positions are now held for a longer period. For example, the best strategy found for the MSCI World Index is a single crossover moving-average rule which generates signals if the price series crosses a 200-day moving average and where the single refinement is a 2.5%-band filter. This strategy generates a trade every 13 months. However due to transaction costs the performance of the technical trading rules decreases and also the percentage of profitable trades and the percentage of days profitable trades last decreases for most indices in comparison with the zero transaction costs case. However for all indices, the Sharpe ratio of the best strategy is still positive. This continues to be the case even if costs are increased to 1% per trade. Similar results are found for the two other trading cases.

CAPM

If no transaction costs are implemented, then for trading case 3 it can be seen from the last column in table 5.3 that the standard deviations of the daily returns during profitable trades are higher than the standard deviations of the daily returns during non-profitable trades for almost all stock market indices, except for the Indonesian Jakarta Composite, the Finnish HEX, the Swiss SMI and the Irish ISEQ. However, if 0.25% costs per trade are calculated, then for only 24 indices out of 51 the standard deviation ratio is larger than one. Similar results are found for the other two trading cases. According to the efficient markets hypothesis it is not possible to exploit a data set with past information to predict future price changes. The good performance of the technical trading rules could therefore be the reward for holding a risky asset needed to attract investors to bear the risk. Since the technical trading rule forecasts only depend on past price history, it seems unlikely that they should result in unusual risk-adjusted profits. To test this hypothesis we regress Sharpe-Lintner capital asset pricing models (CAPMs)

$$r_t^i - r_t^f = \alpha + \beta(r_t^M - r_t^f) + \epsilon_t. \tag{5.1}$$

Here r_t^i is the return on day t of the best strategy applied to index i, r_t^M is the return on day t of a (preferably broad) market portfolio M and r_t^f is the risk-free interest rate. As proxy for the market portfolio M we use the local index itself or the MSCI World Index, both expressed in the same currency according to which the return of the best strategy is computed. Because we considered three different trading cases for computing r_t^i, and combine these with two different choices for the market portfolio M, we estimated in total six different CAPMs for each index. The coefficient β measures the riskiness of the active technical trading strategy relatively to the passive strategy of buying and holding the market portfolio. If β is not significantly different from one, then it is said that the strategy has equal risk as a buying and holding the market portfolio. If $\beta > 1$ ($\beta < 1$), then it is said that the strategy is more risky (less risky) than buying and holding the market portfolio and that it therefore should yield larger (smaller) returns. The coefficient α measures the excess return of the best strategy applied to stock i after correction of bearing risk. If it is not possible to beat a broad market portfolio after correction for risk and hence technical trading rule profits are just the reward for bearing risk, then α should not be significantly different from zero.

We estimated the Sharpe-Lintner CAPMs in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade. For trading case 3 table 5.7 shows in the cases of 0 and 0.50% transaction costs the estimation results if for each index the best strategy is selected by the mean return criterion and if the market portfolio is chosen to be the local main stock market index. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. Table 5.9 summarizes the CAPM estimation results for all trading cases and for all transaction cost cases by showing the number of indices for which significant estimates of α or β are found at the 10% significance level.

For example, for the best strategy applied to the MSCI World Index in the case of zero transaction costs, the estimate of α is significantly positive at the 1% significance level and equal to 13.42 basis points per day, that is approximately 33.8% on a yearly basis. The estimate of β is significantly smaller than one at the 10% significance level, which indicates that although the strategy generates a higher reward than simply buying

Trading case 1	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	51	23	0	23	0
0.10%	0	46	30	0	27	0
0.25%	0	45	29	0	26	0
0.50%	0	36	31	5	22	3
0.75%	0	30	31	6	19	2
1%	1	25	30	7	15	3
Trading case 2						
0%	0	50	19	0	18	0
0.10%	0	44	23	1	20	0
0.25%	0	41	25	1	22	0
0.50%	0	35	25	4	20	1
0.75%	0	29	28	4	17	1
1%	1	27	28	6	16	2
Trading case 3						
0%	0	51	29	0	29	0
0.10%	0	45	28	1	25	0
0.25%	0	44	28	2	26	0
0.50%	0	37	28	3	23	0
0.75%	1	32	33	3	24	0
1%	2	27	34	4	20	1

Table 5.9: **Summary: significance CAPM estimates, mean return criterion.** For each transaction cost case, the table shows the number of indices for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM. The local main stock market index is taken to be the market portfolio in the CAPM estimations. Columns 1 and 2 show the number of indices for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of indices for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of indices for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of indices for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that the number of indices analyzed is equal to 51.

and holding the index, it is less risky. If transaction costs increase to 1% per trade, then α decreases to 1.82 basis points (4.6% yearly), but still is significantly positive at the 10% significance level. However, the estimate of β is not significantly smaller than one anymore, if as little as 0.25% costs per trade are charged. It becomes even significantly larger than one if 1% transaction costs are implemented, which indicates that the strategy applied to the MSCI World Index is riskier than buying and holding the market index.

If the local main stock market index is taken to be the market portfolio in the CAPM estimations and if zero transaction costs are implemented, then, as further can be seen in the tables, also for the other indices the estimate of α is significantly positive at the 10% significance level. Further the estimate of β is significantly smaller than one for 29 indices. For none of the indices the estimate of β is significantly larger than one. The estimate of α in general decreases as costs per trade increases and becomes less significant for more indices. However in the 0.10, 0.25, 0.50, 0.75 and 1% costs per trade cases for example, still for respectively 45, 44, 37, 32 and 27 indices out of 51 the estimate of α is significantly positive at the 10% significance level. The estimate of β is significantly smaller than one for 28, 28, 28, 33 and 34 indices, in the 0.10, 0.25, 0.50, 0.75 and 1% costs per trade cases, indicating that even in the presence of high costs, the best selected technical trading strategies are less risky than the buy-and-hold strategy. The number of data series for which the estimate of β is significantly smaller than one increases as transaction costs increase. This is mainly caused because as transaction costs increase, by the selection criteria strategies are selected which trade less frequently and are thus less risky. Notice that for a large number of cases it is found that the estimate of α is significantly positive while simultaneously the estimate of β is significantly smaller than one. This means that the best-selected strategy did not only generate a statistically significant excess return over the buy-and-hold benchmark, but is also significantly less risky than the buy-and-hold benchmark. The results for the two other trading cases are similar.

If the MSCI World Index is used as market portfolio in the CAPM estimations, then the results for α become less strong[4]. In the case of zero transaction costs for 46 stock market indices it is found that the estimate of α is significantly different from zero. In the 0.10, 0.25, 0.50, 0.75 and 1% costs per trade cases, for respectively 40, 34, 24, 24 and 19 indices out of 51 the estimate of α is significantly positive at the 10% significance level. However still the estimate of β is significantly smaller than one for 41, 41, 40, 40 and 42 indices in the 0.10, 0.25, 0.50, 0.75 and 1% costs per trade case.

From these findings we conclude that there are trend-following technical trading techniques which can profitably be exploited, even after correction for transaction costs, when applied to local main stock market indices. As transaction costs increase, the best strategies selected are those which trade less frequently. Furthermore, if a correction is made for risk by estimating Sharpe-Lintner CAPMs, then it is found for many local main stock market indices that the best strategy has forecasting power, i.e. $\alpha > 0$. It is also found that in general the best strategy is less risky, i.e. $\beta < 1$, than buying and holding the market portfolio. Hence, for most stock market indices, we *can reject* the null hypothesis that the profits of technical trading are just the reward for bearing risk.

Data snooping

The question remains open whether the findings in favour of technical trading for particular indices are the result of chance or of real superior forecasting power. Therefore we

[4]These results are not presented here to save space.

apply White's (2000) Reality Check (RC) and Hansen's (2001) Superior Predictive Ability (SPA) test. Because Hansen (2001) showed that White's RC is biased in the direction of one, p-values are computed for both tests to investigate whether these tests lead in some cases to different inferences.

In the case of 0 and 0.25% transaction costs table 5.8 shows for trading case 3 the nominal, RC and SPA-test p-values, if the best strategy is selected by the mean return criterion[5]. Table 5.10 summarizes the results for all transaction cost cases by showing the number of indices for which the corresponding p-value is smaller than 0.10. That is, the number of data series for which the null hypothesis is rejected at the 10% significance level.

	Trading case 3		
costs	p_n	p_W	p_H
0%	51	8	27
0.10%	51	6	15
0.25%	51	2	6
0.50%	51	0	2
0.75%	51	0	1
1%	51	0	1

Table 5.10: **Summary: Testing for predictive ability, mean return criterion.** For each transaction cost case, the table shows the number of indices for which the nominal (p_n), White's (2000) Reality Check (p_W) or Hansen's (2001) Superior Predictive Ability test (p_H) p-value is smaller than 0.10. Note that the number of indices analyzed is equal to 51.

The nominal p-value, also called data mined p-value, tests the null hypothesis that the *best* strategy *is not* superior to the buy-and-hold benchmark, but does not correct for data snooping. From the tables it can be seen that this null hypothesis is rejected for all indices in all cost cases at the 10% significance level. However, if we correct for data snooping, then in the case of zero transaction costs we find for only 8 of the stock market indices that the null hypothesis that the *best* strategy is not superior to the benchmark after correcting for data snooping *is* rejected by the RC, while for 27 indices the null hypothesis that *none* of the alternative strategies is superior to the buy-and-hold benchmark after correcting for data snooping *is* rejected by the SPA-test. The two data snooping tests thus give contradictory results for 19 indices. Thus the RC misguides the researcher in several cases by not rejecting the null. The number of contradictory results decreases to 9 if 0.10% costs per trade are implemented and to 4, 2, 1 and 1 if 0.25, 0.50, 0.75 and 1% costs per trade are implemented. In the 0.10% costs per trade case, the SPA-test rejects for 15 indices its null hypothesis, but this number declines to 2 in the

[5]Computations are also done for the 0.10, 0.50, 0.75 and 1% costs per trade cases but the results are not presented here to save space. The results are available upon request from the author.

0.50% costs per trade case. Remarkably, only for the Egyptian CMA the SPA-test does reject its null hypothesis, even in the 1% costs per trade case. Hence we conclude that for all but one of the market indices the best strategy, selected by the mean return criterion, is not capable of beating the buy-and-hold benchmark strategy, after a correction is made for transaction costs and data snooping.

5.3.2 Results for the Sharpe ratio criterion

Technical trading rule performance

Similar to tables 5.3 and 5.4, table 5.5 shows for trading case 3 some statistics of the best strategy selected by the Sharpe ratio criterion, if 0 or 0.25% costs per trade are implemented. Only the results for those indices are shown for which the best strategy selected by the Sharpe ratio criterion differs from the best strategy selected by the mean return criterion. Further, to summarize, table 5.6B shows for each index the Sharpe ratio of the best strategy selected by the Sharpe ratio criterion, after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade, in excess of the Sharpe ratio of the buy-and-hold benchmark. For each index and for each transaction costs case it is found that the excess Sharpe ratio is considerably positive. In the last row of table 5.6B it can be seen that on average the excess Sharpe ratio declines from 0.0672 to 0.0320 if transaction costs increase from 0 to 1% per trade. Table 5.5 shows that the best strategies selected in the case of zero transaction costs are mainly strategies which trade frequently. For most indices, except 10, the best-selected strategy is the same as in the case that the best strategy is selected by the mean return criterion. If costs are increased to 0.25%, then the best strategies selected are those which trade less frequently. Now for 22 indices the best-selected strategy differs from the case when the best strategy is selected by the mean return criterion. The results for the two other trading cases are similar.

As for the mean return criterion it is found that for each stock market index the best technical trading strategy, selected by the Sharpe ratio criterion, beats the buy-and-hold benchmark and that this strategy can profitably be exploited, even after correction for transaction costs.

CAPM

The estimation results of the Sharpe-Lintner CAPM shown in tables 5.7B and 5.11 for the Sharpe ratio selection criterion are similar to the estimation results shown in tables 5.7A and 5.9 for the mean return selection criterion. If zero transaction costs are implemented, then it is found for trading case 3 that for all 51 indices the estimate of α is significantly positive at the 10% significance level. This number decreases from 37 to 28 if transaction costs increase from 0.50 to 1% per trade. As for the mean return selection criterion, for many indices it is found that the estimate of α is significantly positive and that simultaneously the estimate of β is significantly smaller than one. Thus, after correction for transaction costs and risk, for more than half of the indices it is found that the best technical trading strategy selected by the Sharpe ratio criterion significantly outperforms the buy-and-hold benchmark strategy and is even significantly less risky.

If the MSCI World Index is taken to be the market portfolio, then the results for α become less strong, as in the mean return selection criterion case. If transaction costs increase from 0% to 0.50 and 1%, then the number of indices for which a significant estimate of α is found declines from 46 to 25 and 18.

Trading case 1	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge \beta < 1$	$\alpha > 0 \wedge \beta > 1$
0%	0	50	26	0	25	0
0.10%	0	46	34	0	29	0
0.25%	0	46	37	0	32	0
0.50%	0	39	43	0	32	0
0.75%	0	33	43	1	28	1
1%	1	27	42	1	22	1
Trading case 2						
0%	0	50	21	0	20	0
0.10%	0	46	30	1	26	0
0.25%	0	43	36	1	30	0
0.50%	0	38	39	1	30	0
0.75%	0	33	37	1	26	0
1%	0	31	36	3	23	1
Trading case 3						
0%	0	51	28	0	28	0
0.10%	0	45	37	0	31	0
0.25%	0	42	41	0	33	0
0.50%	0	37	43	1	33	0
0.75%	1	33	47	1	32	0
1%	2	28	47	1	26	0

Table 5.11: **Summary: significance CAPM estimates, Sharpe ratio criterion.** For each transaction cost case, the table shows the number of indices for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM. The local main stock market index is taken to be the market portfolio in the CAPM estimations. Columns 1 and 2 show the number of indices for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of indices for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of indices for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of indices for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that the number of indices analyzed is equal to 51.

Data snooping

In the case of 0 and 0.25% transaction costs table 5.8B shows for trading case 3 the nominal, White's RC and Hansen's SPA-test p-values, if the best strategy is selected by the Sharpe ratio criterion. For trading case 3 table 5.12 summarizes the results for all transaction cost cases by showing the number of indices for which the corresponding p-value is smaller than 0.10.

	Trading case 3		
costs	p_n	p_W	p_H
0%	51	24	35
0.10%	51	17	28
0.25%	51	7	23
0.50%	51	3	16
0.75%	51	3	15
1%	51	1	13

Table 5.12: **Summary: Testing for predictive ability, Sharpe ratio criterion.** For each transaction cost case, the table shows the number of indices for which the nominal (p_n), White's (2000) Reality Check (p_W) or Hansen's (2001) Superior Predictive Ability test (p_H) p-value is smaller than 0.10. Note that the number of indices analyzed is equal to 51.

The results for the Sharpe ratio selection criterion differ from the results for the mean return selection criterion. If the nominal p-value is used to test the null hypothesis that the best strategy *is not* superior to the benchmark of buy-and-hold, then the null is rejected for all indices at the 10% significance level for all cost cases. If a correction is made for data snooping, then it is found in the case of zero transaction costs that for 24 indices the null hypothesis that the *best* strategy is not superior to the buy-and-hold benchmark *is* rejected by the RC. However, for 35 indices the null hypothesis that *none* of the alternative strategies is superior to the buy-and-hold benchmark after correcting for data snooping *is* rejected by the SPA-test. Thus for half of the indices we find that the best technical trading rule has forecasting power even when correcting for the specification search. These numbers are higher than for the mean return selection criterion. In total we find for 11 indices contradictory results, which is less than for the mean return selection criterion. Even in the case of 0.10% costs per trade, the number of indices for which the RC and the SPA-test reject the null is high, namely for 17 and 28 indices respectively. However, if transaction costs are increased any further, then the number of indices for which the RC rejects its null declines sharply: to 7, 3, 3, 1 in the 0.25, 0.50, 0.75 and 1% transaction costs cases. In contrast, the SPA-test rejects its null for 23, 16, 15 and 13 indices in the 0.25, 0.50, 0.75 and 1% transaction costs cases. Note that these results differ substantially from the mean return selection criterion in which case under 0.25, 0.50, 0.75 and 1% costs per trade the null of no superior predictive ability was rejected for respectively 6, 2, 1 and 1 indices by the SPA-test. Hence we conclude, after a correction is made for transaction costs and data snooping, that the best strategy selected by the Sharpe ratio criterion *is capable* of beating the benchmark of a buy-and-hold strategy for approximately 25% of the indices analyzed. These results are mainly found for the Asian stock market indices, but also for some European stock market indices, such as Italy and Portugal.

5.4 A recursive out-of-sample forecasting approach

In section 3.7 we argued to apply a recursive out-of-sample forecasting approach to test whether technical trading rules have true out-of-sample forecasting power. For example, recursively at the beginning of each month it is investigated which technical trading rule performed the best in the preceding six months (training period) and this strategy is used to generate trading signals during the coming month (testing period). In this section we apply the recursive out-of-sample forecasting procedure to the main local stock market indices examined in this chapter.

We define the training period on day t to last from $t - Tr$ until and including $t - 1$, where Tr is the length of the training period. The testing period lasts from t until and including $t + Te - 1$, where Te is the length of the testing period. At the end of the training period the best strategy is selected by the mean return or Sharpe ratio criterion. Next, the selected technical trading strategy is applied in the testing period to generate trading signals. After the end of the testing period this procedure is repeated again until the end of the data series is reached. For the training and testing periods we use 28 different parameterizations of $[Tr, Te]$ which can be found in Appendix B of Chapter 4.

If trading case 3 is applied, then in the case of 0.25% transaction costs, tables 5.13 and 5.14 show for the local main stock market indices some statistics of the best recursive optimizing and testing procedure, if the best strategy in the training period is selected by the mean return and Sharpe ratio criterion respectively. Because the longest training period is one year, the results are computed for the period 1983:1-2002:6. Tables 5.15A and 5.15B summarize the results for both selection criteria in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade. In the second to last row of table 5.15A it can be seen that, if in the training period the best strategy is selected by the mean return criterion, then the excess return over the buy-and-hold of the best recursive optimizing and testing procedure is, on average, 37.72, 30.60, 21.41, 12.4, 7.05 and 4.47% yearly in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade. If transaction costs increase, then the best recursive optimizing and testing procedure becomes less profitable. Good results, also after correction for transaction costs, are mainly found for the Asian, Latin American, Middle East and Russian stock market indices. For example, the best recursive optimizing and testing procedure generates an excess return over the buy-and-hold of 43.52, 32.42, 20.99, 12.61, 7.50 and 4.88% yearly for the Argentinean Merval, after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% transaction costs. However, for the US, Japanese and most Western European stock market indices the recursive out-of-sample forecasting procedure does not show to be profitable, after implementing transaction costs.

If the Sharpe ratio criterion is used for selecting the best strategy during the training period, then the Sharpe ratio of the best recursive optimizing and testing procedure in excess of the Sharpe ratio of the buy-and-hold benchmark is on average 0.0544, 0.0419, 0.0298, 0.0164, 0.0086 and 0.0052 in the case of 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade (see second to last row of table 5.15B). As for the mean return selection criterion, the best recursive optimizing and testing procedure does not generate excess Sharpe ratios over the buy-and-hold for the US and most Western European indices in the presence of transaction costs. The best results are mainly found for the Latin American, Egyptian and Asian stock market indices.

For comparison, the last rows in tables 5.15A and 5.15B show the average over the results of the best strategies selected by the mean return or Sharpe ratio criterion in sample for each index tabulated. As can be seen, clearly the results of the best strategies selected in sample are better than the results of the best recursive out-of-sample forecasting procedure.

For the cases that the best strategy in the optimizing period is selected by the mean return and Sharpe ratio criterion respectively, tables 5.16A and 5.16B show for the 0 and 0.50% transaction cost cases the estimation results of the Sharpe-Lintner CAPM (see equation 5.1), where the return in US Dollars of the best recursive optimizing and testing procedure in excess of the US risk-free interest rate is regressed against a constant α and the return of the local main stock market index in US Dollars in excess of the US risk-free interest rate. Tables 5.17A, B summarize the CAPM estimation results for the two possible choices of the market portfolio and for all transaction cost cases by showing the number of indices for which significant estimates of α or β are found at the 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

If the local main stock market index is taken to be the market portfolio and if the best strategy in the training period is selected by the mean return criterion, then in the case of zero transaction costs it can be seen in table 5.17A that for 37 indices a significantly positive estimate of α is found. As can be seen in table 5.16A, mainly for the US, Japan

A: Local index as benchmark market portfolio						
Selection criterion: mean return						
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	37	20	1	15	1
0.10%	0	29	21	1	11	0
0.25%	0	26	16	2	9	0
0.50%	3	16	17	2	6	0
0.75%	3	10	17	2	3	0
1%	4	7	13	3	2	0
Selection criterion: Sharpe ratio						
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	40	39	0	30	0
0.10%	0	33	34	0	23	0
0.25%	1	28	36	1	20	0
0.50%	4	15	29	1	9	0
0.75%	6	9	26	0	5	0
1%	6	6	23	1	3	0

B: MSCI World Index as benchmark market portfolio						
Selection criterion: mean return						
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	31	41	1	26	1
0.10%	0	24	40	0	21	0
0.25%	0	18	39	0	15	0
0.50%	2	7	40	1	6	0
0.75%	2	4	39	1	4	0
1%	3	1	38	3	1	0
Selection criterion: Sharpe ratio						
costs	$\alpha < 0$	$\alpha > 0$	$\beta < 1$	$\beta > 1$	$\alpha > 0 \wedge$ $\beta < 1$	$\alpha > 0 \wedge$ $\beta > 1$
0%	0	33	45	0	28	0
0.10%	0	24	44	0	21	0
0.25%	0	17	42	0	16	0
0.50%	0	8	42	1	8	0
0.75%	0	2	42	0	2	0
1%	2	2	41	1	2	0

Table 5.17: **Summary: significance CAPM estimates for best out-of-sample testing procedure.** For each transaction cost case, the table shows the number of indices for which significant estimates are found at the 10% significance level for the coefficients in the Sharpe-Lintner CAPM. In panel A the local main stock market index and in panel B the MSCI World Index is taken to be the market portfolio in the CAPM estimations. Columns 1 and 2 show the number of indices for which the estimate of α is significantly negative and positive. Columns 3 and 4 show the number of indices for which the estimate of β is significantly smaller and larger than one. Column 5 shows the number of indices for which the estimate of α is significantly positive as well as the estimate of β is significantly smaller than one. Column 6 shows the number of indices for which the estimate of α is significantly positive as well as the estimate of β is significantly larger than one. Note that the number of indices analyzed is equal to 51.

and Western European countries the estimate of α is neither significantly negative nor positive at the 10% significance level. As transaction costs increase to 0.50%, the number of significant estimates of α decreases to 16. Significant estimates for α are then mainly found for the Asian stock market indices. As transaction costs increase even further to 1%, then the number of significant estimates of α decreases to 7. Significant estimates for α are then found only for the Peru Lima General, Indonesia Jakarta Composite, Pakistan Karachi 100, Sri Lanka CSE All Share, Thailand SET, and the Egypt CMA. If the Sharpe ratio selection criterion is used to select the best strategy in the training period of the recursive optimizing and testing procedure, then the results are similar as for the mean return selection criterion. If transaction costs increase to 1%, then significant estimates of α are found only for the Chile IPSA, Peru Lima General, Sri Lanka CSE All Share, Norway OSE All Share, Russia Moscow Times, and the Egypt CMA.

However, if the MSCI World Index is taken to be market portfolio in the CAPM regression, then the results become worse, as can be seen in table 5.17B. In the case of the mean return selection criterion the number of significant estimates of α decreases from 31 to 1 if transaction costs increase from 0 to 1%. Only for the Egypt CMA the estimate of α is significantly positive at the 10% significance level if transaction costs are equal to 1% per trade. If the Sharpe ratio selection criterion is used to select the best strategy in the training period, then also for the Russia Moscow Times the estimate of α is significantly positive at the 10% significance level.

Hence, after correction for sufficiently high transaction costs and risk, it can be concluded, independently of the selection criterion used, that the best recursive optimizing and testing procedure shows no statistically significant out-of-sample forecasting power for local main stock market indices world wide. Only for low transaction costs ($\leq 0.25\%$ per trade) technical trading shows statistically significant out-of-sample forecasting power for the Asian, Chilean, Czech, Greece, Mexican, Russian and Turkish stock market indices. In contrast, for the US, Japanese and most Western European stock market indices no significant out-of-sample forecasting power is found, even for low transaction costs.

5.5 Conclusion

In this chapter we apply a set of 787 objective computerized trend-following technical trading techniques to 50 local main stock market indices in Africa, the Americas, Asia, Europe, the Middle East and the Pacific, and to the MSCI World Index in the period January 2, 1981 through June 28, 2002. For each index the best technical trading strategy is selected by the mean return or Sharpe ratio criterion. The advantage of the Sharpe ratio selection criterion over the mean return selection criterion is that it selects the strategy with the highest return/risk pay-off. Although for 23 stock market indices it is found that they could not even beat a continuous risk free investment, we find for both selection criteria that for each index a technical trading strategy can be selected that is capable of beating the buy-and-hold benchmark, even after correction for transaction costs.

The profits generated by the technical trading strategies could be the reward necessary to attract investors to bear the risk of holding the asset. To test this hypothesis we estimate Sharpe-Lintner CAPMs. For each local stock market index the daily return of the best strategy in excess of the risk-free interest rate is regressed against a constant (α) and the daily return of buying and holding a market portfolio in excess of the risk-free interest rate. The coefficient of the last regression term is called β and measures the riskiness of the strategy relatively to buying and holding the market portfolio. The market portfolio is taken to be the local stock market index, but we also examine the possibility that the market portfolio is represented by the MSCI World Index. If technical trading rules do not generate excess profits after correction for risk, then α should not be significantly different from zero. In the case of zero transaction costs case, it is found for the mean return as well as the Sharpe ratio criterion that for all indices the estimate of α is significantly positive at the 10% significance level, if the local index is used as the market portfolio. Even if transaction costs are increased to 1% per trade, then we find for more than half of the indices that the estimate of α is still significantly positive. Moreover it is found that the estimate of β is simultaneously significantly smaller than one for most indices. Thus for both selection criteria we find for approximately half of the indices that in the presence of transaction costs the best technical trading strategies have forecasting power and even reduce risk. If the MSCI World Index is used as market portfolio in the CAPM estimations, then the results for α become less strong, but even in the 0.50% costs per trade case, for almost half of the indices the estimate of α is significantly positive.

An important question is whether the positive results found in favour of technical trading are due to chance or the fact that the best strategy has genuine superior forecasting power over the buy-and-hold benchmark. This is called the danger of data snooping. We apply White's (2000) Reality Check (RC) and Hansen's (2001) Superior Predictive Ability (SPA) test, to test the null hypothesis that the best strategy found in a specification search *is not* superior to the benchmark of a buy-and-hold if a correction is made for data snooping. Hansen (2001) showed that White's RC is biased in the direction of one, caused by the inclusion of poor strategies. Because we compute p-values for both tests, we can investigate whether the two test procedures result in different inferences about forecasting ability. If zero transaction costs are implemented, then we find for the mean return selection criterion that the RC and the SPA-test for 19 out of 51 indices lead to different conclusions. The SPA-test finds for more than half of the indices that the best strategy does beat the buy-and-hold significantly after correction for data snooping and the inclusion of bad strategies. Thus the biased RC misguides the researcher in several cases by not rejecting the null. However, if as little as 0.25% costs per trade are implemented, then both tests lead for almost all indices to the same conclusion: the best technical trading strategy selected by the mean return criterion is not capable of beating the buy-and-hold benchmark after correcting for the specification search that is used to find the best strategy. In contrast, for the Sharpe ratio selection criterion we find totally different results. The SPA-test rejects the null hypothesis for 35 indices in the case of zero transaction costs, while the RC rejects the null hypothesis for 24 indices. If costs are increased further to even 1% per trade, then for approximately a quarter of the indices analyzed, the SPA-tests rejects the null of no superior predictive ability at the 10% significance level, while the RC rejects the null for only one index. We find for the Sharpe ratio selection criterion large differences between the two testing procedures. Thus the inclusion of poor performing strategies, for which is corrected in the SPA-test, can indeed influence the inferences about the predictive ability of technical trading rules.

Next we apply a recursive optimizing and testing method to test whether the best strategy found in a specification search during a training period also shows forecasting power during a testing period thereafter. For example, every month the best strategy from the last 6 months is selected to generate trading signals during that month. In total we examine 28 different training and testing period combinations. In the case of zero transaction costs, the best recursive optimizing and testing procedure yields on average an excess mean return over the buy-and-hold of 37.72% yearly, if the best strategy in the training period is selected by the mean return criterion. Thus the best strategy found in the past continues to generate good results in the future. If transaction costs increase, then the excess mean returns on average decline. In the presence of 1% transaction costs the excess mean return over the buy-and-hold benchmark is on average 4.47% yearly. For both selection criteria, mainly profitable results are found for the Asian, Latin American, Middle East and Russian stock market indices. No profitable results are found for the US, Japanese and Western European stock market indices. However, estimation of Sharpe-Lintner CAPMs indicates that the economic profits of technical trading in almost all stock market indices, except the Egypt CMA and the Russia Moscow Times, can be explained by risk, after a correction is made for sufficiently high transaction costs. Only for transaction costs below or equal to 0.25% some risk-corrected out-of-sample forecasting power is found for the Asian, Latin American, Middle East and Russian stock market indices.

Hence, in short, after correcting for sufficiently high transaction costs, risk, data-snooping and out-of-sample forecasting, we conclude that objective trend-following technical trading techniques, applied to local main stock market indices all over the world, are not genuine superior, as suggested by their in-sample performance results, to the buy-and-hold benchmark. Only for sufficiently low transaction costs some statistically significant risk-corrected out-of-sample forecasting power is found for the Asian, Latin American, Middle East and Russian stock market indices.

5.6 Comparing the US, Dutch and Other Stock Markets

Table 5.18 summarizes for all transaction costs cases the results of testing the set of 787 trend following technical trading techniques on the DJIA and on stocks listed in the DJIA (Chapter 3), on the AEX-index and on stocks listed in the AEX-index (Chapter 4) and on 51 stock market indices world wide (Chapter 5). If the return of the best technical trading strategy, selected in sample, in excess of the risk free interest rate is regressed against a constant α and the return of a market portfolio in excess of the risk free interest rate (see CAPMs (3.5), (4.1) and (5.1)), then the rows labeled "(1) in-sample CAPM: $\alpha > 0$" show for each chapter the fraction of data series for which the estimate of α is significantly positive at the 10% significance level. The rows labeled "(2) $p_W < 0.10$" show the fraction of data series for which White's (2000) RC p-value is smaller than 0.10. The rows labeled "(3) $p_H < 0.10$" show the fraction of data series for which Hansen's (2001) SPA-test p-value is smaller than 0.10. Finally, the rows labeled "(4) out-of-sample CAPM: $\alpha > 0$" show as in the rows labeled "(1) in-sample CAPM: $\alpha > 0$" the fraction of data series for which the estimate of α is significantly positive at the 10% significance level, but this time when the return of the best recursive optimizing and training procedure in excess of the risk free interest rate is regressed against a constant α and the return of a market portfolio in excess of the risk free interest rate. Panel A shows the results if the best technical trading strategy is selected by the mean return criterion and panel B shows the results if the best technical trading strategy is selected by the Sharpe ratio criterion.

In each chapter for all data series a technical trading strategy that is capable of beating the buy-and-hold benchmark can be selected in sample. In the case of zero transaction costs it can be seen in the rows labeled "(1) in-sample CAPM: $\alpha > 0$" that in each chapter for a majority of the data series the estimate of α is significantly positive, indicating that the best selected technical trading rule has statistically significant forecasting power after correction for risk. If transaction costs increase, then the number of data series for which a significantly positive estimate of α is found declines. This can especially be observed in the results for the US stock market in Chapter 3 for which the fraction of data series for which a significantly positive estimate of α is found declines to one quarter if 1% transaction costs are implemented. However, in the case of 1% transaction costs, for approximately half of the Dutch stock market data in Chapter 4 and for approximately half of the stock market indices in Chapter 5, the estimate of α is still significantly positive. If the in-sample CAPM estimation results are compared with the out-of-sample CAPM estimation results, then the results in favour of technical trading of the latter tests are obviously worse than the results of the former tests. However, if transaction costs are zero, then in each chapter a group of data series can be found for which technical trading shows significant out-of-sample forecasting power, after correction for risk. As transaction costs increase, this group becomes smaller and smaller.

White's (2000) RC and Hansen's (2001) SPA-test are utilized to correct for data snooping. If little costs are implemented, then for the US stock market data in Chapter 3, the RC does not reject the null of no superior forecasting ability of the best selected technical trading rule over the buy-and-hold benchmark for all data series for both selection criteria. For the Dutch stock market data in Chapter 4 the same conclusion can be made, although the results in favour of technical trading are stronger, if the Sharpe ratio criterion is used. For a group of stock market indices in Chapter 5, in the case of zero transaction costs, it is found that the null hypothesis of no superior forecasting ability is rejected, especially if the Sharpe ratio criterion is used. However, if transaction costs increase to 1%, then for almost all data series the null hypothesis is not rejected anymore. The SPA-test corrects for the inclusion of poor and irrelevant strategies. Differences between the RC and SPA-test can especially be seen in Chapters 4 and 5, if the Sharpe ratio selection criterion is used. Then, for both the Dutch stock market data and the local main stock market indices, if 1% transaction costs are implemented, for more than one quarter of the data series the null hypothesis of no superior forecasting ability is rejected. Thus the biased RC leads in numerous cases to the wrong inferences.

If no transaction costs are implemented, then technical trading shows economically and statistically significant forecasting power for a group of data series, in all three chapters. In that case, generally, the results of the Sharpe ratio selection criterion are slightly better than the results of the mean return selection criterion. However, if transaction costs increase, then in Chapters 4 and 5 the Sharpe ratio selection criterion performs better in selecting the best technical trading strategy. If the Sharpe ratio criterion is used in selecting the best strategy, then for transaction costs up to 0.25%, technical trading shows economically and statistically significant forecasting power for approximately one fourth of the Dutch stock market data in Chapter 4. This is the case for approximately one third of the local main stock market indices in Chapter 5, if 0.50% transaction costs are implemented. It can be concluded that the DJIA and stocks listed in the DJIA are weak-form efficient. That is, these data series are not predictable from their own price history at normal transaction costs. The AEX-index and stocks listed in the AEX-index are weak-form efficient, only for transaction costs above 0.25%. For transaction costs below 0.25% profit opportunities exist. From the results in Chapter 5 it can be concluded that technical analysis applied to the stock market indices of emerging markets in Asia, Latin America, the Middle East and Russia has statistically significant forecasting power only for low transaction costs ($\leq$ 0.25% per trade), while for the Japanese, Northern American and Western European stock market indices the null hypothesis of weak-form efficiency cannot be rejected for all transaction costs cases.

Appendix

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Table 5.1: **Summary statistics local main stock market indices in local currency.** The first column shows the names of the indices examined. Columns 2 to 7 show the number of observations, the mean yearly effective return in %/100 terms, the mean, standard deviation, skewness and kurtosis of the daily logarithmic return. Column 8 shows the t-ratio testing whether the mean daily return is significantly different from zero. Column 9 shows the Sharpe ratio. Column 10 shows the largest cumulative loss in %/100 terms. Column 11 shows the Ljung-Box (1978) Q-statistic testing whether the first 20 autocorrelations of the return series as a whole are significantly different from zero. Column 12 shows the heteroskedasticity adjusted Box-Pierce (1970) Q-statistic, as derived by Diebold (1986). The final column shows the Ljung-Box (1978) Q-statistic for testing autocorrelations in the squared returns. Significance level of the (adjusted) Q(20)-test statistic can be evaluated based on the following chi-squared values: a) chi-squared(0.99,20)=37.57, b) chi-squared(0.95,20)=31.41, c) chi-squared(0.90,20)=28.41.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
World MSCI	5346	0.0838	0.000319	0.007529	-0.844	19.639	3.10a	0.011198	-0.3872	289.84a	50.74a	2189.95a
Argentina Merval	2065	-0.0525	-0.000214	0.02492	0.002	7.814	-0.39	-0.024918	-0.7682	81.22a	37.89a	634.96a
Brazil Bovespa	1755	0.1385	0.000515	0.024989	0.519	18.044	0.86	-0.012837	-0.6504	52.54a	24.91	283.11a
Canada TSX Composite	4042	0.0542	0.000209	0.008915	-1.304	22.217	1.49	-0.004028	-0.4281	83.26a	20.6	1330.14a
Chile IPSA	1955	-0.0048	-0.000019	0.012366	0.272	10.652	-0.07	-0.004304	-0.5512	108.58a	41.66a	534.99a
Mexico IPC	1413	0.1058	0.000399	0.018576	0.003	9.272	0.81	-0.015889	-0.4681	34.17b	20.82	225.62a
Peru Lima General	2610	0.2404	0.000855	0.014208	0.372	8.661	3.07a	0.031386	-0.5015	353.19a	125.83a	983.56a
US S&P500	5346	0.1035	0.000391	0.010341	-2.229	52.477	2.76a	0.015047	-0.3677	34.84b	11.77	353.99a
US DJIA	5346	0.1175	0.000441	0.010593	-2.872	72.566	3.04a	0.019429	-0.3613	36.13b	10.49	264.85a
US Nasdaq100	4825	0.114	0.000428	0.017764	-0.112	11.043	1.68c	0.011826	-0.7826	55.27a	22.1	2940.35a
US NYSE Composite	5346	0.0996	0.000377	0.009362	-2.543	61.538	2.94a	0.015129	-0.3302	41.47a	11.61	365.68a
US Russel2000	3520	0.0853	0.000325	0.009567	-0.5	8.374	2.02b	0.013897	-0.3725	134.56a	56.12a	2980.48a
US Wilshire5000	4565	0.0993	0.000376	0.009687	-1.817	31.044	2.62a	0.0172	-0.3966	61.30a	26.46	580.38a
Venezuela Industrial	1956	0.238	0.000847	0.0253	0.721	26.063	1.48	0.014105	-0.7945	52.71a	36.70b	370.72a
Australia ASX All Ordinaries	3987	0.0424	0.000165	0.009974	-6.715	182.588	1.04	-0.014138	-0.5009	161.89a	28.03	118.71a
China Shanghai Composite	1953	0.1372	0.00051	0.019896	0.894	27.342	1.13	0.025638	-0.4245	34.67b	21.42	304.15a
Hong Kong Hang Seng	4042	0.0924	0.000351	0.01826	-3.446	77.531	1.22	0.007494	-0.6005	62.73a	19.53	75.87a
India BSE30	2478	0.0222	0.000087	0.016375	-0.064	5.6	0.26	-0.012132	-0.5618	41.68a	28.88c	259.83a
Indonesia Jakarta Composite	3260	0.0184	0.000072	0.015387	0.472	14.164	0.27	-0.036795	-0.6726	248.18a	86.34a	1030.01a
Japan Nikkei225	4042	-0.035	-0.000142	0.014357	-0.084	11.004	-0.63	-0.017261	-0.7579	53.49a	30.95c	479.80a
Malaysia KLSE Composite	4316	0.0665	0.000256	0.01681	-0.228	35.098	1	0.002812	-0.8001	98.53a	17.96	2152.29a
New Zealand NZSE30	2739	0.0137	0.000054	0.009982	-0.879	22.581	0.28	-0.020997	-0.3731	27.01	20.81	374.84a
Pakistan Karachi100	2444	0.0409	0.000159	0.017111	-0.275	10.18	0.46	-0.014939	-0.7123	59.61a	27.41	726.48a
Philippines PSE Composite	3781	0.0237	0.000093	0.016238	0.45	11.136	0.35	-0.026353	-0.7159	206.55a	110.44a	259.51a
Singapore Straits Times	3979	0.0333	0.00013	0.014729	-2.045	55.318	0.56	-0.000133	-0.6278	149.90a	25.42	756.63a
South-Korea Kospi200	2239	0.0071	0.000028	0.02288	0.144	6.939	0.06	-0.016157	-0.7521	38.11a	20.99	670.90a
Sri Lanka CSE All Share	1756	0.013	0.000051	0.009578	4.142	82.322	0.22	-0.057186	-0.5591	243.99a	42.02a	46.77a

Table 5.1 continued.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
Thailand SET	2474	-0.0805	-0.000333	0.018359	0.475	7.116	-0.9	-0.037278	-0.8818	100.50a	53.14a	685.33a
Taiwan TSE Composite	1805	-0.0342	-0.000138	0.01742	-0.053	5.279	-0.34	-0.018072	-0.6446	37.91a	27.84	304.13a
Austria ATX	2625	0.0239	0.000094	0.010313	-0.468	8.71	0.47	-0.007528	-0.397	77.09a	39.04a	695.30a
Belgium Bel20	2999	0.082	0.000313	0.009315	0.015	8.035	1.84c	0.011453	-0.3692	98.69a	47.72a	876.67a
Czech Republic PX50	1711	-0.0045	-0.000018	0.012599	-0.143	5.115	-0.06	-0.029454	-0.5368	60.44a	39.38a	596.07a
Denmark KFX	3020	0.0844	0.000322	0.010205	-0.292	5.76	1.73c	0.007603	-0.3636	60.41a	33.25b	893.77a
Finland HEX General	2413	0.2032	0.000734	0.020716	-0.508	10.265	1.74c	0.027515	-0.6965	18.79	10.45	412.14a
France CAC40	2846	0.0721	0.000276	0.012618	-0.116	5.448	1.17	0.005279	-0.4731	37.56b	26.55	400.48a
Germany DAX30	2781	0.0967	0.000366	0.012964	-0.423	6.537	1.49	0.013836	-0.5304	35.81b	19.44	1370.48a
Greece ASE General	1885	0.1433	0.000532	0.018091	-0.081	6.348	1.28	0.008178	-0.6687	58.10a	29.15c	422.98a
Italy MIB30	1750	0.1028	0.000388	0.015235	-0.136	5.363	1.07	0.011711	-0.5257	51.56a	31.21c	950.01a
Netherlands AEX	4042	0.0874	0.000332	0.012368	-0.576	13.646	1.71c	0.00959	-0.4673	86.86a	25.78	3851.18a
Norway OSE All Share	1435	0.0241	0.000094	0.011935	-0.567	6.423	0.3	-0.01163	-0.4568	31.63b	17.86	596.97a
Portugal PSI General	1760	0.1122	0.000422	0.0106	-0.566	9.745	1.67c	0.021932	-0.5067	83.43a	38.09a	401.71a
Russia Moscow Times	1782	0.6278	0.001933	0.035371	-0.472	10.927	2.31b	0.024207	-0.8489	128.93a	41.12a	1372.96a
Slovakia SAX16	2016	-0.0683	-0.000281	0.013817	-0.595	11.449	-0.91	-0.052416	-0.6899	19.51	16.63	37.78a
Spain IGBM	2487	0.1308	0.000488	0.011977	-0.327	5.852	2.03b	0.020543	-0.4342	52.95a	29.59c	1202.23a
Sweden OMX	2238	0.1033	0.00039	0.015015	0.038	6.124	1.23	0.012589	-0.6316	36.84b	24.02	696.72a
Switzerland SMI	3391	0.1003	0.000379	0.011144	-0.648	11.227	1.98b	0.019659	-0.3925	33.10b	16.88	792.31a
Turkey ISE100	3520	0.7513	0.002224	0.031633	-0.076	5.904	4.17a	0.070295	-0.6343	76.84a	41.78a	840.06a
UK FTSE100	4042	0.0657	0.000252	0.010173	-0.981	16.334	1.58	-0.00539	-0.3602	57.71a	20.41	2023.87a
Ireland ISEQ	3250	0.04	0.000156	0.009608	-0.858	12.772	0.92	-0.011046	-0.4349	87.61a	43.15a	381.79a
Egypt CMA	1695	0.1734	0.000635	0.006712	1.228	12.71	3.89a	0.094564	-0.2362	314.92a	133.79a	160.04a
Israel TA100	2996	0.1489	0.000551	0.013648	-0.52	9.43	2.21b	0.004681	-0.5321	81.44a	50.49a	287.13a

Table 5.2: **Summary statistics local main stock market indices in US Dollars.** The stock market indices are recomputed in US Dollars. The columns are as in table 5.1. For the Sharpe ratio in column 9, the interest rate on 1-month US certificates of deposits is used. Results for the US stock market indices can be found in table 5.1.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
Argentina Merval	2065	-0.1962	-0.000867	0.027511	-0.859	20.5	-1.43	-0.038201	-0.913	99.35a	31.77b	421.98a
Brazil Bovespa	1755	-0.0248	-0.0001	0.027338	0.053	9.628	-0.15	-0.010343	-0.7114	40.43a	21.32	718.38a
Canada TSX Composite	4042	0.048	0.000186	0.009801	-1.183	18.119	1.21	-0.001455	-0.4638	81.35a	22.54	1425.46a
Chile IPSA	1955	-0.0718	-0.000296	0.013714	0.09	9.553	-0.95	-0.035064	-0.6082	118.80a	53.96a	405.63a

Table 5.2 continued.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
Mexico IPC	1413	0.0593	0.000229	0.021103	-0.243	10.526	0.41	0.002199	-0.6114	58.90a	33.41b	234.74a
Peru Lima General	2610	0.1128	0.000424	0.015438	0.145	8.876	1.4	0.016531	-0.6236	203.03a	81.99a	875.43a
Venezuela Industrial	1956	-0.0517	-0.000211	0.030961	-5.855	159.591	-0.3	-0.012783	-0.8263	42.49a	40.97a	2.82
Australia ASX All Ordinaries	3987	0.0294	0.000115	0.012157	-4.24	98.862	0.6	-0.006986	-0.539	97.51a	24.97	148.46a
China Shanghai Composite	1953	0.1401	0.00052	0.019893	0.885	27.243	1.16	0.016854	-0.426	34.57b	21.39	305.56a
Hong Kong Hang Seng	4042	0.0923	0.00035	0.018291	-3.457	77.541	1.22	0.008195	-0.601	63.24a	19.67	76.36a
India BSE30	2478	-0.0318	-0.000128	0.017095	-0.443	9.872	-0.37	-0.017557	-0.6359	35.01b	24.75	74.24a
Indonesia Jakarta Composite	3260	-0.0991	-0.000414	0.026494	-1.664	43.393	-0.89	-0.022479	-0.9389	236.50a	27.63	2588.78a
Japan Nikkei225	4042	-0.0181	-0.000073	0.016386	0.036	10.151	-0.28	-0.016662	-0.7425	42.46a	28.51c	325.02a
Malaysia KLSE Composite	4316	0.039	0.000152	0.018434	0.086	31.573	0.54	-0.002808	-0.8727	142.66a	22.57	2285.44a
New Zealand NZSE30	2739	0.0039	0.000015	0.011854	-0.539	11.848	0.07	-0.012825	-0.5987	21.81	17.31	264.54a
Pakistan Karachi100	2444	-0.0449	-0.000182	0.017969	-0.357	10.202	-0.5	-0.019761	-0.8156	37.78a	17.29	711.36a
Philippines PSE Composite	3781	-0.0351	-0.000142	0.018152	0.526	14.497	-0.48	-0.018701	-0.8558	220.38a	91.24a	340.05a
Singapore Straits Times	3979	0.0457	0.000177	0.015387	-1.809	49.482	0.73	-0.001464	-0.6997	148.37a	25.72	779.97a
South-Korea Kospi200	2239	-0.0372	-0.000151	0.026226	-0.037	12.275	-0.27	-0.012584	-0.878	251.77a	53.39a	3674.31a
Sri Lanka CSE All Share	1756	-0.0717	-0.000295	0.009984	3.652	70.937	-1.24	-0.047927	-0.7114	203.66a	40.36a	44.29a
Thailand SET	2474	-0.1249	-0.00053	0.020911	0.402	8.034	-1.26	-0.033558	-0.9262	117.09a	49.78a	1308.61a
Taiwan TSE Composite	1805	-0.0654	-0.000268	0.018188	-0.117	5.583	-0.63	-0.024837	-0.7058	35.12b	26.24	258.45a
Austria ATX	2625	0.0029	0.000012	0.011465	-0.321	5.263	0.05	-0.013702	-0.5183	21.67	14.91	478.74a
Belgium Bel20	2999	0.0571	0.000221	0.011007	0.043	8.093	1.1	0.004447	-0.5094	28.66c	19.44	290.86a
Czech Republic PX50	1711	-0.0203	-0.000082	0.014104	-0.197	4.689	-0.24	-0.018733	-0.6139	70.91a	50.41a	371.22a
Denmark KFX	3020	0.0607	0.000234	0.011782	-0.217	6.152	1.09	0.005221	-0.338	32.21b	22.48	359.91a
Finland HEX General	2413	0.2005	0.000725	0.021293	-0.387	9.573	1.67c	0.025897	-0.7049	20.42	12.27	342.88a
France CAC40	2846	0.0617	0.000238	0.012632	-0.13	6.179	1	0.005495	-0.4744	43.08a	30.62c	186.66a
Germany DAX30	2781	0.0804	0.000307	0.013576	-0.221	5.297	1.19	0.010269	-0.5532	39.86a	24.86	955.12a
Greece ASE General	1885	0.0788	0.000301	0.019219	-0.111	6.084	0.68	0.006072	-0.7236	46.67a	25.67	382.96a
Italy MIB30	1750	0.0711	0.000273	0.015151	-0.024	5.122	0.75	0.005911	-0.548	34.61b	23.06	642.86a
Netherlands AEX	4042	0.0858	0.000327	0.012963	-0.319	10.562	1.6	0.009747	-0.4775	59.95a	18.51	3156.92a
Norway OSE All Share	1435	-0.0013	-0.000005	0.012838	-0.345	5.55	-0.01	-0.014581	-0.4642	31.10c	16.51	926.37a
Portugal PSI General	1760	0.0655	0.000252	0.01169	-0.175	6.81	0.9	0.005878	-0.5601	39.29a	24.24	289.77a
Russia Moscow Times	1782	0.234	0.000834	0.033932	-0.288	7.915	1.04	0.01919	-0.9426	51.56a	23.27	912.28a
Slovakia SAX16	2016	-0.1082	-0.000455	0.015344	-0.525	9.145	-1.33	-0.041685	-0.7907	26.54	22.68	41.61a
Spain IGBM	2487	0.0843	0.000321	0.012772	-0.097	5.286	1.25	0.01171	-0.4622	29.22c	19.26	641.92a
Sweden OMX	2238	0.0938	0.000356	0.016323	0.023	5.806	1.03	0.01079	-0.6578	39.19a	25.64	658.19a
Switzerland SMI	3391	0.1108	0.000417	0.012252	-0.172	7.71	1.98b	0.018825	-0.4199	21.67	14.7	421.85a
Turkey ISE100	3520	0.0783	0.000299	0.034929	-0.288	7.319	0.51	0.003063	-0.8704	82.85a	43.08a	895.86a

Table 5.2 continued.

Data set	N	Yearly	Mean	Std.Dev.	Skew.	Kurt.	t-ratio	Sharpe	Max.loss	Q20	Adj Q20	Q20 r2
UK FTSE100	4042	0.0679	0.000261	0.011301	-0.822	14.148	1.47	0.005322	-0.4307	35.65b	17.41	1338.35a
Ireland ISEQ	3250	0.0221	0.000087	0.011081	-0.484	8.459	0.45	-0.008499	-0.3997	21.93	17.89	332.65a
Egypt CMA	1695	0.1205	0.000451	0.007462	0.214	14.211	2.49b	0.036029	-0.3609	196.80a	117.79a	42.62a
Israel TA100	2996	0.0676	0.00026	0.016554	-0.6	9.001	0.86	0.005322	-0.5359	137.64a	91.70a	263.49a

Table 5.3: **Statistics best strategy: mean return criterion, 0% costs.** Statistics of the best strategy, selected by the mean return criterion, if no transaction costs are implemented, for each index listed in the first column. Column 2 shows the strategy parameters. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio. Column 7 shows the largest cumulative loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades. The results are computed for an US-based trader who applies the technical trading rule set to the local main stock market indices recomputed in US Dollars. The daily interest rate on 1-month US certificates of deposits is used to compute the Sharpe and excess Sharpe ratio in columns 5 and 6.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
World MSCI	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.5152	0.3980	0.1461	0.1349	-0.1868	2215	0.748	0.859	1.4453
Argentina Merval	[FR: 0.010, 0, 50,]	0.2691	0.5789	0.0266	0.0648	-0.6139	61	0.656	0.854	1.4492
Brazil Bovespa	[MA: 1, 5, 0.000, 0, 0, 0.025]	0.4663	0.5036	0.0425	0.0528	-0.5389	455	0.686	0.809	1.1355
Canada TSX Composite	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.3988	0.3347	0.0879	0.0894	-0.4481	1241	0.737	0.850	1.0806
Chile IPSA	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.6768	0.8065	0.1046	0.1396	-0.3578	659	0.707	0.842	1.4096
Mexico IPC	[MA: 1, 2, 0.001, 0, 0, 0.000]	1.1004	0.9829	0.1026	0.1004	-0.3558	556	0.710	0.820	1.5576
Peru Lima General	[MA: 1, 2, 0.001, 0, 0, 0.000]	1.2380	1.0112	0.1447	0.1281	-0.3233	814	0.720	0.846	1.4390
US S&P500	[FR: 0.005, 0, 0]	0.2310	0.1156	0.0434	0.0284	-0.3795	1409	0.725	0.822	1.2534
US DJIA	[MA: 1, 2 0.000, 0, 0, 0.000]	0.2060	0.0791	0.0351	0.0157	-0.4630	2667	0.695	0.795	1.2852
US Nasdaq100	[MA: 1, 2 0.001, 0, 0, 0.000]	0.3972	0.2543	0.0480	0.0362	-0.8507	1821	0.717	0.821	1.1472
US NYSE Composite	[MA: 1, 2 0.000, 0, 0, 0.000]	0.2630	0.1486	0.0561	0.0410	-0.2849	2543	0.712	0.815	1.3261
US Russel2000	[MA: 1, 2 0.001, 0, 0, 0.000]	0.5653	0.4423	0.1273	0.1134	-0.2872	989	0.762	0.874	1.1298
US Wilshire5000	[MA: 1, 2 0.000, 0, 0, 0.000]	0.3202	0.2010	0.0711	0.0539	-0.5005	2115	0.722	0.825	1.2656
Venezuela Industrial	[MA: 1, 2 0.000, 0, 0, 0.000]	1.2107	1.3313	0.0835	0.0963	-0.4630	857	0.704	0.823	1.5636
Australia ASX All Ordinaries	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2837	0.2470	0.0506	0.0576	-0.4159	1855	0.699	0.814	1.1426
China Shanghai Composite	[FR: 0.005, 2, 0]	0.5693	0.3764	0.0558	0.0389	-0.4502	266	0.711	0.824	1.2988
Hong Kong Hang Seng	[MA: 1, 5, 0.000, 0, 0, 0.000]	0.6507	0.5112	0.0870	0.0788	-0.3691	870	0.721	0.858	1.3489
India BSE30	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.6566	0.7110	0.0775	0.0950	-0.4509	867	0.713	0.844	1.0448
Indonesia Jakarta Composite	[FR: 0.005, 0, 0]	1.2643	1.5135	0.0884	0.1109	-0.7013	739	0.747	0.878	0.8928

Table 5.3 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
Japan Nikkei225	[MA: 5, 10, 0.000, 4, 0, 0.000]	0.1563	0.1776	0.0184	0.0350	-0.6483	296	0.703	0.802	1.1137
Malaysia KLSE Composite	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.9261	0.8537	0.0988	0.1016	-0.5149	1457	0.725	0.845	1.4378
New Zealand NZSE30	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.1580	0.1535	0.0269	0.0397	-0.4712	1315	0.687	0.806	1.3303
Pakistan Karachi100	[FR: 0.005, 0, 0]	0.5733	0.6473	0.0676	0.0874	-0.3842	672	0.710	0.841	1.0956
Philippines PSE Composite	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.9814	1.0536	0.1027	0.1214	-0.3457	1348	0.714	0.830	1.4767
Singapore Straits Times	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.7293	0.6537	0.1005	0.1020	-0.4133	1757	0.714	0.833	1.6259
South-Korea Kospi200	[FR: 0.005, 0, 0]	0.8663	0.9385	0.0660	0.0786	-0.4491	710	0.725	0.845	1.3776
Sri Lanka CSE All Share	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.6559	0.7839	0.1287	0.1766	-0.2126	409	0.731	0.868	1.7512
Thailand SET	[MA: 1, 5, 0.000, 0, 0, 0.025]	0.6785	0.9181	0.0718	0.1053	-0.6064	525	0.710	0.844	1.1477
Taiwan TSE Composite	[MA: 1, 10, 0.000, 0, 0, 0.000]	0.3018	0.3928	0.0410	0.0658	-0.3560	242	0.682	0.856	1.4028
Austria ATX	[FR: 0.025, 0, 25]	0.1616	0.1582	0.0335	0.0472	-0.2883	151	0.689	0.824	1.0489
Belgium Bel20	[SR: 10, 0.000, 0, 50, 0.000]	0.1525	0.0902	0.0282	0.0237	-0.2711	96	0.740	0.872	1.0449
Czech Republic PX50	[FR: 0.005, 0, 0]	0.5962	0.6293	0.0900	0.1087	-0.3120	477	0.730	0.857	1.2415
Denmark KFX	[FR: 0.005, 0, 5]	0.2166	0.1470	0.0401	0.0349	-0.2979	642	0.646	0.701	1.0276
Finland HEX General	[SR: 25, 0.000, 4, 0, 0.000]	0.4692	0.2238	0.0524	0.0265	-0.4667	52	0.769	0.866	0.9368
France CAC40	[MA: 1, 2, 0.000, 0, 0, 0.000]	0.2094	0.1391	0.0344	0.0289	-0.4030	1383	0.694	0.803	1.2673
Germany DAX30	[MA: 1, 2, 0.000, 0, 10, 0.000]	0.2130	0.1227	0.0326	0.0223	-0.3935	303	0.680	0.821	1.0603
Greece ASE General	[FR: 0.005, 0, 0]	0.9309	0.7898	0.0962	0.0901	-0.4239	595	0.726	0.836	1.3280
Italy MIB30	[MA: 1, 2, 0.000, 0, 50, 0.000]	0.3026	0.2161	0.0473	0.0414	-0.4097	45	0.711	0.854	1.2225
Netherlands AEX	[MA: 5, 25, 0.000, 0, 50, 0.000]	0.1572	0.0657	0.0264	0.0166	-0.5858	124	0.758	0.843	1.0739
Norway OSE All Share	[SR: 5, 0.000, 0, 0, 0.000]	0.3418	0.3435	0.0625	0.0771	-0.1751	144	0.757	0.860	1.2095
Portugal PSI General	[MA: 1, 5, 0.000, 0, 0, 0.025]	0.4210	0.3336	0.0817	0.0758	-0.3514	394	0.695	0.844	1.2825
Russia Moscow Times	[FR: 0.005, 0, 0]	2.6707	1.9746	0.1142	0.0950	-0.6517	590	0.741	0.859	1.1977
Slovakia SAX16	[MA: 25, 200, 0.050, 0, 0, 0.000]	0.0857	0.2175	0.0095	0.0512	-0.4280	4	0.750	0.904	1.4098
Spain IGBM	[FR: 0.005, 0, 0]	0.2441	0.1473	0.0404	0.0286	-0.3333	793	0.702	0.809	1.2348
Sweden OMX	[FR: 0.010, 0, 0]	0.3569	0.2406	0.0466	0.0358	-0.5876	540	0.713	0.827	1.1050
Switzerland SMI	[MA: 1, 5, 0.000, 0, 50, 0.000]	0.2360	0.1127	0.0407	0.0219	-0.5320	111	0.694	0.855	0.8339
Turkey ISE100	[FR: 0.005, 0, 0]	1.3096	1.1419	0.0673	0.0643	-0.8882	1307	0.719	0.832	1.1805
UK FTSE100	[FR: 0.005, 0, 0]	0.1635	0.0895	0.0269	0.0216	-0.3811	1242	0.702	0.814	1.1872
Ireland ISEQ	[MA: 1, 25, 0.000, 0, 50, 0.000]	0.1608	0.1357	0.0284	0.0369	-0.4451	99	0.717	0.832	0.9301
Egypt CMA	[MA: 1, 2, 0.001, 0, 0, 0.000]	0.5158	0.3528	0.1423	0.1063	-0.2460	420	0.698	0.861	1.4805
Israel TA100	[MA: 2, 5, 0.000, 0, 0, 0.050]	0.2567	0.1771	0.0354	0.0301	-0.4236	612	0.722	0.830	1.1227

Table 5.4: **Statistics best strategy: mean return criterion, 0.25% costs.** Columns as in table 5.3.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
World MSCI	[MA: 1, 200, 0.025, 0, 0, 0.000]	0.1492	0.0604	0.0332	0.0221	-0.2591	19	0.842	0.955	1.0955
Argentina Merval	[FR: 0.010, 0, 50]	0.2456	0.5501	0.0240	0.0623	-0.6142	61	0.639	0.850	1.4653
Brazil Bovespa	[SR: 20, 0.001, 0, 0, 0.000]	0.3899	0.4257	0.0413	0.0517	-0.5308	41	0.659	0.855	1.3801
Canada TSX Composite	[MA: 1, 25, 0.005, 0, 0, 0.000]	0.1578	0.1049	0.0327	0.0342	-0.3146	176	0.341	0.656	1.0849
Chile IPSA	[FR: 0.020, 0, 0]	0.2694	0.3680	0.0431	0.0782	-0.4024	188	0.277	0.506	0.9045
Mexico IPC	[MA: 1, 5, 0.000, 0, 0, 0.050]	0.5489	0.4629	0.0606	0.0585	-0.3213	321	0.227	0.384	0.8530
Peru Lima General	[FR: 0.010, 0, 0]	0.7477	0.5709	0.0957	0.0793	-0.4778	420	0.224	0.346	1.0951
US S&P500	[MA: 1, 200, 0.050, 0, 0, 0.000]	0.1617	0.0529	0.0268	0.0118	-0.3268	11	1.000	1.000	NA
US DJIA	[SR: 50, 0.025, 0, 0, 0.000]	0.1533	0.0321	0.0311	0.0117	-0.2942	5	0.800	0.969	1.1554
US Nasdaq100	[MA: 1, 100, 0.025, 0, 0, 0.000]	0.2163	0.0920	0.0286	0.0168	-0.5527	51	0.627	0.875	1.1226
US NYSE Composite	[MA: 2, 5, 0.025, 0, 0, 0.000]	0.1405	0.0373	0.0271	0.0120	-0.2683	11	0.727	0.964	0.7816
US Russel2000	[SR: 5, 0.010, 0, 0, 0.000]	0.2219	0.1261	0.0529	0.0390	-0.3048	88	0.511	0.874	0.6334
US Wilshire5000	[FR: 0.120, 2, 0]	0.1438	0.0406	0.0241	0.0070	-0.5276	14	0.643	0.917	0.8450
Venezuela Industrial	[FR: 0.005, 0, 0]	0.4879	0.5696	0.0395	0.0523	-0.6257	581	0.210	0.316	0.7833
Australia ASX All Ordinaries	[FR: 0.020, 0, 50]	0.1586	0.1257	0.0245	0.0315	-0.4966	129	0.682	0.729	1.1199
China Shanghai Composite	[FR: 0.005, 3, 0]	0.4222	0.2478	0.0424	0.0256	-0.3520	146	0.295	0.567	1.2350
Hong Kong Hang Seng	[MA: 1, 5, 0.005, 0, 0, 0.000]	0.3228	0.2112	0.0434	0.0352	-0.5703	560	0.236	0.442	1.0851
India BSE30	[SR: 5, 0.000, 0, 50, 0.000]	0.1711	0.2099	0.0203	0.0379	-0.6945	83	0.554	0.660	1.0689
Indonesia Jakarta Composite	[FR: 0.005, 0, 0]	0.7656	0.9602	0.0594	0.0819	-0.7517	739	0.235	0.395	0.7857
Japan Nikkei225	[SR: 100, 0.025, 0, 0, 0.000]	0.1041	0.1246	0.0140	0.0307	-0.3604	7	1.000	1.000	NA
Malaysia KLSE Composite	[FR: 0.010, 0, 0]	0.4358	0.3821	0.0496	0.0524	-0.5651	760	0.249	0.421	0.9173
New Zealand NZSE30	[MA: 10, 25, 0.050, 0, 0, 0.000]	0.1077	0.1036	0.0161	0.0290	-0.4231	4	1.000	1.000	NA
Pakistan Karachi100	[SR: 5, 0.010, 0, 0, 0.000]	0.3336	0.3967	0.0421	0.0619	-0.4130	128	0.406	0.623	1.0918
Philippines PSE Composite	[FR: 0.010, 0, 0]	0.4644	0.5180	0.0535	0.0723	-0.4586	760	0.224	0.372	1.0759
Singapore Straits Times	[FR: 0.025, 0, 0]	0.2639	0.2089	0.0374	0.0389	-0.5301	312	0.282	0.521	0.7085
South-Korea Kospi200	[MA: 1, 25, 0.000, 0, 0, 0.000]	0.3863	0.4403	0.0402	0.0528	-0.5323	164	0.262	0.660	1.3717
Sri Lanka CSE All Share	[FR: 0.015, 0, 0]	0.3138	0.4158	0.0621	0.1102	-0.2045	133	0.338	0.564	1.1930
Thailand SET	[SR: 25, 0.000, 0, 0, 0.000]	0.3706	0.5666	0.0482	0.0819	-0.4167	41	0.659	0.866	1.4849
Taiwan TSE Composite	[MA: 1, 25, 0.000, 0, 0, 0.075]	0.1783	0.2611	0.0224	0.0473	-0.5332	151	0.245	0.608	0.9980
Austria ATX	[FR: 0.025, 0, 25]	0.1209	0.1179	0.0224	0.0362	-0.2883	151	0.464	0.503	1.1183
Belgium Bel20	[SR: 10, 0.000, 0, 50, 0.000]	0.1292	0.0684	0.0224	0.0180	-0.2831	96	0.708	0.830	1.0036
Czech Republic PX50	[FR: 0.030, 0, 0]	0.2908	0.3181	0.0445	0.0634	-0.4742	124	0.331	0.611	0.8085
Denmark KFX	[SR: 150, 0.025, 0, 0, 0.000]	0.1107	0.0474	0.0213	0.0161	-0.3159	3	1.000	1.000	NA
Finland HEX General	[SR: 25, 0.000, 4, 0, 0.000]	0.4302	0.1916	0.0482	0.0224	-0.4821	52	0.500	0.750	1.1126

Table 5.4 continued.

Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	#tr.	%tr. > 0	%d > 0	SDR
France CAC40	[FR: 0.300, 4, 0]	0.1111	0.0468	0.0129	0.0075	-0.4289	2	1.000	1.000	NA
Germany DAX30	[FR: 0.180, 3, 0]	0.1550	0.0693	0.0218	0.0116	-0.3575	9	0.889	0.967	0.7431
Greece ASE General	[FR: 0.020, 0, 0]	0.4924	0.3839	0.0567	0.0507	-0.5695	255	0.212	0.330	0.9890
Italy MIB30	[MA: 1, 2, 0.000, 0, 50, 0.000]	0.2771	0.1928	0.0430	0.0372	-0.4299	45	0.644	0.781	1.2051
Netherlands AEX	[SR: 25, 0.050, 0, 0, 0.000]	0.1440	0.0538	0.0233	0.0136	-0.3882	4	0.750	0.949	0.9584
Norway OSE All Share	[FR: 0.040, 3, 0]	0.2513	0.2534	0.0415	0.0562	-0.3115	52	0.519	0.768	0.9366
Portugal PSI General	[FR: 0.080, 3, 0]	0.3020	0.2224	0.0565	0.0507	-0.2312	20	0.650	0.906	1.1021
Russia Moscow Times	[MA: 1, 5, 0.000, 0, 0, 0.000]	1.9105	1.3593	0.0947	0.0755	-0.7254	366	0.249	0.433	0.8564
Slovakia SAX16	[MA: 25, 200, 0.050, 0, 0, 0.000]	0.0839	0.2159	0.0090	0.0508	-0.4328	4	0.750	0.904	1.4098
Spain IGBM	[FR: 0.040, 0, 50]	0.2021	0.1089	0.0365	0.0249	-0.4048	69	0.696	0.725	0.9860
Sweden OMX	[MA: 25, 200, 0.050, 0, 0, 0.000]	0.2768	0.1677	0.0451	0.0344	-0.3288	4	1.000	1.000	NA
Switzerland SMI	[MA: 1, 5, 0.000, 0, 50, 0.000]	0.2094	0.0890	0.0353	0.0166	-0.5344	111	0.640	0.775	0.8875
Turkey ISE100	[SR: 15, 0.000, 0, 0, 0.000]	0.7537	0.6267	0.0531	0.0501	-0.7020	113	0.522	0.746	1.2321
UK FTSE100	[MA: 10, 25, 0.050, 0, 0, 0.000]	0.1152	0.0445	0.0133	0.0081	-0.5638	4	1.000	1.000	NA
Ireland ISEQ	[MA: 1, 25, 0.000, 0, 50, 0.000]	0.1384	0.1140	0.0231	0.0316	-0.4578	99	0.687	0.778	0.8604
Egypt CMA	[FR: 0.015, 0, 0]	0.3421	0.1983	0.0931	0.0573	-0.3240	99	0.263	0.543	1.0064
Israel TA100	[MA: 10, 200, 0.001, 0, 0, 0.000]	0.2048	0.1288	0.0254	0.0201	-0.3815	21	0.619	0.887	1.4522

Table 5.5: **Statistics best strategy: Sharpe ratio criterion, 0 and 0.25% costs.** Statistics of the best strategy, selected by the Sharpe ratio criterion, if 0 and 0.25% costs per trade are implemented, for each index listed in the first column. The results are computed for an US-based trader who applies the technical trading rule set to the local main stock market indices recomputed in US Dollars. Column 2 shows the parameters of the best strategy. Columns 3 and 4 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 5 and 6 show the Sharpe and excess Sharpe ratio (here the daily interest rate on 1-month US certificates of deposits is used in the computations). Column 7 shows the largest cumulative loss of the strategy in %/100 terms. Columns 8, 9 and 10 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades. Results are only shown for those indices for which a different best strategy is selected by the Sharpe ratio criterion than by the mean return criterion.

0% costs per trade Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	#tr.	%tr. > 0	%d > 0	SDR
Brazil Bovespa	[SR: 20, 0.001, 0, 0, 0.000]	0.4294	0.4657	0.0454	0.0558	-0.5075	41	0.829	0.916	1.3860
US DJIA	[FR: 0.005, 0, 0]	0.2014	0.0750	0.0357	0.0163	-0.3194	1459	0.714	0.815	1.2992
US Wilshire5000	[FR: 0.005, 0, 0]	0.3188	0.1997	0.0722	0.0550	-0.2372	1039	0.736	0.840	1.2514
Belgium Bel20	[MA: 2, 5, 0.000, 0, 10, 0.000]	0.1522	0.0899	0.0283	0.0239	-0.4269	393	0.634	0.717	1.0197

Table 5.5 continued.

0% costs per trade Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
Finland HEX General	[SR: 200, 0.000, 4, 0, 0.000]	0.3828	0.1518	0.0544	0.0285	-0.3823	3	1.000	1.000	NA
Netherlands AEX	[FR: 0.045, 0, 50]	0.1557	0.0643	0.0317	0.0220	-0.3998	113	0.735	0.884	1.0743
Portugal PSI General	[MA: 1, 2, 0.025, 0, 0, 0.000]	0.2202	0.1452	0.0835	0.0776	-0.1735	4	1.000	1.000	NA
Russia Moscow Times	[MA: 1, 5, 0.000, 0, 0, 0.000]	2.6618	1.9674	0.1168	0.0976	-0.7031	366	0.754	0.878	1.2155
Spain IGBM	[FR: 0.045, 0, 50]	0.2230	0.1279	0.0434	0.0317	-0.3896	73	0.712	0.809	1.0747
UK FTSE100	[MA: 1, 25, 0.000, 0, 10, 0.000]	0.1457	0.0729	0.0269	0.0216	-0.3111	343	0.665	0.678	0.9716
0.25% costs per trade Data set	Strategy parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr.$	$\%tr. > 0$	$\%d > 0$	SDR
World MSCI	[MA: 1, 10, 0.050, 0, 0, 0.000]	0.1252	0.0383	0.0345	0.0234	-0.2156	5	0.800	0.969	1.1816
US S&P500	[SR: 50, 0.025, 0, 0, 0.000]	0.1466	0.0392	0.0289	0.0139	-0.2767	5	0.800	0.969	1.0532
US Nasdaq100	[SR: 100, 0.025, 0, 0, 0.000]	0.2117	0.0878	0.0331	0.0213	-0.4633	5	0.800	0.919	1.3541
US Wilshire5000	[FR: 0.100, 0, 50]	0.1357	0.0333	0.0338	0.0167	-0.2969	30	0.700	0.885	0.7503
Australia ASX All Ordinaries	[MA: 5, 10, 0.000, 0, 25, 0.000]	0.1439	0.1114	0.0268	0.0338	-0.3663	227	0.546	0.591	1.1789
Hong Kong Hang Seng	[MA: 1, 10, 0.000, 0, 0, 0.100]	0.3179	0.2067	0.0440	0.0358	-0.4383	526	0.202	0.443	1.0970
India BSE30	[MA: 2, 100, 0.010, 0, 0, 0.000]	0.1596	0.1980	0.0214	0.0390	-0.5671	29	0.655	0.918	0.9743
Japan Nikkei225	[SR: 100, 0.050, 0, 0, 0.000]	0.0781	0.0981	0.0165	0.0332	-0.1883	2	1.000	1.000	NA
Malaysia KLSE Composite	[MA: 5, 50, 0.001, 0, 0, 0.000]	0.3780	0.3264	0.0573	0.0602	-0.3697	87	0.552	0.885	1.6523
New Zealand NZSE30	[MA: 2, 10, 0.050, 0, 0, 0.000]	0.1021	0.0981	0.0207	0.0336	-0.4231	4	1.000	1.000	NA
Singapore Straits Times	[SR: 15, 0.010, 0, 0, 0.000]	0.2570	0.2023	0.0430	0.0445	-0.5026	76	0.618	0.847	1.1832
Czech Republic PX50	[MA: 1, 25, 0.010, 0, 0, 0.000]	0.2763	0.3033	0.0460	0.0649	-0.4318	61	0.426	0.776	1.1062
Finland HEX General	[SR: 200, 0.000, 4, 0, 0.000]	0.3815	0.1511	0.0542	0.0283	-0.3823	3	1.000	1.000	NA
France CAC40	[MA: 10, 25, 0.000, 0, 50, 0.000]	0.1057	0.0417	0.0148	0.0094	-0.5647	86	0.674	0.816	0.9545
Germany DAX30	[MA: 5, 50, 0.000, 0, 50, 0.000]	0.1354	0.0512	0.0242	0.0140	-0.4855	62	0.710	0.794	0.9216
Netherlands AEX	[FR: 0.045, 0, 50]	0.1358	0.0461	0.0258	0.0161	-0.4028	113	0.717	0.860	1.0887
Norway OSE All Share	[MA: 1, 2, 0.000, 4, 0, 0.000]	0.2392	0.2413	0.0450	0.0598	-0.3157	48	0.583	0.839	1.2401
Portugal PSI General	[MA: 1, 2, 0.025, 0, 0, 0.000]	0.2181	0.1436	0.0823	0.0766	-0.1777	4	0.750	0.999	NA
Russia Moscow Times	[SR: 10, 0.001, 0, 0, 0.000]	1.6640	1.1596	0.0957	0.0765	-0.4612	83	0.422	0.700	1.1650
Spain IGBM	[FR: 0.045, 0, 50]	0.2006	0.1075	0.0383	0.0266	-0.3927	73	0.671	0.764	1.0464
UK FTSE100	[SR: 100, 0.025, 0, 0, 0.000]	0.1067	0.0365	0.0224	0.0171	-0.2905	4	1.000	1.000	NA
Egypt CMA	[SR: 25, 0.010, 0, 0, 0.000]	0.3285	0.1861	0.1138	0.0780	-0.1512	11	0.818	0.946	1.0548

Table 5.6: **Performance best strategy in excess of performance buy-and-hold.** Panel A shows the mean return of the best strategy, selected by the mean return criterion after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade, in excess of the mean return of the buy-and-hold benchmark for each index listed in the first column. Panel B shows the Sharpe ratio of the best strategy, selected by the Sharpe ratio criterion after implementing 0, 0.10, 0.25, 0.50, 0.75 and 1% costs per trade, in excess of the Sharpe ratio of the buy-and-hold benchmark for each index listed in the first column. The row labeled "Average 3" at the bottom of the table shows for trading case 3 the average over the results as shown in the table for each transaction costs case. The rows labeled "Average 1" and "Average 2" show the average over the results for the two other trading cases 1 and 2.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
World MSCI	0.3980	0.2201	0.0604	0.0562	0.0519	0.0500	0.1349	0.0779	0.0234	0.0229	0.0223	0.0218
Argentina Merval	0.5789	0.5673	0.5501	0.5218	0.4939	0.4665	0.0648	0.0638	0.0623	0.0597	0.0572	0.0546
Brazil Bovespa	0.5036	0.4496	0.4257	0.3867	0.3487	0.3132	0.0558	0.0541	0.0517	0.0475	0.0434	0.0393
Canada TSX Composite	0.3347	0.1817	0.1049	0.0494	0.0474	0.0453	0.0894	0.0518	0.0342	0.0236	0.0231	0.0226
Chile IPSA	0.8065	0.5672	0.3680	0.2518	0.2085	0.1666	0.1396	0.1074	0.0782	0.0619	0.0527	0.0435
Mexico IPC	0.9829	0.7003	0.4629	0.3220	0.2928	0.2643	0.1004	0.0824	0.0585	0.0451	0.0413	0.0375
Peru Lima General	1.0112	0.7629	0.5709	0.3279	0.2788	0.2504	0.1281	0.1023	0.0793	0.0535	0.0486	0.0436
US S&P500	0.1156	0.0543	0.0529	0.0506	0.0484	0.0461	0.0284	0.0141	0.0139	0.0136	0.0133	0.0130
US DJIA	0.0791	0.0394	0.0321	0.0313	0.0306	0.0298	0.0163	0.0119	0.0117	0.0114	0.0111	0.0108
US Nasdaq100	0.2543	0.1076	0.0920	0.0869	0.0859	0.0850	0.0362	0.0215	0.0213	0.0211	0.0208	0.0206
US NYSE Composite	0.1486	0.0386	0.0373	0.0350	0.0327	0.0305	0.0410	0.0125	0.0120	0.0111	0.0103	0.0094
US Russel2000	0.4423	0.2773	0.1261	0.0916	0.0721	0.0602	0.1134	0.0736	0.0390	0.0306	0.0255	0.0224
US Wilshire5000	0.2010	0.0813	0.0406	0.0371	0.0363	0.0356	0.0550	0.0211	0.0167	0.0149	0.0130	0.0121
Venezuela Industrial	1.3313	0.9638	0.5696	0.1866	0.1059	0.1063	0.0963	0.0768	0.0523	0.0204	0.0129	0.0129
Australia ASX All Ordinaries	0.2470	0.1393	0.1257	0.1032	0.0811	0.0594	0.0576	0.0408	0.0338	0.0264	0.0239	0.0236
China Shanghai Composite	0.3764	0.3190	0.2478	0.1440	0.1258	0.1078	0.0389	0.0333	0.0256	0.0186	0.0160	0.0134
Hong Kong Hang Seng	0.5112	0.3756	0.2112	0.1142	0.0934	0.0734	0.0788	0.0602	0.0358	0.0250	0.0211	0.0188
India BSE30	0.7110	0.4822	0.2099	0.1845	0.1658	0.1500	0.0950	0.0706	0.0390	0.0362	0.0334	0.0306
Indonesia Jakarta Composite	1.5135	1.2757	0.9602	0.6410	0.5394	0.4962	0.1109	0.0993	0.0819	0.0754	0.0715	0.0675
Japan Nikkei225	0.1776	0.1351	0.1246	0.1229	0.1211	0.1194	0.0350	0.0333	0.0332	0.0331	0.0329	0.0327
Malaysia KLSE Composite	0.8537	0.6284	0.3821	0.3049	0.2774	0.2682	0.1016	0.0799	0.0602	0.0549	0.0497	0.0460
New Zealand NZSE30	0.1535	0.1052	0.1036	0.1020	0.1004	0.0988	0.0397	0.0339	0.0336	0.0330	0.0324	0.0319
Pakistan Karachi100	0.6473	0.4944	0.3967	0.3145	0.2778	0.2420	0.0874	0.0741	0.0619	0.0533	0.0481	0.0428
Philippines PSE Composite	1.0536	0.7989	0.5180	0.3372	0.3025	0.2687	0.1214	0.0994	0.0723	0.0586	0.0533	0.0481
Singapore Straits Times	0.6537	0.3933	0.2089	0.1779	0.1621	0.1465	0.1020	0.0719	0.0445	0.0394	0.0361	0.0328
South-Korea Kospi200	0.9385	0.6940	0.4403	0.3241	0.3092	0.3064	0.0786	0.0630	0.0528	0.0465	0.0461	0.0457
Sri Lanka CSE All Share	0.7839	0.6097	0.4158	0.2913	0.2321	0.2111	0.1766	0.1469	0.1102	0.0844	0.0735	0.0685

Table 5.6 continued.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
Thailand SET	0.9181	0.7545	0.5666	0.5360	0.5058	0.4762	0.1053	0.0916	0.0819	0.0783	0.0747	0.0711
Taiwan TSE Composite	0.3928	0.3280	0.2611	0.2243	0.2206	0.2168	0.0658	0.0573	0.0473	0.0428	0.0421	0.0415
Austria ATX	0.1582	0.1419	0.1179	0.0789	0.0515	0.0414	0.0472	0.0428	0.0362	0.0251	0.0170	0.0140
Belgium Bel20	0.0902	0.0814	0.0684	0.0504	0.0494	0.0488	0.0239	0.0214	0.0180	0.0156	0.0151	0.0146
Czech Republic PX50	0.6293	0.4446	0.3181	0.2626	0.2325	0.2030	0.1087	0.0825	0.0649	0.0581	0.0523	0.0466
Denmark KFX	0.1470	0.0805	0.0474	0.0468	0.0463	0.0457	0.0349	0.0192	0.0161	0.0159	0.0157	0.0156
Finland HEX General	0.2238	0.2108	0.1916	0.1747	0.1656	0.1565	0.0285	0.0284	0.0283	0.0282	0.0281	0.0280
France CAC40	0.1391	0.0595	0.0468	0.0461	0.0455	0.0449	0.0289	0.0123	0.0094	0.0074	0.0073	0.0072
Germany DAX30	0.1227	0.0861	0.0693	0.0653	0.0613	0.0574	0.0223	0.0164	0.0140	0.0138	0.0136	0.0135
Greece ASE General	0.7898	0.5638	0.3839	0.1966	0.1939	0.1912	0.0901	0.0694	0.0507	0.0308	0.0282	0.0265
Italy MIB30	0.2161	0.2067	0.1928	0.1839	0.1805	0.1771	0.0414	0.0397	0.0372	0.0329	0.0325	0.0322
Netherlands AEX	0.0657	0.0576	0.0538	0.0530	0.0523	0.0515	0.0220	0.0196	0.0161	0.0134	0.0132	0.0130
Norway OSE All Share	0.3435	0.2873	0.2534	0.1987	0.1582	0.1349	0.0771	0.0665	0.0598	0.0522	0.0458	0.0393
Portugal PSI General	0.3336	0.2633	0.2224	0.2068	0.1915	0.1762	0.0776	0.0772	0.0766	0.0755	0.0745	0.0734
Russia Moscow Times	1.9746	1.7075	1.3593	1.0428	0.9321	0.8271	0.0976	0.0887	0.0765	0.0706	0.0647	0.0587
Slovakia SAX16	0.2175	0.2168	0.2159	0.2143	0.2126	0.2110	0.0512	0.0510	0.0508	0.0504	0.0501	0.0497
Spain IGBM	0.1473	0.1201	0.1089	0.0904	0.0722	0.0542	0.0317	0.0297	0.0266	0.0216	0.0165	0.0116
Sweden OMX	0.2406	0.1690	0.1677	0.1656	0.1634	0.1613	0.0358	0.0346	0.0344	0.0340	0.0336	0.0332
Switzerland SMI	0.1127	0.1031	0.0890	0.0657	0.0616	0.0596	0.0219	0.0197	0.0166	0.0112	0.0092	0.0091
Turkey ISE100	1.1419	0.8497	0.6267	0.5642	0.5040	0.4459	0.0643	0.0540	0.0501	0.0459	0.0417	0.0375
UK FTSE100	0.0895	0.0544	0.0445	0.0433	0.0422	0.0411	0.0216	0.0173	0.0171	0.0168	0.0164	0.0160
Ireland ISEQ	0.1357	0.1269	0.1140	0.0926	0.0716	0.0629	0.0369	0.0348	0.0316	0.0263	0.0228	0.0205
Egypt CMA	0.3528	0.2564	0.1983	0.1801	0.1773	0.1745	0.1063	0.0800	0.0780	0.0746	0.0712	0.0676
Israel TA100	0.1771	0.1341	0.1288	0.1198	0.1109	0.1021	0.0301	0.0210	0.0201	0.0187	0.0174	0.0164
Average 3	0.4914	0.3709	0.2725	0.2089	0.1875	0.1722	0.0672	0.0535	0.0435	0.0372	0.0343	0.0320
Average 1	0.5391	0.3935	0.2759	0.1984	0.1656	0.1470	0.0801	0.0599	0.0462	0.0379	0.0339	0.0315
Average 2	0.5764	0.4238	0.2994	0.2142	0.1862	0.1710	0.0769	0.0578	0.0451	0.0376	0.0342	0.0317

Table 5.7: **Estimation results CAPM.** Coefficient estimates of the Sharpe-Lintner CAPM: $r_t^i - r_t^f = \alpha + \beta(r_t^{Local} - r_t^f) + \epsilon_t$. That is, the return in US Dollars of the best recursive optimizing and testing procedure, when selection in the optimizing period is done by the mean return criterion (Panel A) or by the Sharpe ratio criterion (Panel B), in excess of the US risk-free interest rate is regressed against a constant and the return of the local main stock market index in US Dollars in excess of the US risk-free interest rate. Estimation results for the 0 and 0.10% costs per trade cases are shown. a, b, c indicates that the corresponding coefficient is, in the case of α, significantly different from zero, or in the case of β, significantly different from one, at the 1, 5, 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.50%		0%		0.50%	
Data set	α	β	α	β	α	β	α	β
World MSCI	0.001342a	0.850c	0.000223b	0.913	0.001342a	0.850c	0.000188b	0.506a
Argentina Merval	0.001297a	0.509a	0.001148b	0.508a	0.001297a	0.509a	0.001148b	0.508a
Brazil Bovespa	0.001558a	0.749a	0.001163b	0.546a	0.001386a	0.547a	0.001163b	0.546a
Canada TSX Composite	0.001144a	0.878	0.000193	1.087	0.001144a	0.878	0.000157	0.322a
Chile IPSA	0.002290a	0.878c	0.000715b	0.640a	0.002290a	0.878c	0.000715b	0.640a
Mexico IPC	0.002716a	0.849b	0.001140b	0.714a	0.002716a	0.849b	0.001140b	0.714a
Peru Lima General	0.002781a	0.973	0.001146a	0.913	0.002781a	0.973	0.001101a	0.853c
US S&P500	0.000454a	0.875	0.000199c	0.975	0.000454a	0.875	0.000202c	0.662a
US DJIA	0.000315b	0.94	0.000201c	0.616a	0.000316b	0.859	0.000201c	0.616a
US Nasdaq100	0.000930a	0.860a	0.000407b	0.627a	0.000930a	0.860a	0.000407b	0.627a
US NYSE Composite	0.000567a	0.876	0.000169	0.770b	0.000567a	0.876	0.000169	0.770b
US Russel2000	0.001471a	0.873a	0.000386b	0.726a	0.001471a	0.873a	0.000380b	0.609a
US Wilshire5000	0.000752a	0.849c	0.000111	1.206a	0.000753a	0.821b	0.000161c	0.721a
Venezuela Industrial	0.003238a	0.691	0.000598	0.801	0.003238a	0.691	0.000588	0.778
Australia ASX All Ordinaries	0.000861a	0.832	0.000378c	0.87	0.000861a	0.832	0.000378c	0.87
China Shanghai Composite	0.001238a	1.127	0.000565	0.932	0.001238a	1.127	0.000565	0.932
Hong Kong Hang Seng	0.001691a	0.655a	0.000412	1.126	0.001691a	0.655a	0.000428b	0.641a
India BSE30	0.002126a	0.98	0.000641c	0.891	0.002126a	0.98	0.000576c	0.715a
Indonesia Jakarta Composite	0.003589a	0.882	0.001850a	0.808b	0.003589a	0.882	0.001384a	0.392a
Japan Nikkei225	0.000592b	0.793a	0.000295c	0.397a	0.000592b	0.793a	0.000134	0.130a
Malaysia KLSE Composite	0.002452a	0.925	0.001033a	0.651a	0.002452a	0.925	0.000997a	0.564a
New Zealand NZSE30	0.000542a	0.855b	0.000367c	0.886	0.000542a	0.855b	0.000275	0.414a
Pakistan Karachi100	0.001950a	0.925	0.001005a	0.791b	0.001950a	0.925	0.001005a	0.791b
Philippines PSE Composite	0.002842a	0.958	0.001052a	0.697a	0.002842a	0.958	0.001052a	0.697a
Singapore Straits Times	0.001990a	0.844c	0.000648a	0.633a	0.001990a	0.844c	0.000648a	0.633a

Table 5.7 continued.

selection criterion	Panel A Mean return				Panel B Sharpe ratio			
costs per trade	0%		0.50%		0%		0.50%	
Data set	α	β	α	β	α	β	α	β
South-Korea Kospi200	0.002608a	0.929	0.000986b	0.622a	0.002608a	0.929	0.000897b	0.457a
Sri Lanka CSE All Share	0.002336a	1.078	0.001062a	1.103	0.002336a	1.078	0.001062a	1.103
Thailand SET	0.002512a	0.893c	0.001469a	0.666a	0.002512a	0.893c	0.001469a	0.666a
Taiwan TSE Composite	0.001197a	0.700a	0.000640c	0.663a	0.001197a	0.700a	0.000640c	0.663a
Austria ATX	0.000540a	0.727a	0.000256	0.723a	0.000540a	0.727a	0.000256	0.723a
Belgium Bel20	0.000348b	0.882	0.000204	0.824b	0.000343c	0.916	0.000203	0.710a
Czech Republic PX50	0.001914a	0.897b	0.000856b	0.756a	0.001914a	0.897b	0.000856b	0.756a
Denmark KFX	0.000550a	0.978	0.000205	0.565a	0.000550a	0.978	0.000205	0.565a
Finland HEX General	0.000906b	0.805b	0.000712b	0.865c	0.000696a	0.754a	0.000691a	0.754a
France CAC40	0.000521b	0.921c	0.000152	1.404a	0.000521b	0.921c	0.000152	1.404a
Germany DAX30	0.000462b	0.949	0.000237	1.086	0.000462b	0.949	0.000251	0.782a
Greece ASE General	0.002340a	0.896c	0.000722b	1.062	0.002340a	0.896c	0.000673c	0.771a
Italy MIB30	0.000815b	0.764a	0.000658b	0.966	0.000815b	0.764a	0.000664c	0.763a
Netherlands AEX	0.000287c	0.729a	0.000231	0.794a	0.000307b	0.526a	0.000231	0.794a
Norway OSE All Share	0.001125a	0.782b	0.000704b	0.927	0.001125a	0.782b	0.000580b	0.554a
Portugal PSI General	0.001151a	0.831b	0.000751a	0.936	0.000585a	0.288a	0.000574a	0.286a
Russia Moscow Times	0.004420a	0.877c	0.003003a	0.755a	0.004426a	0.851c	0.003003a	0.755a
Slovakia SAX16	0.000461c	0.507a	0.000448c	0.507a	0.000461c	0.507a	0.000448c	0.507a
Spain IGBM	0.000560b	0.924c	0.000365c	0.832b	0.000516b	0.764a	0.000373c	0.764a
Sweden OMX	0.000878a	0.943	0.000637b	0.760a	0.000878a	0.943	0.000637b	0.760a
Switzerland SMI	0.000450b	0.89	0.000281	0.887	0.000450b	0.89	0.000281	0.887
Turkey ISE100	0.003030a	0.921c	0.001810a	0.685a	0.003030a	0.921c	0.001810a	0.685a
UK FTSE100	0.000348b	0.879c	0.000156	1.221a	0.000287b	0.872	0.000175	0.407a
Ireland ISEQ	0.000502a	0.958	0.000350b	0.957	0.000502a	0.958	0.000350b	0.957
Egypt CMA	0.001202a	1.003	0.000674a	0.939	0.001202a	1.003	0.000721a	0.721a
Israel TA100	0.000667b	0.806a	0.000439c	1.067	0.000667b	0.806a	0.000439c	1.067

Table 5.8: **Testing for predictive ability.** Nominal (p_n), White's (2000) Reality Check (p_W) and Hansen's (2001) Superior Predictive Ability test (p_H) p-values, if the best strategy is selected by the mean return criterion (Panel A) or if the best strategy is selected by the Sharpe ratio criterion, in the case of 0 and 0.25% costs per trade. The results are computed for an US-based trader who applies the technical trading rule set to the local main stock market indices recomputed in US Dollars.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
costs per trade	0%			0.25%			0%			0.25%		
Data set	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
World MSCI	0	0	0	0	0.96	0.37	0	0	0	0.04	0.98	0.33
Argentina Merval	0	1	0.88	0	1	0.91	0	0.11	0.08	0	0.12	0.08
Brazil Bovespa	0	1	0.85	0	1	0.95	0	0.39	0.11	0	0.52	0.11
Canada TSX Composite	0	0	0	0	0.81	0.14	0	0	0	0	0.59	0.21
Chile IPSA	0	0.36	0	0	0.6	0.38	0	0	0	0	0.22	0.01
Mexico IPC	0	1	0.01	0	1	0.8	0	0.04	0	0	0.81	0.08
Peru Lima General	0	0	0	0	0.01	0	0	0	0	0	0.02	0
US S&P500	0	0.97	0.08	0	1	0.87	0	1	0.1	0.02	1	0.46
US DJIA	0	1	0.66	0.01	1	0.99	0	1	0.61	0.02	1	0.52
US Nasdaq100	0	1	0.44	0	1	1	0	0.86	0.02	0	1	0.3
US NYSE Composite	0	0.28	0.02	0	1	0.98	0	0.45	0.04	0.03	1	0.64
US Russel2000	0	0	0	0	0.94	0.02	0	0	0	0	0.86	0.04
US Wilshire5000	0	0.02	0	0.01	1	0.78	0	0.04	0	0	1	0.48
Venezuela Industrial	0	1	0.04	0	1	0.94	0	0	0	0	0.38	0.09
Australia ASX All Ordinaries	0	0.94	0.06	0	1	0.98	0	0.03	0.01	0	0.75	0.11
China Shanghai Composite	0	0.5	0.03	0	0.98	0.12	0	0.82	0.07	0	1	0.26
Hong Kong Hang Seng	0	0	0	0	0.83	0.81	0	0	0	0	0.58	0.06
India BSE30	0	1	0	0	1	0.79	0	0	0	0	0.88	0.18
Indonesia Jakarta Composite	0	1	0	0	1	0.11	0	0	0	0	0.02	0
Japan Nikkei225	0	0.97	0.57	0	1	0.8	0	0.63	0.08	0	0.7	0.08
Malaysia KLSE Composite	0	1	0	0	1	0.21	0	0	0	0	0.03	0.01
New Zealand NZSE30	0	0.99	0.68	0	1	0.92	0	0.78	0.24	0	0.96	0.29
Pakistan Karachi100	0	1	0	0	1	0.18	0	0.04	0	0	0.2	0.06
Philippines PSE Composite	0	0.92	0	0	0.93	0.08	0	0	0	0	0.02	0
Singapore Straits Times	0	0.99	0	0	1	0.82	0	0	0	0	0.22	0.03
South-Korea Kospi200	0	1	0.08	0	1	0.92	0	0.04	0	0	0.49	0.06

Table 5.8 continued.

Selection criterion	Panel A: Mean return						Panel B: Sharpe ratio					
costs per trade	0%			0.25%			0%			0.25%		
Data set	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H	p_n	p_W	p_H
Sri Lanka CSE All Share	0	0	0	0	0.05	0	0	0	0	0	0.05	0
Thailand SET	0	1	0.1	0	1	0.47	0	0	0	0	0.02	0
Taiwan TSE Composite	0	1	0.62	0	1	0.88	0	0.27	0.03	0	0.86	0.26
Austria ATX	0	0.98	0.86	0	1	0.95	0	0.42	0.03	0	0.91	0.13
Belgium Bel20	0	1	0.91	0	1	0.92	0	1	0.56	0	1	0.57
Czech Republic PX50	0	0.24	0.24	0	0.93	0.83	0	0.05	0	0	0.65	0.25
Denmark KFX	0	0.95	0.1	0	1	0.9	0	0.91	0.04	0	1	0.54
Finland HEX General	0	1	0.94	0	1	0.96	0	1	0.48	0	1	0.4
France CAC40	0	1	0.43	0	1	1	0	1	0.18	0	1	0.97
Germany DAX30	0	1	0.96	0	1	1	0	1	0.72	0	1	0.91
Greece ASE General	0	0.89	0.06	0	0.96	0.64	0	0	0	0	0.5	0.02
Italy MIB30	0	0.99	0.73	0	1	0.8	0	0.98	0.14	0	1	0.1
Netherlands AEX	0	1	1	0	1	0.96	0	1	0.45	0	1	0.48
Norway OSE All Share	0	0.12	0	0	0.65	0.07	0	0.08	0.01	0	0.41	0.1
Portugal PSI General	0	0.98	0.1	0	1	0.37	0	0.28	0.02	0	0.27	0.02
Russia Moscow Times	0	1	0.12	0	1	0.24	0	0.18	0	0	0.53	0.01
Slovakia SAX16	0	1	0.56	0	1	0.53	0	0.51	0.22	0	0.51	0.18
Spain IGBM	0	1	0.3	0	1	0.36	0	1	0.24	0	1	0.29
Sweden OMX	0	1	0.6	0	1	0.85	0	1	0.24	0	1	0.2
Switzerland SMI	0	1	0.39	0	1	0.27	0	1	0.28	0	1	0.32
Turkey ISE100	0	1	0.13	0	1	0.62	0	0.02	0	0	0.1	0.01
UK FTSE100	0	1	0.64	0	1	0.91	0	1	0.55	0	1	0.47
Ireland ISEQ	0	0.77	0.45	0	0.94	0.67	0	0.7	0.21	0	0.89	0.25
Egypt CMA	0	0.02	0	0	0.51	0	0	0.05	0	0	0.34	0
Israel TA100	0	1	0.83	0	1	0.96	0	0.99	0.29	0	1	0.55

Table 5.13: **Statistics best out-of-sample testing procedure: mean return criterion, 0.25% costs.** Statistics of the best recursively optimizing and testing procedure applied to the local main stock market indices listed in the first column in the case of 0.25% costs per trade. The best strategy in the optimizing period is selected on the basis of the mean return criterion. Column 2 shows the sample period. Column 3 shows the parameters: [length optimizing period, length testing period]. Columns 4 and 5 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 6 and 7 show the Sharpe and excess Sharpe ratio. Column 8 shows the largest cumulative loss in %/100 terms. Columns 9, 10 and 11 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades. The results are computed for an US-based trader who applies the technical trading rule set to the local main stock market indices recomputed in US Dollars.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr > 0$	$\%d > 0$	SDR
World MSCI	12/21/82 - 6/28/02	[252, 63]	0.50	0.1113	0.0493	0.0368	-0.2368	736	0.308	0.582	0.9429
Argentina Merval	7/19/95 - 6/28/02	[252, 21]	0.0095	0.2099	-0.0044	0.0350	-0.6802	211	0.308	0.518	0.9341
Brazil Bovespa	9/25/96 - 6/28/02	[5, 1]	0.2457	0.3229	0.0208	0.0383	-0.5796	594	0.279	0.356	0.7282
Canada TSX Composite	12/21/87 - 6/28/02	[252, 126]	0.1715	0.1262	0.0331	0.0355	-0.4191	443	0.307	0.693	1.0272
Chile IPSA	12/20/95 - 6/28/02	[252, 1]	0.3501	0.4332	0.0615	0.1017	-0.2851	300	0.253	0.488	1.1244
Mexico IPC	1/16/98 - 6/28/02	[252, 63]	0.5145	0.4800	0.0500	0.0521	-0.4411	300	0.197	0.377	1.0408
Peru Lima General	6/16/93 - 6/28/02	[252, 10]	0.4885	0.4786	0.0730	0.0827	-0.5448	383	0.261	0.517	1.0024
US S&P500	12/21/82 - 6/28/02	[126, 42]	0.0593	-0.0436	0.0003	-0.0157	-0.3877	426	0.392	0.565	1.0668
US DJIA	12/21/82 - 6/28/02	[252, 42]	0.1048	-0.0111	0.0124	-0.0076	-0.3744	358	0.466	0.678	1.1000
US Nasdaq100	12/19/84 - 6/28/02	[252, 126]	0.0811	-0.0524	0.0037	-0.0123	-0.9658	393	0.344	0.602	1.0298
US NYSE Composite	12/21/82 - 6/28/02	[126, 63]	0.0770	-0.0222	0.0059	-0.0105	-0.3294	390	0.405	0.604	0.8420
US Russel2000	12/20/89 - 6/28/02	[21, 1]	0.2418	0.1581	0.0541	0.0401	-0.3691	784	0.337	0.472	0.7052
US Wilshire5000	12/18/85 - 6/28/02	[63, 10]	0.0384	-0.0512	-0.0044	-0.0182	-0.6333	485	0.363	0.536	1.0589
Venezuela Industrial	12/19/95 - 6/28/02	[252, 5]	0.5495	0.5769	0.0437	0.0543	-0.4984	442	0.210	0.363	1.1968
Australia ASX	3/07/88 - 6/28/02	[252, 10]	0.1542	0.1105	0.0250	0.0276	-0.3613	293	0.433	0.667	0.9447
China Shanghai Composite	12/22/95 - 6/28/02	[21, 5]	0.3531	0.1818	0.0405	0.0159	-0.4810	252	0.329	0.506	1.1991
Hong Kong Hang Seng	12/21/87 - 6/28/02	[5, 1]	0.2936	0.1831	0.0394	0.0266	-0.5788	1409	0.310	0.379	0.7703
India BSE30	12/17/93 - 6/28/02	[10, 1]	0.1976	0.2544	0.0259	0.0506	-0.4002	698	0.269	0.344	0.8968
Indonesia Jakarta Composite	12/19/90 - 6/28/02	[5, 1]	0.7264	0.8291	0.0539	0.0760	-0.7819	958	0.310	0.398	0.7512
Japan Nikkei225	12/21/87 - 6/28/02	[252, 10]	-0.0516	-0.0057	-0.0208	0.0029	-0.7133	294	0.381	0.623	0.9086
Malaysia KLSE Composite	12/02/86 - 6/28/02	[5, 1]	0.5185	0.4750	0.0584	0.0601	-0.6204	1378	0.319	0.399	0.9771
New Zealand NZSE30	12/17/92 - 6/28/02	[126, 5]	0.0380	0.0294	-0.0015	0.0099	-0.5436	272	0.338	0.502	0.9380
Pakistan Karachi100	2/03/94 - 6/28/02	[21, 1]	0.2568	0.3585	0.0297	0.0624	-0.4138	521	0.274	0.410	1.0583
Philippines PSE Composite	12/20/88 - 6/28/02	[5, 1]	0.6073	0.6445	0.0694	0.0880	-0.4182	1220	0.293	0.361	1.0754
Singapore Straits Times	3/17/88 - 6/28/02	[10, 1]	0.3079	0.2523	0.0489	0.0476	-0.4661	1169	0.297	0.382	0.8930
South-Korea Kospi200	11/17/94 - 6/28/02	[42, 1]	0.3682	0.4553	0.0308	0.0507	-0.7459	459	0.264	0.431	0.9370
Sri Lanka CSE All Share	9/24/96 - 6/28/02	[252, 21]	0.4593	0.5117	0.0853	0.1226	-0.1444	222	0.311	0.628	1.2987

Table 5.13 continued.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr > 0$	$\%d > 0$	SDR
Thailand SET	12/23/93 - 6/28/02	[21, 1]	0.2291	0.4190	0.0224	0.0693	-0.7942	566	0.261	0.346	1.1670
Taiwan TSE Composite	7/17/96 - 6/28/02	[10, 5]	0.0399	0.1286	-0.0012	0.0284	-0.5981	240	0.300	0.486	0.9699
Austria ATX	5/26/93 - 6/28/02	[252, 126]	0.0617	0.0409	0.0047	0.0131	-0.4850	148	0.439	0.641	1.1216
Belgium Bel20	12/19/91 - 6/28/02	[126, 63]	0.0637	0.0044	0.0051	-0.0006	-0.5859	226	0.407	0.544	0.8259
Czech Republic PX50	11/26/96 - 6/28/02	[252, 1]	0.2286	0.2823	0.0314	0.0583	-0.4457	226	0.230	0.511	1.0208
Denmark KFX	11/20/91 - 6/28/02	[252, 63]	0.0027	-0.0592	-0.0099	-0.0160	-0.5036	170	0.435	0.619	0.9315
Finland HEX General	3/18/94 - 6/28/02	[21, 10]	0.2873	0.1521	0.0287	0.0140	-0.5073	291	0.357	0.503	0.9817
France CAC40	7/21/92 - 6/28/02	[126, 42]	0.0063	-0.0440	-0.0082	-0.0102	-0.5954	181	0.403	0.625	0.9856
Germany DAX30	10/20/92 - 6/28/02	[42, 21]	0.0500	-0.0338	0.0013	-0.0094	-0.6310	243	0.366	0.599	0.9495
Greece ASE General	3/27/96 - 6/28/02	[10, 1]	0.5593	0.4880	0.0622	0.0577	-0.3888	529	0.299	0.357	0.8994
Italy MIB30	10/02/96 - 6/28/02	[126, 10]	0.1264	0.0654	0.0149	0.0115	-0.4792	147	0.333	0.522	0.9747
Netherlands AEX	12/21/87 - 6/28/02	[126, 63]	0.0703	-0.0377	0.0043	-0.0129	-0.5241	315	0.416	0.658	0.8524
Norway OSE All Share	12/17/97 - 6/28/02	[63, 5]	0.1624	0.1925	0.0238	0.0463	-0.2813	135	0.311	0.569	0.9697
Portugal PSI General	9/18/96 - 6/28/02	[126, 5]	0.2733	0.2292	0.0481	0.0490	-0.3297	189	0.349	0.541	0.9301
Russia Moscow Times	8/19/96 - 6/28/02	[5, 1]	1.2044	1.0412	0.0674	0.0555	-0.7146	550	0.305	0.384	0.8085
Slovakia SAX16	9/26/95 - 6/28/02	[126, 63]	0.0244	0.1274	-0.0041	0.0353	-0.5690	86	0.465	0.625	0.9164
Spain IGBM	12/06/93 - 6/28/02	[63, 42]	0.1420	0.0604	0.0177	0.0076	-0.7088	201	0.363	0.551	1.0715
Sweden OMX	11/18/94 - 6/28/02	[42, 10]	0.0504	-0.0158	0.0005	-0.0037	-0.5889	247	0.332	0.503	1.0641
Switzerland SMI	6/19/90 - 6/28/02	[126, 21]	0.0933	-0.0047	0.0101	-0.0059	-0.5295	297	0.360	0.591	0.8487
Turkey ISE100	12/20/89 - 6/28/02	[10, 1]	0.4749	0.5022	0.0288	0.0371	-0.8799	1055	0.283	0.380	0.8919
UK FTSE100	12/21/87 - 6/28/02	[252, 63]	0.0224	-0.0337	-0.0073	-0.0091	-0.6128	264	0.432	0.585	1.0021
Ireland ISEQ	1/02/91 - 6/28/02	[21, 5]	0.0704	0.0217	0.0067	0.0051	-0.3324	429	0.298	0.452	0.9366
Egypt CMA	12/18/96 - 6/28/02	[252, 1]	0.3819	0.2974	0.0989	0.0808	-0.1773	156	0.301	0.588	1.1224
Israel TA100	12/24/91 - 6/28/02	[252, 21]	0.1428	0.0975	0.0168	0.0163	-0.6316	366	0.276	0.558	0.9378

Table 5.14: **Statistics best out-of-sample testing procedure: Sharpe ratio criterion, 0.25% costs.** Statistics of the best recursively optimizing and testing procedure applied to the local main stock market indices listed in the first column in the case of 0.25% costs per trade. The best strategy in the optimizing period is selected on the basis of the Sharpe ratio criterion. Column 2 shows the sample period. Column 3 shows the parameters: [length optimizing period, length testing period]. Columns 4 and 5 show the mean return and excess mean return on a yearly basis in %/100 terms. Columns 6 and 7 show the Sharpe and excess Sharpe ratio. Column 8 shows the largest cumulative loss in %/100 terms. Columns 9, 10 and 11 show the number of trades, the percentage of profitable trades and the percentage of days these profitable trades lasted. The last column shows the standard deviation of returns during profitable trades divided by the standard deviation of returns during non-profitable trades. The results are computed for an US-based trader who applies the technical trading rule set to the local main stock market indices recomputed in US Dollars.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr>0$	$\%d>0$	SDR
World MSCI	12/21/82 - 6/28/02	[252, 63]	0.1772	0.0935	0.0470	0.0345	-0.3409	600	0.355	0.623	0.9476
Argentina Merval	7/19/95 - 6/28/02	[252, 5]	-0.0183	0.1821	-0.0079	0.0315	-0.7451	231	0.255	0.463	0.8697
Brazil Bovespa	9/25/96 - 6/28/02	[126, 1]	0.1213	0.1985	0.0091	0.0266	-0.6559	223	0.309	0.503	0.9222
Canada TSX Composite	12/21/87 - 6/28/02	[252, 21]	0.1266	0.0813	0.0240	0.0264	-0.4496	356	0.371	0.622	0.8949
Chile IPSA	12/20/95 - 6/28/02	[63, 1]	0.3566	0.4397	0.0685	0.1087	-0.2042	293	0.331	0.539	0.9860
Mexico IPC	1/16/98 - 6/28/02	[252, 63]	0.3561	0.3216	0.0363	0.0384	-0.5057	252	0.183	0.493	1.0082
Peru Lima General	6/16/93 - 6/28/02	[252, 126]	0.4452	0.4353	0.0673	0.0770	-0.6088	368	0.277	0.486	0.9316
US S&P500	12/21/82 - 6/28/02	[252, 63]	0.0733	-0.0296	0.0044	-0.0116	-0.4291	349	0.430	0.605	1.0756
US DJIA	12/21/82 - 6/28/02	[126, 63]	0.1019	-0.0140	0.0124	-0.0076	-0.4244	374	0.468	0.577	1.0549
US Nasdaq100	12/19/84 - 6/28/02	[63, 21]	0.1778	0.0443	0.0202	0.0042	-0.7823	549	0.344	0.491	1.1590
US NYSE Composite	12/21/82 - 6/28/02	[252, 63]	0.0585	-0.0407	0.0001	-0.0163	-0.4517	344	0.430	0.596	0.7990
US Russel2000	12/20/89 - 6/28/02	[63, 1]	0.2231	0.1394	0.0537	0.0397	-0.3659	573	0.339	0.562	0.7307
US Wilshire5000	12/18/85 - 6/28/02	[63, 10]	0.0561	-0.0335	0.0011	-0.0127	-0.6567	509	0.411	0.548	0.9887
Venezuela Industrial	12/19/95 - 6/28/02	[252, 5]	0.3535	0.3809	0.0267	0.0373	-0.5929	388	0.247	0.388	1.0575
Australia ASX	3/07/88 - 6/28/02	[252, 5]	0.1473	0.1036	0.0257	0.0283	-0.3421	339	0.381	0.624	1.0518
China Shanghai Composite	12/22/95 - 6/28/02	[126, 5]	0.5150	0.3437	0.0704	0.0458	-0.3331	157	0.427	0.648	1.0809
Hong Kong Hang Seng	12/21/87 - 6/28/02	[5, 1]	0.2352	0.1247	0.0341	0.0213	-0.5250	1547	0.337	0.375	0.7756
India BSE30	12/17/93 - 6/28/02	[21, 1]	0.1838	0.2406	0.0255	0.0502	-0.4230	622	0.265	0.362	0.8613
Indonesia Jakarta Composite	12/19/90 - 6/28/02	[5, 1]	0.5526	0.6553	0.0484	0.0705	-0.6310	1081	0.337	0.371	0.8210
Japan Nikkei225	12/21/87 - 6/28/02	[126, 63]	-0.0165	0.0294	-0.0131	0.0106	-0.6752	229	0.415	0.608	1.0573
Malaysia KLSE Composite	12/02/86 - 6/28/02	[5, 1]	0.4141	0.3706	0.0510	0.0527	-0.4796	1568	0.349	0.376	0.9594
New Zealand NZSE30	12/17/92 - 6/28/02	[21, 5]	0.0885	0.0799	0.0113	0.0227	-0.4270	388	0.322	0.424	0.9576
Pakistan Karachi100	2/03/94 - 6/28/02	[42, 1]	0.1390	0.2407	0.0143	0.0470	-0.5913	521	0.313	0.418	0.9061
Philippines PSE Composite	12/20/88 - 6/28/02	[5, 1]	0.4247	0.4619	0.0547	0.0733	-0.3502	1334	0.301	0.337	1.0882
Singapore Straits Times	3/17/88 - 6/28/02	[63, 1]	0.2326	0.1770	0.0378	0.0365	-0.3679	791	0.291	0.470	1.0758
South-Korea Kospi200	11/17/94 - 6/28/02	[21, 1]	0.2399	0.3270	0.0200	0.0399	-0.6106	589	0.299	0.387	0.9735
Sri Lanka CSE All Share	9/24/96 - 6/28/02	[252, 21]	0.4948	0.5472	0.0943	0.1316	-0.1606	200	0.320	0.596	1.5490

Table 5.14 continued.

Data set	Period	Parameters	$\overline{r}$	$\overline{r}^e$	S	S^e	ML	$\#tr$	$\%tr > 0$	$\%d > 0$	SDR
Thailand SET	12/23/93 - 6/28/02	[63, 5]	0.1703	0.3602	0.0161	0.0630	-0.7485	312	0.301	0.467	1.1553
Taiwan TSE Composite	7/17/96 - 6/28/02	[21, 10]	0.0382	0.1269	-0.0017	0.0279	-0.6458	194	0.330	0.491	0.9601
Austria ATX	5/26/93 - 6/28/02	[126, 1]	0.0498	0.0290	0.0013	0.0097	-0.4206	347	0.323	0.530	1.0148
Belgium Bel20	12/19/91 - 6/28/02	[252, 63]	0.0695	0.0102	0.0076	0.0019	-0.5068	196	0.408	0.597	0.9877
Czech Republic PX50	11/26/96 - 6/28/02	[252, 10]	0.2726	0.3263	0.0372	0.0641	-0.5573	177	0.288	0.610	0.9209
Denmark KFX	11/20/91 - 6/28/02	[21, 10]	0.0106	-0.0513	-0.0084	-0.0145	-0.4764	381	0.333	0.456	0.8865
Finland HEX General	3/18/94 - 6/28/02	[42, 10]	0.3293	0.1941	0.0364	0.0217	-0.4799	245	0.359	0.517	1.0787
France CAC40	7/21/92 - 6/28/02	[252, 63]	-0.0012	-0.0515	-0.0097	-0.0117	-0.6428	210	0.414	0.593	0.9638
Germany DAX30	10/20/92 - 6/28/02	[126, 63]	-0.0305	-0.1143	-0.0169	-0.0276	-0.6148	154	0.474	0.679	0.9333
Greece ASE General	3/27/96 - 6/28/02	[42, 1]	0.3930	0.3217	0.0475	0.0430	-0.5344	395	0.278	0.429	0.9537
Italy MIB30	10/02/96 - 6/28/02	[21, 5]	0.1522	0.0912	0.0198	0.0164	-0.4994	209	0.340	0.475	1.0810
Netherlands AEX	12/21/87 - 6/28/02	[252, 10]	0.0844	-0.0236	0.0086	-0.0086	-0.4538	302	0.434	0.617	0.8951
Norway OSE All Share	12/17/97 - 6/28/02	[252, 42]	0.2266	0.2567	0.0391	0.0616	-0.2573	60	0.450	0.735	0.9775
Portugal PSI General	9/18/96 - 6/28/02	[63, 5]	0.2626	0.2185	0.0551	0.0560	-0.3628	227	0.344	0.520	1.0275
Russia Moscow Times	8/19/96 - 6/28/02	[126, 63]	1.1498	0.9866	0.0742	0.0623	-0.6347	149	0.456	0.668	1.1245
Slovakia SAX16	9/26/95 - 6/28/02	[126, 63]	0.0735	0.1765	0.0054	0.0447	-0.5512	84	0.500	0.699	1.0657
Spain IGBM	12/06/93 - 6/28/02	[63, 5]	0.0201	-0.0615	-0.0061	-0.0162	-0.6451	310	0.326	0.460	1.0523
Sweden OMX	11/18/94 - 6/28/02	[63, 1]	0.0864	0.0202	0.0075	0.0033	-0.5023	420	0.317	0.458	0.9048
Switzerland SMI	6/19/90 - 6/28/02	[252, 10]	0.1002	0.0022	0.0136	-0.0024	-0.3344	282	0.418	0.526	0.8583
Turkey ISE100	12/20/89 - 6/28/02	[252, 1]	0.5291	0.5564	0.0329	0.0412	-0.7598	445	0.335	0.573	1.0130
UK FTSE100	12/21/87 - 6/28/02	[63, 10]	0.0435	-0.0126	-0.0020	-0.0038	-0.5442	452	0.316	0.484	1.0903
Ireland ISEQ	1/02/91 - 6/28/02	[63, 42]	0.0402	-0.0085	-0.0010	-0.0026	-0.6260	228	0.399	0.601	0.9129
Egypt CMA	12/18/96 - 6/28/02	[126, 10]	0.3100	0.2255	0.0898	0.0717	-0.3523	149	0.342	0.622	1.3125
Israel TA100	12/24/91 - 6/28/02	[252, 126]	0.1146	0.0693	0.0133	0.0128	-0.5281	278	0.313	0.574	1.0276

Table 5.15: **Excess performance best out-of-sample testing procedure.** Panel A shows the yearly mean return of the best recursive out-of-sample testing procedure, selected by the mean return criterion, in excess of the yearly mean return of the buy-and-hold. Panel B shows the Sharpe ratio of the best recursive out-of-sample testing procedure, selected by the Sharpe ratio criterion, in excess of the Sharpe ratio of the buy-and-hold. Results are presented for the 0, 0.10, 0.25, 0.50, 0.75 and 1% transaction costs cases. The row labeled "Average: out-of-sample" shows the average over the results as presented in the table. The row labeled "Average: in sample" shows the average over the results of the best strategy selected in sample for each index. The results are computed for an US-based trader who applies the technical trading rule set to the local main stock market indices recomputed in US Dollars.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
World MSCI	0.3919	0.2675	0.1113	-0.0068	-0.0013	-0.0071	0.1155	0.0693	0.0345	0.0027	-0.0055	-0.0166
Argentina Merval	0.4352	0.3242	0.2099	0.1261	0.0750	0.0488	0.0559	0.0445	0.0315	0.0343	0.0329	0.0270
Brazil Bovespa	0.4400	0.4362	0.3229	0.2278	0.0671	0.0380	0.0492	0.0413	0.0266	0.0262	0.0168	0.0184
Canada TSX Composite	0.3056	0.1908	0.1262	0.0343	-0.0125	0.0030	0.0681	0.0483	0.0264	0.0149	0.0048	-0.0008
Chile IPSA	0.6686	0.5342	0.4332	0.3034	0.2695	0.1649	0.1308	0.1091	0.1087	0.0861	0.0653	0.0544
Mexico IPC	0.6690	0.5766	0.4800	0.3090	0.1214	0.0703	0.0808	0.0625	0.0384	0.0151	0.0010	-0.0061
Peru Lima General	0.6644	0.5859	0.4786	0.4118	0.2540	0.1739	0.1044	0.0977	0.0770	0.0607	0.0458	0.0373
US S&P500	0.0372	-0.0151	-0.0436	-0.0842	-0.0604	-0.0833	0.0118	-0.0011	-0.0116	-0.0146	-0.0165	-0.0171
US DJIA	0.0493	-0.0015	-0.0111	-0.0415	-0.0526	-0.0679	0.0032	-0.0052	-0.0076	-0.0214	-0.0263	-0.0238
US Nasdaq100	0.1531	0.0452	-0.0524	-0.1164	-0.1287	-0.1380	0.0259	0.0080	0.0042	-0.0095	-0.0099	-0.0119
US NYSE Composite	0.1030	0.0121	-0.0222	-0.0447	-0.0717	-0.0540	0.0352	-0.0043	-0.0163	-0.0241	-0.0279	-0.0258
US Russel2000	0.4399	0.3460	0.1581	0.0333	-0.0093	-0.0358	0.0978	0.0733	0.0397	0.0161	0.0071	-0.0015
US Wilshire5000	0.1353	0.0421	-0.0512	-0.0846	-0.0468	-0.0467	0.0446	0.0120	-0.0127	-0.0284	-0.0312	-0.0398
Venezuela Industrial	0.8696	0.8050	0.5769	0.2384	0.0692	0.0242	0.0653	0.0568	0.0373	0.0280	0.0159	0.0088
Australia ASX All Ordinaries	0.1558	0.1242	0.1105	0.0508	0.0364	0.0171	0.0444	0.0335	0.0283	0.0164	0.0091	0.0068
China Shanghai Composite	0.2973	0.2659	0.1818	0.0918	0.0652	0.1339	0.0465	0.0456	0.0458	0.0341	0.0233	0.0185
Hong Kong Hang Seng	0.3698	0.3260	0.1831	0.0554	0.0593	0.0520	0.0563	0.0458	0.0213	0.0032	-0.0036	-0.0013
India BSE30	0.4842	0.3855	0.2544	0.1347	0.0557	-0.0093	0.0810	0.0687	0.0502	0.0241	0.0076	-0.0033
Indonesia Jakarta Composite	1.1893	0.9802	0.8291	0.6649	0.5068	0.4426	0.0884	0.0834	0.0705	0.0551	0.0409	0.0309
Japan Nikkei225	0.0541	0.0282	-0.0057	-0.0361	-0.0211	-0.0436	0.0163	0.0116	0.0106	0.0041	0.0009	-0.0045
Malaysia KLSE Composite	0.7683	0.6175	0.4750	0.2818	0.1799	0.0864	0.0757	0.0692	0.0527	0.0257	0.0182	0.0146
New Zealand NZSE30	0.0986	0.0711	0.0294	-0.0184	-0.0875	-0.0878	0.0438	0.0339	0.0227	-0.0092	-0.0173	-0.0168
Pakistan Karachi100	0.4970	0.4012	0.3585	0.2602	0.2245	0.2112	0.0704	0.0629	0.0470	0.0372	0.0358	0.0355
Philippines PSE Composite	0.8376	0.8145	0.6445	0.4390	0.3094	0.1979	0.0987	0.0892	0.0733	0.0488	0.0314	0.0286
Singapore Straits Times	0.4749	0.4138	0.2523	0.1106	0.0232	0.0266	0.0719	0.0568	0.0365	0.0154	0.0053	0.0084
South-Korea Kospi200	0.5053	0.5061	0.4553	0.3071	0.1777	0.1224	0.0610	0.0482	0.0399	0.0326	0.0301	0.0256
SriLanka CSE All Share	0.7466	0.6436	0.5117	0.3879	0.3617	0.2747	0.1669	0.1494	0.1316	0.0978	0.0787	0.0647

Table 5.15 continued.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
Data set	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
Thailand SET	0.5727	0.5007	0.4190	0.2913	0.2737	0.2951	0.0817	0.0710	0.0630	0.0586	0.0544	0.0476
Taiwan TSE Composite	0.2485	0.1528	0.1286	0.0690	0.0229	0.0111	0.0469	0.0431	0.0279	0.0161	0.0103	0.0112
Austria ATX	0.0530	0.0321	0.0409	0.0067	-0.0310	-0.0303	0.0276	0.0217	0.0097	-0.0075	-0.0131	-0.0137
Belgium Bel20	0.0671	0.0185	0.0044	-0.0622	-0.1210	-0.1306	0.0161	0.0068	0.0019	-0.0103	-0.0222	-0.0218
Czech Republic PX50	0.5005	0.5041	0.2823	0.2161	0.1508	0.1239	0.0963	0.0834	0.0641	0.0420	0.0313	0.0366
Denmark KFX	0.0998	0.0334	-0.0592	-0.0728	-0.0505	-0.0570	0.0186	0.0073	-0.0145	-0.0308	-0.0260	-0.0235
Finland HEX General	0.2917	0.1997	0.1521	0.0556	0.0446	0.0052	0.0288	0.0252	0.0217	0.0118	0.0095	0.0061
France CAC40	0.0204	-0.0452	-0.0440	-0.0402	-0.0620	-0.0928	0.0106	-0.0131	-0.0117	-0.0065	-0.0127	-0.0126
Germany DAX30	-0.0264	-0.0424	-0.0338	-0.0737	-0.0753	-0.0669	-0.0081	-0.0201	-0.0276	-0.0292	-0.0174	-0.0304
Greece ASE General	0.7763	0.6760	0.4880	0.2301	0.1079	0.0316	0.0718	0.0594	0.0430	0.0286	0.0101	0.0068
Italy MIB30	0.1368	0.1417	0.0654	0.0089	-0.0375	-0.0614	0.0378	0.0265	0.0164	0.0112	-0.0006	0.0060
Netherlands AEX	0.0149	-0.0056	-0.0377	-0.0532	-0.0608	-0.0678	0.0045	0.0017	-0.0086	-0.0118	-0.0252	-0.0325
Norway OSE All Share	0.2836	0.2749	0.1925	0.1707	0.1466	0.1277	0.0640	0.0591	0.0616	0.0580	0.0510	0.0552
Portugal PSI General	0.5386	0.3880	0.2292	0.1413	0.0663	0.0704	0.0808	0.0675	0.0560	0.0286	0.0177	0.0054
Russia MoscowTimes	1.7811	1.5672	1.0412	0.8313	0.4889	0.3705	0.0660	0.0631	0.0623	0.0536	0.0473	0.0359
Slovakia SAX16	0.2256	0.2392	0.1274	0.1179	0.1520	0.1414	0.0405	0.0456	0.0447	0.0322	0.0337	0.0246
Spain IGBM	0.0835	0.0281	0.0604	-0.0139	-0.0389	-0.0458	0.0313	-0.0013	-0.0162	-0.0264	-0.0260	-0.0305
Sweden OMX	0.0960	0.0476	-0.0158	-0.0231	-0.0655	-0.1019	0.0249	0.0205	0.0033	-0.0174	-0.0179	-0.0193
Switzerland SMI	0.0600	0.0171	-0.0047	-0.0069	-0.0351	-0.0400	0.0111	-0.0012	-0.0024	-0.0157	-0.0205	-0.0165
Turkey ISE100	0.7669	0.6091	0.5022	0.2757	0.1597	0.1328	0.0388	0.0396	0.0412	0.0327	0.0180	0.0113
UK FTSE100	0.0498	0.0221	-0.0337	-0.0466	-0.0422	-0.0318	0.0129	0.0055	-0.0038	-0.0037	-0.0114	-0.0081
Ireland ISEQ	0.0794	0.0430	0.0217	-0.0085	-0.0234	-0.0176	0.0151	0.0044	-0.0026	-0.0108	-0.0136	-0.0175
Egypt CMA	0.3987	0.3330	0.2974	0.2645	0.2545	0.1954	0.1016	0.0852	0.0717	0.0662	0.0405	0.0457
Israel TA100	0.2759	0.1419	0.0975	0.0088	0.0053	0.0023	0.0441	0.0274	0.0128	-0.0026	-0.0106	-0.0096
Average: out-of-sample	0.3772	0.3060	0.2141	0.1240	0.0705	0.0447	0.0544	0.0419	0.0298	0.0164	0.0086	0.0052
Average: in sample	0.4870	0.3684	0.2737	0.2186	0.1958	0.1798	0.0689	0.0546	0.0441	0.0387	0.0358	0.0335

Table 5.16: **Estimation results CAPM for best out-of-sample testing procedure.** Coefficient estimates of the Sharpe-Lintner CAPM: $r_t^i - r_t^f = \alpha + \beta(r_t^{Local} - r_t^f) + \epsilon_t$. That is, the return in US Dollars of the best recursive optimizing and testing procedure, when selection in the optimizing period is done by the mean return criterion (Panel A) or by the Sharpe ratio criterion (Panel B), in excess of the US risk-free interest rate is regressed against a constant and the return of the local stock market index in US Dollars in excess of the US risk-free interest rate. Estimation results for the 0 and 0.50% costs per trade cases are shown. a, b, c indicates that the corresponding coefficient is, in the case of α, significantly different from zero, or in the case of β, significantly different from one, at the 1, 5, 10% significance level. Estimation is done with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.50%		0%		0.50%	
Data set	α	β	α	β	α	β	α	β
World MSCI	0.001241a	0.849c	-2.02E-05	0.969	0.001129a	0.802b	6.60E-05	0.711a
Argentina Merval	0.001469a	0.771a	0.000367	0.784b	0.001075b	0.614a	0.000638	0.757a
Brazil Bovespa	0.001412b	0.735a	0.000748	0.750a	0.001273b	0.615a	0.000561	0.594a
Canada TSX Composite	0.001016a	0.942	0.000127	1.028	0.000752a	0.777a	0.000159	0.809a
Chile IPSA	0.002085a	0.833b	0.001028a	0.800b	0.001870a	0.791a	0.001057a	0.707a
Mexico IPC	0.002000a	0.949	0.001054c	0.871	0.002285a	0.904	0.000454	0.994
Peru Lima General	0.001995a	0.911	0.001347a	0.923	0.001916a	0.919	0.001045a	0.868c
US S&P500	0.000144	0.902	-0.000324b	1.03	0.000213c	0.838	-0.00012	0.87
US DJIA	0.000202	0.851	-0.0001	0.774c	0.000114	0.693a	-0.0002	0.847
US Nasdaq100	0.000465c	1.135c	-0.000476c	1.154b	0.000653a	0.712a	-0.00012	0.942
US NYSE Composite	0.000388a	0.783b	-0.00015	0.918	0.000406a	0.734a	-0.0002	0.753b
US Russel2000	0.001361a	0.939	0.000129	0.935	0.001155a	0.689a	0.000247	0.744a
US Wilshire5000	0.000495a	0.771a	-0.000325b	1.031	0.000525a	0.715a	-0.000284b	0.823b
Venezuela Industrial	0.002564a	1.075	0.000791	0.702b	0.002230a	0.925	0.000989b	1.093
Australia ASX All Ordinaries	0.000547a	1.027	0.000185	1.107c	0.000573a	0.865b	0.000206	0.905
China Shanghai Composite	0.001014b	0.735a	0.000304	0.983	0.001125a	0.684a	0.000896b	0.686a
Hong Kong Hang Seng	0.001162a	0.842b	0.00023	0.764b	0.001067a	0.702a	0.00013	0.653a
India BSE30	0.001566a	0.808a	0.000459	0.830a	0.001368a	0.777a	0.000462	1.159b
Indonesia Jakarta Composite	0.003274a	0.873	0.002154a	0.921	0.002661a	0.825b	0.001540a	0.791b
Japan Nikkei225	0.000134	0.774a	-0.00024	0.782a	0.000155	0.763a	-6.91E-05	0.894c
Malaysia KLSE Composite	0.002191a	0.952	0.000950a	0.947	0.001708a	0.871	0.000603b	0.846
New Zealand NZSE30	0.000357c	0.872a	-7.91E-05	0.932	0.000548a	0.710a	-0.00019	0.883c
Pakistan Karachi100	0.001712a	0.929	0.000809b	0.661a	0.001423a	0.888c	0.000763c	1.058
Philippines PSE Composite	0.002450a	0.912c	0.001467a	0.942	0.002065a	0.860b	0.000944a	0.799a
Singapore Straits Times	0.001476a	0.906	0.000398c	0.868c	0.001138a	0.785a	0.000269	0.775a

Table 5.16 continued.

	Panel A				Panel B			
selection criterion	Mean return				Sharpe ratio			
costs per trade	0%		0.50%		0%		0.50%	
Data set	α	β	α	β	α	β	α	β
South-Korea Kospi200	0.001701a	0.914	0.001054c	0.820a	0.001809a	0.826a	0.000759	0.668a
Sri Lanka CSE All Share	0.002353a	1.12	0.001397a	1.091	0.002399a	1.098	0.001095a	0.876
Thailand SET	0.002001a	0.886	0.001126b	0.915	0.001858a	0.879	0.001066b	0.759b
Taiwan TSE Composite	0.000866b	0.814a	0.00016	0.744a	0.000749b	0.718a	0.000143	0.754a
Austria ATX	0.000197	0.939	4.53E-06	0.754a	0.000337c	0.801a	-0.00014	0.795a
Belgium Bel20	0.000242	1.019	-0.00024	0.986	0.000247	0.897	-0.00011	0.824a
Czech Republic PX50	0.001658a	0.927	0.000793b	0.939	0.001788a	0.953	0.000685c	0.941
Denmark KFX	0.000362c	0.966	-0.00028	1.015	0.000291	0.851a	-0.000463b	1.014
Finland HEX General	0.000971b	0.794a	0.00024	0.835b	0.000838b	0.710a	0.000434	0.796a
France CAC40	7.79E-05	0.927c	-0.00016	1.075	0.000166	0.830a	-0.0001	1.012
Germany DAX30	-7.69E-05	0.882b	-0.00026	0.897	-7.90E-05	0.811a	-0.000462b	0.894
Greece ASE General	0.002186a	0.787a	0.000787c	0.861b	0.001652a	0.769a	0.000734	0.777a
Italy MIB30	0.000482	0.849b	3.00E-05	0.886	0.000725b	0.870c	0.000224	0.908
Netherlands AEX	2.99E-05	1.082	-0.00019	0.925	0.000148	0.812a	-0.0001	0.923
Norway OSE All Share	0.000966a	0.829c	0.000587	0.812c	0.000882b	0.783b	0.000819b	0.796c
Portugal PSI General	0.001649a	0.923	0.0005	0.883	0.001133a	0.756a	0.000404	0.711a
Russia Moscow Times	0.003745a	0.877	0.002219a	0.832b	0.002736a	0.763a	0.002280a	0.672a
Slovakia SAX16	0.000806b	0.852	0.000495	1	0.000462	0.705a	0.000458	0.987
Spain IGBM	0.000297	0.941	-4.26E-05	0.974	0.000507b	0.800a	-0.000427c	1.006
Sweden OMX	0.000349	0.926	-8.57E-05	0.932	0.000503c	0.741a	-0.00031	0.743a
Switzerland SMI	0.000219	0.952	-7.53E-06	0.902	0.000243	0.838a	-0.00016	0.853a
Turkey ISE100	0.002297a	0.94	0.000980c	0.942	0.001732a	0.984	0.001393b	0.895c
UK FTSE100	0.000179	0.891b	-0.00019	1.026	0.00018	0.943	-5.44E-05	1.041
Ireland ISEQ	0.000295	0.913	-3.42E-05	0.908	0.000213	0.814a	-0.00015	0.947
Egypt CMA	0.001220a	1.167	0.000863a	1.018	0.000990a	0.932	0.000740a	0.936
Israel TA100	0.000925a	0.943	3.77E-05	1.005	0.000879a	0.877c	-5.67E-05	0.907

Table 5.18: **Summary of the results found in Chapters 3, 4 and 5.** The table shows for different transaction costs cases the fraction of data series analyzed for which (1) at the 10% significance level a significantly positive estimate of α is found in the CAPMs (3.5), (4.1) and (5.1), if the best strategy is selected in sample, (2) White's (2000) RC p-value is smaller than 0.10, (3) Hansen's (2001) SPA-test p-value is smaller than 0.10, (4) at the 10% significance level a significantly positive estimate of α is found in the CAPMs (3.5), (4.1) and (5.1), if the best recursive out-of-sample testing procedure is applied. Panel A shows the results for the mean return selection criterion and Panel B shows the results for the Sharpe ratio selection criterion. In Chapters 3 and 5 the results are in US Dollars and in Chapter 4 the results are in Dutch Guilders. For entries marked with X no results are computed.

	Panel A						Panel B					
selection criterion	Mean return						Sharpe ratio					
costs per trade	0%	0.10%	0.25%	0.50%	0.75%	1%	0%	0.10%	0.25%	0.50%	0.75%	1%
Chapter 3	**DJIA and stocks listed in the DJIA: 1973-2001 (35 data series)**											
(1) in-sample CAPM: $\alpha > 0$	0.83	0.49	0.29	0.2	0.2	0.23	0.83	0.51	0.37	0.26	0.26	0.26
(2) $p_W < 0.10$	0	0	0	0	0	0	0.11	0	0	0	0	0
(3) $p_H < 0.10$	0.23	0	0	0	0	0	0.46	0.09	0	0	0	0
(4) out-of-sample CAPM: $\alpha > 0$	0.34	0.09	0.03	0	X	X	0.4	0.2	0.17	0.03	X	X
Chapter 4	**AEX-index and stocks listed in the AEX-index: 1983-2002 (51 data series)**											
(1) in-sample CAPM: $\alpha > 0$	0.73	0.73	0.63	0.61	0.51	0.47	0.76	0.75	0.69	0.63	0.57	0.49
(2) $p_W < 0.10$	0.04	0	0	0	0	0	0.20	0.08	0.08	0.08	0.04	0.04
(3) $p_H < 0.10$	0.27	0.04	0.04	0.04	0.02	0.02	0.59	0.33	0.25	0.29	0.29	0.29
(4) out-of-sample CAPM: $\alpha > 0$	0.61	0.41	0.20	0.08	0.06	0.04	0.65	0.47	0.22	0.04	0.04	0.04
Chapter 5	**Local main stock market indices: 1981-2002 (51 data series)**											
(1) in-sample CAPM: $\alpha > 0$	1	0.88	0.86	0.73	0.63	0.53	1	0.88	0.82	0.73	0.65	0.55
(2) $p_W < 0.10$	0.16	0.12	0.04	0	0	0	0.47	0.33	0.14	0.06	0.06	0.02
(3) $p_H < 0.10$	0.53	0.29	0.12	0.04	0.02	0.02	0.69	0.55	0.45	0.31	0.29	0.25
(4) out-of-sample CAPM: $\alpha > 0$	0.61	0.47	0.35	0.14	0.08	0.02	0.65	0.47	0.33	0.16	0.04	0.04

Chapter 6

An Evolutionary Adaptive Learning Model with Fundamentalists and Moving Average Traders

6.1 Introduction

Chapters 2 through 5 of this thesis contain empirical analyses whether technical trading has statistically significant forecasting power and yields economically significant profits when applied to financial time series. The present chapter builds a simple theoretical financial market model with fundamentalists and technical analysts.

An important question in heterogeneous agents modeling is whether irrational traders can survive in the market, or whether they would lose money and are driven out of the market by rational investors, who would trade against them and drive prices back to fundamentals, as argued by e.g. Friedman (1953). In the last decade a number of theoretical and/or computational heterogeneous agent models, with fundamentalist traders competing against technical analysts, have been developed, see e.g. in Frankel and Froot (1988), De Long et al. (1989, 1990), Kirman (1991), Wang (1994), Lux (1995), Arthur et al. (1997), Brock and Hommes (1997, 1998), Farmer (1998), Hong and Stein (1999) and LeBaron et al. (1999). A common feature of these contributions is that technical traders may at times earn positive profits, survive evolutionary competition and need not be driven out of the market by trading strategies based upon economic fundamentals.

Brock and Hommes (1998) investigate the dynamical behavior of a simple financial market model with heterogeneous adaptively learning traders, where the fraction of traders following a certain forecasting rule changes over time. The traders are restricted to choose from a finite set of fundamental and trend following trading techniques. How many traders are using a particular technique in predicting prices depends on the past performances of these techniques, as measured by past profits or forecasting accuracy. Emphasis is placed on the change in dynamical behavior when the intensity of choice parameter, measuring how quickly agents switch between forecasting techniques, is varied. It is found that increasing this intensity of choice can lead to market instability and the emergence of complicated dynamics for asset prices and returns, with irregular switching between phases where prices are near to the fundamental value and phases of optimism where traders extrapolate trends. An extremely rich asset price dynamics emerges, with bifurcation routes to strange attractors, especially if switching to more successful strategies becomes more rapid. It is also found that even when costs of information gathering and trading are zero, then fundamentalists are in general not able to drive other trader types out of the market. Thus it is concluded that simple technical trading rules may survive evolutionary competition in a heterogeneous world where prices and beliefs coevolve over time and that therefore the Friedman argument should be considered with care. See e.g. Hommes (2001) for a survey and an extensive discussion of these points.

One of the goals of heterogeneous agents modeling is to develop simple financial asset pricing models that mimic the well-known characteristics of real financial return distributions, such as little autocorrelation in the returns, volatility clustering and fat tails. Gaunersdorfer and Hommes (2000) develop a model in which volatility clustering becomes an endogenous phenomenon by the interaction of heterogeneous agents. Volatility clustering is caused by the coexistence of attractors, a stable fundamental steady state and a stable (quasi) periodic cycle. The time series properties of the model are compared with the daily closing prices of the S&P 500 in the period August 1961 through May 2000 and furthermore a GARCH model is estimated. It is concluded that the model approximates reality fairly well.

This chapter is an extension of the Brock and Hommes (1998) model in that it adds a real moving-average technical trading strategy to the set of beliefs the traders can choose from. Moving averages are well known and frequently used prediction rules in financial practice. They are intended to smooth out an otherwise volatile time series and to show its underlying directional trend. Furthermore, the model proposed in this chapter assumes that traders have constant relative risk aversion. That is, every trader in a given belief group invests the same proportion of his individual wealth in the risky asset. Hence, traders take the same amount of risk relative to their wealth. In the Brock and Hommes (1998) model, in contrast, it is assumed that the traders have constant absolute risk aversion. Irrespective of their individual wealth every trader in a certain belief group will buy or sell short the same amount of stocks. Thus traders with less wealth are prepared to take greater relative risks than traders with more wealth. It should be noted that in the case of zero supply of outside stocks, the model developed in this chapter reduces to the Brock and Hommes (1998) model.

In nonlinear dynamical models it is in general impossible to obtain explicit analytic expressions for the periodic and chaotic solutions. Therefore in applied nonlinear dynamics it is common practice to use a mixture of theoretical and numerical methods to analyze the dynamics. We perform a bifurcation analysis of the steady state by using numerical tools, such as delay and phase diagrams, bifurcation diagrams and the computation of Lyapunov exponents. In particular we show analytically that the fundamental steady state may become unstable due to a Hopf bifurcation.

In section 6.2 the Brock and Hommes (1998) financial market model with adaptively learning agents is reviewed. Thereafter, in section 6.3, the heterogeneous agents model with fundamentalists versus moving average traders, resulting in an eight dimensional nonlinear dynamical system, is derived. In section 6.4 a procedure is developed to determine trading volume. Section 6.5 presents an analytical stability analysis of the fundamental steady state. The eigenvalues of the linearized system are computed and it is examined which kind of bifurcations can occur. In section 6.6 numerical simulations are used to study the dynamical behavior of the model, especially when the steady state is locally unstable. Finally section 6.7 summarizes and concludes.

6.2 The Brock-Hommes heterogeneous agents model

In this section we discuss the discounted value asset pricing model with heterogeneous beliefs of Brock and Hommes (1998)[1]. Consider a market with N agents who can select independently from each other a strategy h from a finite set of H different beliefs or forecasting rules to base trading decisions upon. Agents have to make a capital allocation decision between a risky asset P and a risk free asset F. There are no restrictions on the amount of money which can be borrowed or lend and there are also no restrictions on the number of shares that can be bought or sold short. Agent j can choose to buy or sell short $z_{j,t}$ shares of the risky asset at time t. The wealth of agent j at time $t+1$ is then equal to

$$W_{j,t+1} = RW_{j,t} + z_{j,t}(P_{t+1} + D_{t+1} - RP_t), \tag{6.1}$$

[1]Henceforth abbreviated as BH.

where $R = (1 + r^F)$ is the risk free gross return, r^F is the risk free net return assumed to be constant, P_t is the equilibrium price of the risky asset at time t and D_t is the dividend paid at time t. The term $(P_{t+1} + D_{t+1} - RP_t)$ is equal to the excess profit of one long position in the risky asset.

BH make the following assumptions regarding the trading process. All agents are price takers. That is, an agent cannot influence the market's equilibrium price by his individual investment decision. The demand for the risky asset $z_{j,t}$ is a continuous monotonically decreasing function of the price P_t at time t. Further, the model follows a Walrasian equilibrium price scenario. Before the setting of the equilibrium price at time t, each agent j chooses a trading strategy h and makes an optimal investment decision $z^h_{j,t}$ in the time interval $(t-1, t)$. Expectations about future prices and dividends are made on the basis of the information set of past equilibrium prices and dividends $\{P_{t-i}, D_{t-i} : i \geq 1\}$ (note that P_t and D_t are not included). Through the market mechanism an equilibrium price is set so that the market clears. Dividends D_t paid at time t can immediately be reinvested at time t.

Demand

BH define the information set $I_t = \{P_{t-i}, D_{t-i} : i \geq 1\} \cup \{P_t, D_t\}$, where $\{P_{t-i} : i \geq 1\}$ are past *equilibrium* prices, $\{D_{t-i} : i \geq 1\}$ are past dividends, $\{D_t\}$ is current dividend, but where $\{P_t\}$ is not yet necessarily the equilibrium price. The conditional expected wealth of agent j at time t who invests according to strategy h is then equal to

$$E^h_j(W_{j,t+1}|I_t) = E^h_{j,t}(W_{j,t+1}) = RW_{j,t} + z^h_{j,t} E^h_t(P_{t+1} + D_{t+1} - RP_t), \tag{6.2}$$

where $E^h_t(P_{t+1} + D_{t+1} - RP_t)$ is the forecast strategy h makes about the excess profit of the risky asset at time $t+1$ conditioned on I_t. The agent also makes a forecast about the dispersion of his expected wealth conditioned on I_t

$$V^h_j(W_{j,t+1}|I_t) = V^h_{j,t}(W_{j,t+1}) = (z^h_{j,t})^2 V^h_t(P_{t+1} + D_{t+1}), \tag{6.3}$$

where $V^h_t(P_{t+1} + D_{t+1})$ is the forecast of belief h about the dispersion of expected price plus dividend. It is assumed that if the conditional expected excess profit of belief h is positive, then the agent holds a long position in the market ($z^h_{j,t} \geq 0$) and if the conditional expected excess profit is strictly negative, then the agent holds a short position in the market ($z^h_{j,t} < 0$), so that conditional expected wealth is always equal or larger than $RW_{j,t}$.

Solving the conditional variance equation (6.3) for $z^h_{j,t}$ yields

$$z^h_{j,t} = \pm\sqrt{\frac{V^h_{j,t}(W_{j,t+1})}{V^h_t(P_{t+1} + D_{t+1})}}, \tag{6.4}$$

where the $\pm$ sign depends on the sign of the expected excess profit on the risky asset by belief h. The capital allocation line (CAL) of agent j with belief h is derived by substituting (6.4) in the conditional expectations equation (6.2) which yields

$$E^h_{j,t}(W_{j,t+1}) = RW_{j,t} + S^h_t \sqrt{V^h_{j,t}(W_{j,t+1})} \text{ if } E^h_t(P_{t+1} + D_{t+1} - RP_t) \geq 0; \tag{6.5}$$

$$E^h_{j,t}(W_{j,t+1}) = RW_{j,t} - S^h_t \sqrt{V^h_{j,t}(W_{j,t+1})} \text{ if } E^h_t(P_{t+1} + D_{t+1} - RP_t) < 0; \tag{6.6}$$

$$S^h_t = \frac{E^h_t(P_{t+1} + D_{t+1} - RP_t)}{\sqrt{V^h_t(P_{t+1} + D_{t+1})}} = \frac{E^h_t(P_{t+1} + D_{t+1} - RP_t)/P_t}{\sqrt{V^h_t(P_{t+1} + D_{t+1})/P_t^2}} = \frac{E^h_t(r^P_{t+1} - r^f)}{\sqrt{V^h_t(r^P_{t+1})}}.$$

Here r^P_{t+1} is the return of the risky asset at time $t+1$ and $|S^h_t|$ is the reward to variability ratio, or stated differently, the extra expected return to be gained per extra point of expected risk to be taken. The CAL shows the relation between the expected wealth and the expected dispersion of the wealth by agent j. The CAL is always an increasing function of $\sqrt{V^h_{j,t}(W_{j,t+1})}$, which means that the more risk the agent expects to take, the more he expects to earn.

BH assume that each agent has constant absolute risk aversion (CARA) and that the utility of the asset allocation decision of agent j who invests according to belief h at time t is given by

$$U^h_{j,t} = E^h_{j,t}(W_{j,t+1}) - \frac{a_j}{2} V^h_{j,t}(W_{j,t+1}), \tag{6.7}$$

where a_j is the risk aversion parameter of agent j. Every agent chooses an asset allocation that maximizes his utility, that is

$$\text{Max}_{z^h_{j,t}} E^h_{j,t}(W_{j,t+1}) - \frac{a_j}{2} V^h_{j,t}(W_{j,t+1}) \text{ under the CAL (6.5) or (6.6).} \tag{6.8}$$

This maximization yields the optimal choice of the number of stocks to be bought or sold short

$$z^h_{j,t}(P_t) = \frac{E^h_t(P_{t+1} + D_{t+1} - RP_t)}{a_j V^h_t(P_{t+1} + D_{t+1})}, \tag{6.9}$$

where $z^h_{j,t}(P_t) \in \mathbb{R}$ is the demand for shares as a continuous monotonically decreasing function of P_t. If $z^h_{j,t} > 0$, then a long position in the market is taken and if $z^h_{j,t} < 0$, then a short position in the market is taken. If it is assumed that all agents have the same risk aversion parameter $a_j = a$, then all agents with the same belief buy or sell short the same number of shares irrespective of their wealth. If $j \in$ belief h, then $z_{j,t} = z^h_{j,t} = z^h_t$, where z^h_t is the number of shares recommended to be bought or sold short by belief h at time t.

Market equilibrium

Equilibrium of demand and supply yields

$$\sum_{j=1}^{N} z_{j,t} = \sum_{h=1}^{H} \left(\sum_{\{j \in \text{ belief h}\}} z_{j,t}^{h} \right) = S, \tag{6.10}$$

where S is the total number of shares available in the market. Hence in equilibrium the total number of shares demanded by the agents should be equal to the total number of shares available. Equilibrium equation (6.10) can be rewritten as

$$\sum_{h=1}^{H} N_t^h z_t^h = S, \tag{6.11}$$

where N_t^h is the number of agents having belief h at time t. If both sides of equation (6.11) are divided by the total number of agents N trading in the market, then

$$\sum_{h=1}^{H} n_t^h z_t^h = s, \tag{6.12}$$

where $n_t^h = N_t^h/N$ is the fraction of agents with belief h and $s = S/N$ is the number of shares available per agent.

Further, BH assume that the conditional variance $V_t^h(P_{t+1} + D_{t+1}) = \sigma^2$ is constant through time and equal for all beliefs. This assumption of homogeneous, constant beliefs on variance is made primarily for analytical tractability. Notice however that heterogeneity in conditional expectations in fact leads to heterogeneity in conditional variance as well, but this second-order effect will be ignored. Equilibrium equation (6.12) can be solved for P_t to yield the equilibrium price

$$P_t = \frac{1}{R} \sum_{h=1}^{H} \left\{ n_t^h E_t^h (P_{t+1} + D_{t+1}) \right\} - \frac{1}{R} a\sigma^2 s. \tag{6.13}$$

If the number of outside shares per trader is zero, i.e. if $s = 0$, then the equilibrium price at time t is equal to the net present value of the average expected price plus dividends at time $t + 1$.

Evolutionary dynamics

The fraction of agents who choose to invest according to belief or forecasting rule h are determined by a discrete choice model. Every agent chooses the belief with the highest fitness he observes. Individually observed fitness is derived from a random utility model and given by:

$$\widetilde{F_{j,t}^h} = F_{j,t}^h + \epsilon_{j,t}^h, \tag{6.14}$$

where $F_{j,t}^h$ is the deterministic part of the fitness measure and $\epsilon_{j,t}^h$ represents personal observational noise. If $\epsilon_{j,t}^h \neq 0$, then this model means that agent j cannot observe the true fitness $F_{j,t}^h$ of belief h perfectly, but only with some observational noise. Assuming that the noise $\epsilon_{j,t}^h$ is iid drawn across beliefs $h = 1, ..., H$ and across agents $j = 1, ..., N$ from a double exponential distribution, then the probability that agent j chooses belief h is equal to

$$q_{j,t}^h = \frac{\exp(\beta_j F_{j,t-1}^h)}{\sum_{k=1}^H \exp(\beta_j F_{j,t-1}^k)}. \tag{6.15}$$

Here β_j is called the intensity of choice, measuring how sensitive agent j is to selecting the optimal belief. The intensity of choice β_j is inversely related to the variance of the noise terms $\epsilon_{j,t}^h$. If agent j can perfectly observe the fitness of each belief in each period, then $V(\epsilon_{j,t}^h) \downarrow 0$ and $\beta_j \to \infty$ and the agent chooses the best belief with probability 1. If agent j cannot observe differences in fitness, then $V(\epsilon_{j,t}^h) \to \infty$ and $\beta_j \downarrow 0$ and the agent chooses each belief with equal probability $1/H$.

The excess profit of an agent following strategy h in period t is equal to $(P_t + D_t - RP_{t-1})\ z_{t-1}^h$. Therefore the fitness measure of strategy type h as observed by agent j is defined as

$$F_{j,t}^h = (P_t + D_t - RP_{t-1}) z_{t-1}^h - C_j^h + \eta_j F_{j,t-1}^h.$$

Here $0 \leq \eta_j \leq 1$ is the personal memory parameter and C_j^h is the average per period cost of obtaining forecasting strategy h for agent j. If $\eta_j = 1$, the memory of the agent is infinite and $F_{j,t}^h$ is equal to the cumulative excess profits of belief h until time t. In this case $F_{j,t}^h$ measures the total excess profit of the belief from the beginning of the process. If $\eta_j = 0$, the agent has no memory and $F_{j,t}^h$ is equal to the excess profit on time $t-1$. If $0 < \eta_j < 1$, then $F_{j,t}^h$ is a weighted average of past excess profits with exponentially declining weights. The higher the costs C_j^h, the more costly it is for the agent to obtain and invest according to belief h, and the more unlikely it will be that the agent chooses belief h.

BH assume that $\beta_j = \beta$, $\eta_j = \eta$ and $C_j^h = C^h$ for all agents, so that $F_{j,t}^h = F_t^h$ and $q_{j,t}^h = q_t^h$ are equal for all agents. This means that all agents have the same intensity of choice, have the same memory and face the same costs for trading. Under this assumption, in the limit, as the number of agents goes to infinity, the fraction of agents who choose to invest according to belief h converges in probability to q_t^h. Thus in the equilibrium price equation (6.13) n_t^h can be replaced by q_t^h. Furthermore, it is assumed that all agents have the same risk aversion parameter $a_j = a$, so that agents who follow the same forecasting rule have the same demand. Hence, in the end, in the heterogeneous agents model of Brock and Hommes (1998), the agents are only heterogeneous in the beliefs they can choose from.

6.3 A modified heterogeneous agents asset pricing model

6.3.1 Utility-maximizing beliefs

As in the BH model we consider a market with N agents who can select independently from each other a strategy h from a finite set of H different beliefs or forecasting rules to base trading decisions upon. Agents have to make a capital allocation decision between a risky asset P and a risk free asset F. Agent j can choose to invest at time t a fraction $y_{j,t}$ of his wealth $W_{j,t}$ in the risky asset P and a fraction $1 - y_{j,t}$ in the risk free asset F. If P_t is the price of the risky asset at time t and D_t is the dividend paid at time t, then the net return of the risky asset at time $t+1$ is defined as $r^P_{t+1} = (P_{t+1} + D_{t+1} - P_t)/P_t$ and the net risk free return is denoted by r^F and is assumed to be constant. The net return of the agent's j complete portfolio C at time $t+1$ is then equal to

$$r^c_{j,t+1} = (1 - y_{j,t})r^F + y_{j,t}r^P_{t+1} = r^F + y_{j,t}(r^P_{t+1} - r^F),$$

where $r^P_{t+1} - r^F$ is the excess return on the risky asset. In this section we derive the demand function for the risky asset if the agent has constant relative risk aversion and determines his optimal demand for the risky asset by maximizing his mean-variance utility curve on his capital allocation line. The demand function is derived under the assumption that the agent makes price predictions. In subsection 6.3.2 we present the demand function for the risky asset if the agent does not make price predictions, but only chooses to buy or sell short the asset on the basis of a technical trading strategy.

We make the following assumptions regarding the trading process. All agents are price takers. That is, an agent cannot influence the market's equilibrium price by his individual investment decision. Further, the model follows a Walrasian equilibrium price scenario. Each agent j chooses a strategy h and makes an optimal investment decision $y^h_{j,t}$ in the time interval $(t-1, t)$, before the setting of the *equilibrium* price at time t. Expectations about future prices and dividends are made on the basis of the information set of past equilibrium prices and dividends $\{P_{t-i}, D_{t-i} : i \geq 1\}$ (note that P_t and D_t

are not included). Through the market mechanism an equilibrium price is set so that the market clears. Dividends D_t paid at time t can immediately be reinvested at time t.

We define the information set $I_t = \{P_{t-i}, D_{t-i} : i \geq 1\} \cup \{P_t, D_t\}$, where $\{P_{t-i} : i \geq 1\}$ are past equilibrium prices, $\{D_{t-i} : i \geq 1\}$ are past dividends, $\{D_t\}$ is current dividend, but where $\{P_t\}$ is not yet necessarily the equilibrium price. The conditional expected portfolio return of agent j at time t who invests according to strategy h is then equal to

$$E_j^h(r_{j,t+1}^c|I_t) = E_{j,t}^h(r_{j,t+1}^c) = r^F + y_{j,t}^h E_t^h(r_{t+1}^P - r^F), \tag{6.16}$$

where $E_t^h(r_{t+1}^P - r^F)$ is the forecast belief h makes about the excess return of the risky asset at time $t+1$ conditioned on I_t. If the conditional expected excess return of belief h is positive, then the fraction invested in the risky asset is positive ($y_{j,t}^h \geq 0$) and if the conditional expected excess return is strictly negative, then the fraction invested in the risky asset is strictly negative ($y_{j,t}^h < 0$). Hence agent j with belief h can choose to buy shares or to sell shares short. Agent j does not only forecast his portfolio return but also the dispersion of the portfolio return which is equal to

$$V_j^h(r_{j,t+1}^c|I_t) = V_{j,t}^h(r_{j,t+1}^c) = (y_{j,t}^h)^2 V_t^h(r_{t+1}^P), \tag{6.17}$$

where $V_t^h(r_{t+1}^P)$ is the forecast of belief h about the dispersion of the excess return of the risky asset. Solving (6.17) for $y_{j,t}^h$ yields

$$y_{j,t}^h = \pm\sqrt{\frac{V_{j,t}^h(r_{t+1}^c)}{V_t^h(r_{t+1}^P)}} \text{ if } V_t^h(r_{t+1}^P) > 0, \tag{6.18}$$

where the $\pm$ sign depends on the conditional expected excess return of the risky asset. The capital allocation line (CAL) can be derived by substituting (6.18) in the conditional expectations equation (6.16), that is

$$E_{j,t}^h(r_{j,t+1}^c) = r^F + S_t^h\sqrt{V_{j,t}^h(r_{j,t+1}^c)} \text{ if } E_t^h(r_{t+1}^P - r^F) \geq 0; \tag{6.19}$$

$$E_{j,t}^h(r_{j,t+1}^c) = r^F - S_t^h\sqrt{V_{j,t}^h(r_{j,t+1}^c)} \text{ if } E_t^h(r_{t+1}^P - r^F) < 0; \tag{6.20}$$

$$S_t^h = \frac{E_t^h(r_{t+1}^P - r^F)}{\sqrt{V_t^h(r_{t+1}^P)}}.$$

Here $|S_t^h|$ is the reward to variability ratio, or stated differently, the extra expected return to be gained per extra point of expected risk to be taken. The CAL shows the relation between the expected return and the expected dispersion of the return. The CAL is always an increasing function of $\sqrt{V_{j,t}^h(r_{j,t+1}^c)}$. This implies that the more risk the agent expects to take, the more he expects to earn.

We assume that the agents have a constant relative risk aversion so that the utility of the capital allocation decision by agent j with belief h is given by

$$U_{j,t}^h = E_{j,t}^h(r_{j,t+1}^c) - \frac{a_j}{2}V_{j,t+1}^h(r_{j,t}^c), \tag{6.21}$$

where a_j is the risk aversion parameter of agent j. Every agent chooses an asset allocation that maximizes his utility

$$\text{Max}_{y_{j,t}^h} E_{j,t}^h(r_{j,t+1}^c) - \frac{a_j}{2}V_{j,t}^h(r_{j,t+1}^c) \text{ under CAL (6.19) or (6.20).} \tag{6.22}$$

The first order condition of (6.22) is

$$\frac{dU_{j,t}^h}{dy_{j,t}^h} = E_t^h(r_{t+1}^P - r^F) - a_j y_{j,t}^h V_t^h(r_{t+1}^P) = 0.$$

This implies that the optimal fraction of individual wealth invested in the risky asset by agent j with belief h as function of the price P_t is equal to

$$y_{j,t}^h(P_t) = \frac{E_t^h(r_{t+1}^P - r^F)}{a_j V_t^h(r_{t+1}^P)}. \tag{6.23}$$

Since the second order condition

$$\frac{d^2U_{j,t}^h}{d(y_{j,t}^h)^2} = -a_j V_t^h(r_{t+1}^P) < 0$$

is satisfied, utility is maximized. If $y_{j,t}^h > 0$, then a long position in the risky asset is held. If $y_{j,t}^h < 0$, then a short position in the risky asset is held. If we assume that all agents have the same risk aversion parameter $a_j = a$, then all agents with the same belief h invest the same fraction of their individual wealth in the risky asset. If agent j has belief h, then $y_{j,t} = y_{j,t}^h = y_t^h$, where y_t^h is the optimal fraction of wealth invested in the risky asset at time t recommended by belief h. Under the assumption that $a_j = a$ it is also true that $U_{j,t}^h = U_t^h$ for all j. Further we assume that the conditional variance $V_t^h(r_{t+1}^P) = \sigma^2$ is constant through time and equal for all beliefs. $y_t^h(P_t)$ can now be rewritten as:

$$y_t^h(P_t) = \frac{\frac{1}{P_t}E_t^h(P_{t+1} + D_{t+1}) - R}{a\sigma^2}, \tag{6.24}$$

which is a convex monotonically decreasing function of P_t. Note that we can bring P_t outside the expectations formula, because the price is not a random variable, but an equilibrium price set by the market auctioneer. Stated differently, the fraction of wealth invested in the risky asset at time t depends on the price set by the market at time t and the forecast or belief about the price at time $t + 1$, based on all available information until time t but not including P_t. Figure 6.1 illustrates the demand function of the mean-variance utility maximizing belief.

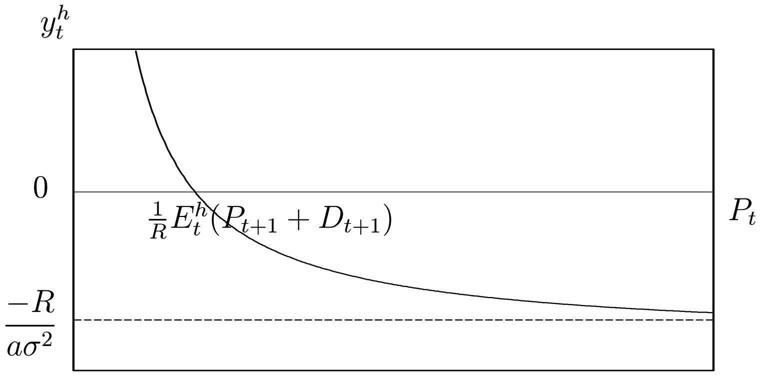


Figure 6.1: Demand function of the mean-variance utility maximizing belief

6.3.2 Non-utility-maximizing beliefs: technical traders

In subsection 6.3.1 we have derived the demand function for the risky asset under the assumptions that agents make price predictions and maximize a constant relative risk aversion utility function on a capital allocation line. However, if investors use technical trading rules, then they often do not try to make a point forecast of the price directly, but they make an investment decision based on the direction of a trend in prices. Pring (1992) defines technical analysis as the art of detecting a price trend in an early stage and maintaining a market position until there is enough weight of evidence that the trend has reversed. Thus, if we want to model technical traders, then we must define a demand function for the risky asset in another way as we did in section 6.3.1.

We take as an example the exponential moving-average trading rule. The advantage of this rule over the usual equally weighted moving-average trading rule is that it keeps the dimension of our model low. Demand functions for other technical trading rules can be derived according to the same concept. The exponential moving average at time t is equal to

$$MA_t = \mu P_t + (1-\mu)MA_{t-1} = \mu \sum_{j=0}^{t-1}(1-\mu)^j P_{t-j} + (1-\mu)^t MA_0, \tag{6.25}$$

where $0 < \mu < 1$. In this formula more recent prices get a higher weight than prices further into the past. The advantage of moving-average rules is that they follow the trend, are easy to compute and smooth an otherwise volatile series. The smaller μ, the more the moving average smoothes the price series, or stated differently, the more the moving average follows the price series at a distance. A small μ places little weight on current price and can be used to detect long term trends, while a large μ places large weight on current price and can be used to detect short term trends.

Trading signals are generated by the crossing of the price through the moving average. If the price crosses the moving average upwards, i.e. $P_t > MA_t \wedge P_{t-1} \leq MA_{t-1}$, then a buy signal is generated and at time $t+1$ a long position in the market is taken. If the price crosses the moving average downwards, i.e. $P_t < MA_t \wedge P_{t-1} \geq MA_{t-1}$, then a sell signal is generated and at time $t+1$ a short position in the market is taken. The magnitude of the position held in the market can also be conditioned on the distance between the price and the moving average. If P_t is close to MA_t, small positions should be held, because it is uncertain whether the strategy generated correct signals. It also seems reasonable to assume that if P_t is very far away from MA_t, then small positions should be held, because the price exploded too fast away from MA_t.

To satisfy above conditions the demand of the moving average forecasting rule, as a fraction of individual wealth at time t, y_t^{MA}, is defined as a continuous function of past prices and moving averages in the following way:

$$\begin{aligned} x_{t-1} &= \frac{1}{\lambda(1-\mu)}\frac{P_{t-1}-MA_{t-1}}{MA_{t-2}} = \frac{1}{\lambda}\frac{P_{t-1}-MA_{t-2}}{MA_{t-2}}; \\ y_t^{MA} &= f(x_{t-1}) = 2\gamma\frac{x_{t-1}}{1+x_{t-1}^2}, \end{aligned} \tag{6.26}$$

where $\lambda > 0, \gamma > 0$. Notice that in contrast to the fraction $y_t^h(P_t)$ in (6.24), the fraction y_t^{MA} of wealth invested by moving average traders in the risky asset does not depend upon the (unknown) market equilibrium price P_t, but only upon past price observations and moving averages.

The demand function (6.26) has the following properties (see figure 6.2 for illustration):

- $y_t^{MA} < 0$ if $P_{t-1} < MA_{t-1}$
- $y_t^{MA} = 0$ if $P_{t-1} = MA_{t-1}$
- $y_t^{MA} > 0$ if $P_{t-1} > MA_{t-1}$
- $\lim\limits_{P_{t-1}\to\infty} y_t^{MA} = 0$
- $\lim\limits_{P_{t-1}\downarrow 0} y_t^{MA} = -2\gamma\,\dfrac{\lambda}{1+\lambda^2}$
- $\dfrac{dy_t^{MA}}{dP_{t-1}} = 2\gamma\left(\dfrac{1}{\lambda MA_{t-2}}\right)\dfrac{1-x^2}{(1+x^2)^2}$
- minimum: $(P_{t-1}, y_t^{MA}) = ((1-\lambda)MA_{t-2},\ -\gamma)$
- maximum: $(P_{t-1}, y_t^{MA}) = ((1+\lambda)MA_{t-2},\ \gamma)$

The parameter γ controls for the maximum and minimum fraction of wealth the technical trader can invest in the risky asset. The parameter λ controls for the location of the extrema. Within some band around the moving average, which depends on the value of λ, y_t^{MA} increases (or decreases) to a maximum (or minimum) value γ (or -γ). Outside this band the further away price deviates from the moving average, the more y_t^{MA} decreases in absolute value.

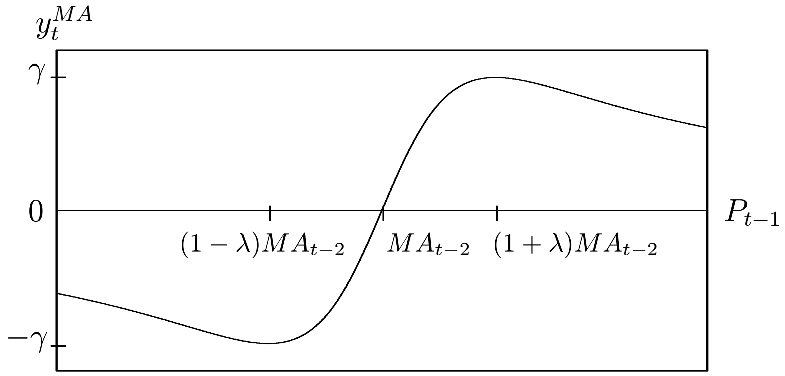


Figure 6.2: Demand function exponential moving average belief

6.3.3 Market equilibrium

Wealth per agent, total wealth and market clearing

The number of shares agent j who follows belief h holds in the risky asset at time t depends on his individual wealth and the equilibrium price, that is

$$z_{j,t}^h = \frac{y_t^h W_{j,t}}{P_t}. \tag{6.27}$$

Here $W_{j,t}$ is the wealth of agent j at time t, which depends on the fraction of the wealth invested at time $t-1$, that is

$$\begin{aligned} W_{j,t} = \; & \left(1 + r^F + y_{j,t-1}(r_t^P - r^F)\right) W_{j,t-1} = \\ & \left(1 + r^F + y_{j,t-1}\left(\frac{P_t + D_t}{P_{t-1}} - (1 + r^F)\right)\right) W_{j,t-1} = \\ & RW_{j,t-1} + (P_t + D_t - RP_{t-1}) \; \frac{y_{j,t-1}W_{j,t-1}}{P_{t-1}} = \\ & RW_{j,t-1} + (P_t + D_t - RP_{t-1})\, z_{j,t-1}. \end{aligned} \tag{6.28}$$

The total wealth of all N agents at time t is equal to

$$\begin{aligned} W_t = \; & \textstyle\sum_{j=1}^N W_{j,t} = \\ & R\textstyle\sum_{j=1}^N W_{j,t-1} + (P_t + D_t - RP_{t-1})\textstyle\sum_{j=1}^N z_{j,t-1} = \\ & RW_{t-1} + (P_t + D_t - RP_{t-1})s = \\ & R(W_{t-1} - sP_{t-1}) + sD_t + sP_t, \end{aligned} \tag{6.29}$$

where s is the total number of shares available to trade. $R(W_{t-1} - sP_{t-1}) + sD_t$ is the total amount of money invested in the risk free asset and sP_t is the total amount of money invested in the risky asset by all agents at time t. If the total initial market wealth is equal to W_0, then the total wealth at time t is equal to

$$\begin{aligned} W_t = \; & R^t(W_0 - sP_0) + s\textstyle\sum_{i=0}^{t-1}(R^i D_{t-i}) + sP_t = \\ & (W_0 - sP_0) + \textstyle\sum_{i=0}^{t-1}\left(R^i(r^F(W_0 - sP_0) + sD_{t-i})\right) + sP_t. \end{aligned} \tag{6.30}$$

Naturally $D_t \geq 0$ at each date. Suppose that $W_0 = M + sP_0$, then the total amount of money invested in the risk free asset, $W_t - sP_t$, at time t is greater than or equal to zero for $t = 0, ..., T$, if the initial amount of money invested in the risk free asset, M, is positive. We assume throughout this chapter that $M \geq 0$.

We assume that at time t each of the N agents hands over his demand function (6.27) for the risky asset to a market auctioneer. The auctioneer collects the demand functions and computes the final equilibrium price P_t so that the market clears. Equilibrium of demand and supply so that the market clears yields

$$\sum_{j=1}^N z_{j,t} = \sum_{h=1}^H \left(\sum_{j \,\in\, \text{belief h}} z_{j,t}^h \right) = s. \tag{6.31}$$

By substituting (6.27) in (6.31) the equilibrium equation (6.31) can be rewritten as

$$\begin{aligned} & \sum_{h=1}^H \left(\sum_{j \,\in\, \text{belief h}} \frac{y_t^h W_{j,t}}{P_t} \right) = \sum_{h=1}^H \left(\frac{y_t^h}{P_t} \sum_{j \,\in\, \text{belief h}} W_{j,t} \right) = \sum_{h=1}^H \left(\frac{y_t^h W_t^h}{P_t} \right) = s, \\ & \text{or equivalently} \sum_{h=1}^H \left(y_t^h W_t^h \right) = sP_t. \end{aligned} \tag{6.32}$$

Here W_t^h is the total wealth of all agents who use forecasting rule h at time t. Recall that the demand y_t^h is a function of P_t. To solve the equilibrium equation (6.32) for P_t, we first have to determine how much wealth is assigned to each belief, W_t^h, by all agents. In Appendix B we show that under the assumption that at date $t = 0$ wealth is equally divided among agents and under the assumption that each agent has zero market power at each date, it is true that the fraction of total wealth invested according to belief h at time t converges in probability to the probability that an agent chooses belief h, that is

$$\frac{W_t^h}{W_t} \xrightarrow{p} q_t^h. \tag{6.33}$$

Notice that we use slightly different choice probabilities as in (6.15) by introducing a lower bound on the probabilities as motivated by Westerhoff (2002); see Appendix B for details.

The heterogeneous agents model equilibrium equation

Now that we have shown that the fraction of total market wealth invested according to a certain belief converges in probability to the probability that the belief is chosen, we can solve equation (6.32) for P_t to get the equilibrium price. Equilibrium equation (6.32) can be rewritten as

$$\sum_{h=1}^{H}\left(\frac{y_t^h \frac{W_t^h}{W_t} W_t}{P_t}\right) \xrightarrow{p} \sum_{h=1}^{H}\left(\frac{y_t^h q_t^h W_t}{P_t}\right) = s,$$

or equivalently

$$\sum_{h=1}^{H} y_t^h q_t^h = \frac{sP_t}{W_t}. \tag{6.34}$$

The left hand side of equation (6.34) is the demand for the risky asset as a fraction of total wealth, while the right hand side is the worth of the supply of shares as a fraction of the total wealth. Using (6.29) the right hand side can be rewritten to

$$S(P_t) = \frac{P_t}{R\left(\frac{W_{t-1}}{s} - P_{t-1}\right) + D_t + P_t}.$$

The first and second derivative of the supply function $S(P_t)$ are equal to

$$\frac{dS(P_t)}{dP_t} = \frac{c}{(c+P_t)^2};$$

$$\frac{d^2S(P_t)}{dP_t^2} = \frac{-2c(c+P_t)}{(c+P_t)^4},$$

where $c = R\left(\frac{W_{t-1}}{s} - P_{t-1}\right) + D_t$ is the amount of money invested in the risk free asset per risky share. We assume that $c > 0$ (see also equation (6.30)). Thus for $P_t \geq 0$ the supply function is a continuous monotonically increasing and concave function of P_t which starts at 0 and converges to 1 as P_t goes to infinity. Notice that this equals the total fraction of wealth invested in the risky asset, which means that the market as a whole never borrows from an outside supplier of money, but that borrowing and lending occurs within the market.

Recall that for the utility maximizing agents the demand as a fraction of individual wealth, y_t^h, in (6.24) is a decreasing function of P_t. For the non utility maximizing agents y_t^h does not depend on P_t, but only on past prices. Hence the left hand side of equilibrium equation (6.34) is a decreasing function of P_t. Although the right hand side of (6.34) is an increasing function of P_t, some additional restrictions for the demand of the non utility maximizing agents must hold for a unique positive equilibrium price to exist. This will be shown in the next section.

The equilibrium price

We split the set of beliefs or forecasting rules the agents can choose from in a set B_1 of utility maximizing beliefs based upon price predictions and the set B_2 of non utility maximizing beliefs, not using price predictions but technical trading strategies. Equation (6.34) can then be rewritten as

$$\sum_{h \in B_1} q_t^h y_t^h + \sum_{h \in B_2} q_t^h y_t^h = \frac{sP_t}{W_t}. \tag{6.35}$$

If the supply of outside shares is equal to zero, i.e. $s = 0$, then substituting (6.24) in (6.35) to solve for P_t yields

$$P_t = \frac{1}{R - a\sigma^2 \frac{\sum_{h \in B_2} q_t^h y_t^h}{\sum_{h \in B_1} q_t^h}} \sum_{h \in B_1} \frac{q_t^h}{\sum_{h \in B_1} q_t^h} E_t^h(P_{t+1} + D_{t+1}). \tag{6.36}$$

Several assumptions have to be made for the equilibrium price to exist. First we have to assume that there is a belief $h \in B_1$ for which $q_t^h > 0$. If for all beliefs $h \in B_1$: $q_t^h = 0$, then there is no solution for P_t. Further, for the equilibrium equation to be solvable for P_t an upperbound has to be posed on the fraction of total market wealth the technical traders in B_2 can go long in the risky asset. If $s = 0$, then according to equilibrium equation (6.35) the fraction of total market wealth traders in belief group B_2 go long is equal to the fraction of total market wealth traders in belief group B_1 go short, that is

$$\sum_{h \in B_2} q_t^h y_t^h = -\sum_{h \in B_1} q_t^h y_t^h.$$

Because of the characteristics of the demand function (6.24) for the risky asset, traders in belief group B_1 are restricted in the fraction of individual wealth they can go short, that is

$$-\frac{R}{a\sigma^2} < y_t^h < \infty.$$

This implies that there is an upperbound on the fraction of total wealth traders in belief group B_2 can go long, that is

$$\sum_{h \in B_2} q_t^h y_t^h = -\sum_{h \in B_1} q_t^h y_t^h < \frac{R}{a\sigma^2} \sum_{h \in B_1} q_t^h.$$

This restriction implies that the denominator of the ratio in the first part of the right hand side of (6.36) is positive. There is a positive equilibrium price in the case of zero supply of outside stocks, because price and dividend expectations are restricted to be always positive. If $B_2 = \emptyset$, then $\sum_{h \in B_2} (q_t^h y_t^h) = 0$ and the equilibrium price is equal to the net present value of the average of the expected price plus dividend by the traders in belief group B_1. This is the same solution for the equilibrium price as in the BH model. For $s = 0$ as in the BH model, wealth plays no role anymore. For every short position there must be an offsetting long position. If the gross risk free rate under borrowing and lending is always equal to R, then wealth at time t is just equal to $W_t = RW_{t-1}$.

The derivation of the equilibrium price for a strictly positive supply of outside shares, i.e. if $s > 0$, is presented in Appendix C.

The EMH benchmark with rational agents

In a world where all agents are identical, expectations are homogeneous and all traders are risk neutral, i.e. $a \downarrow 0$, equilibrium equation (6.36) in the case of $s = 0$ and equilibrium equation (6.61) in the case of $s > 0$ both reduce to

$$P_t = \frac{1}{R} E_t(P_{t+1} + D_{t+1}). \tag{6.37}$$

This arbitrage market equilibrium equation states that today's price of the risky asset must be equal to the sum of tomorrow's expected price and expected dividend, discounted by the risk-free interest rate. The arbitrage equation (6.37) can be used recursively to derive the price at time t

$$P_t = \frac{E_t(P_{t+k})}{R^k} + \sum_{j=1}^{k} \frac{E_t(D_{t+j})}{R^j}. \tag{6.38}$$

If the transversality condition

$$\lim_{k \to \infty} \frac{E_t(P_{t+k})}{R^k} = 0,$$

holds, which means that the long run growth rate of price is less than the discount rate r^f, then the price is equal to the net present value of all future dividends

$$P_t^* = \lim_{k\to\infty} \sum_{j=1}^{k} \frac{E_t(D_{t+j})}{R^j}.$$

This price is called the efficient markets hypothesis (EMH) fundamental rational expectations price, or fundamental price for short.

We will focus on the case where for all beliefs h expectations on dividend are equal: $E_t^h(D_{t+1}) = E_t(D_{t+1})$ and where the dividend process is iid with mean $\overline{D}$. The fundamental price is then constant and equal to

$$P^* = \frac{\overline{D}}{r}.$$

6.3.4 A heterogeneous agents model with fundamentalists versus moving average traders

Utility maximizing belief: the fundamental trader

Fundamentalists expect that prices return to the fundamental value with speed v, that is

$$E_t^{fund}(P_{t+1}) = P^* + v(P_{t-1} - P^*),\ 0 \leq v \leq 1.$$

If $v = 1$, then the fundamental traders make naive price expectations and if $v = 0$, then the fundamental traders expect the price to be always equal to the fundamental value. The fraction of individual wealth invested in the risky asset is then equal to

$$y_t^{fund}(P_t) = \frac{\frac{1}{P_t}E_t(P_{t+1} + D_{t+1}) - R}{a\sigma^2} = \frac{\frac{1}{P_t}(P^* + v(P_{t-1} - P^*) + \overline{D}) - R}{a\sigma^2},$$

where $a > 0$, $\sigma^2 > 0$ and $R = 1 + r^f > 1$.

Non utility maximizing belief: the exponential moving average trader

Moving average traders buy (sell) if the price crosses the moving average from below (above). We use the exponential moving average $MA_t = \mu P_t + (1-\mu)MA_{t-1}$, where the exponential smoothing constant $0 < \mu < 1$. The fraction of individual wealth invested in the risky asset is then equal to

$$y_t^{ma} = 2\gamma \frac{x_{t+1}}{1 + x_{t+1}^2}, \text{where } x_{t+1} = \frac{1}{\lambda}\frac{P_{t-1} - MA_{t-2}}{MA_{t-2}}, \gamma > 0 \text{ and } \lambda > 0.$$

6.3.5 The dynamical system

Using equations (6.36), (6.25) and (6.52) and setting $\widehat{MA}_t = MA_{t-1}$ and $\hat{F}_t^h = F_{t-1}^h$ the following dynamical system for $s = 0$ is obtained

$$P_t(P_{t-1}, \widehat{MA}_{t-1}, \hat{F}_t^{fund}, \hat{F}_t^{ma});$$

$$\widehat{MA}_t = \mu P_{t-1} + (1-\mu)\widehat{MA}_{t-1};$$

$$\hat{F}_t^h = r^F + y_{t-2}^h(r_{t-1}^P - r^F) + \eta \hat{F}_{t-1}^h, \text{ for } h = (fund, ma).$$

Introducing new variables $P_{i,t-1} = P_{t-i}$ and $\widehat{MA}_{i,t-1} = \widehat{MA}_{t-i}$ the following eight dimensional dynamical system is derived from the above equations

$$P_{1,t} = \frac{q_t^{fund}}{q_t^{fund} R - a\sigma^2 q_t^{MA} y_t^{MA}}(P^* + v(P_{1,t-1} - P^*) + \overline{D});$$

$$P_{2,t} = P_{1,t-1};$$

$$P_{3,t} = P_{1,t-2} = P_{2,t-1};$$

$$\widehat{MA}_{1,t} = \mu P_{1,t-1} + (1-\mu)\widehat{MA}_{1,t-1};$$

$$\widehat{MA}_{2,t} = \widehat{MA}_{1,t-1};$$

$$\widehat{MA}_{3,t} = \widehat{MA}_{1,t-2} = \widehat{MA}_{2,t-1};$$

$$\hat{F}_t^{fund} = r^F + y_{t-2}^{fund}\ (\frac{P_{1,t-1} + D_{t-1}}{P_{2,t-1}} - R) - C^{fund} + \eta \hat{F}_{t-1}^{fund};$$

$$\hat{F}_t^{ma} = r^F + y_{t-2}^{ma}\ (\frac{P_{1,t-1} + D_{t-1}}{P_{2,t-1}} - R) - C^{ma} + \eta \hat{F}_{t-1}^{ma},$$

where

$$D_t = \overline{D} + \delta_t;\ \delta_t \sim N(0, \sigma_\delta^2);$$

$$P^* = \tfrac{\overline{D}}{r^F};$$

$$q_t^{ma} = 1 - q_t^{fund}\ ,\ q_t^{fund} = m^{fund} + (1 - m^{fund} - m^{ma})\ \widetilde{q}_t^{fund},$$

$$\widetilde{q}_t^{fund} = \frac{\exp(\beta\ \hat{F}_t^{fund})}{\exp(\beta\ \hat{F}_t^{fund}) + \exp(\beta\ \hat{F}_t^{ma})};$$

$$y_t^{ma} = 2\gamma \frac{x_{t-1}}{1 + x_{t-1}^2}\ ,\ x_{t-1} = \frac{1}{\lambda}\frac{P_{1,t-1} - \widehat{MA}_{1,t-1}}{\widehat{MA}_{1,t-1}};$$

$$y_{t-2}^{fund} = \frac{\frac{1}{P_{t-2}}(P^* + v(P_{t-3} - P^*) + \overline{D}) - R}{a\sigma^2} = \frac{\frac{1}{P_{2,t-1}}(P^* + v(P_{3,t-1} - P^*) + \overline{D}) - R}{a\sigma^2};$$

$$y_{t-2}^{ma} = 2\gamma \frac{x_{t-3}}{1+x_{t-3}^2}\ ,\ x_{t-3} = \frac{1}{\lambda}\frac{P_{t-3} - \widehat{MA}_{1,t-3}}{\widehat{MA}_{1,t-3}} = \frac{1}{\lambda}\frac{P_{3,t-1} - \widehat{MA}_{3,t-1}}{\widehat{MA}_{3,t-1}}.$$

Here m^{fund} and m^{ma} are the minimum probabilities with which the fundamental and moving average forecasting rule are chosen; see Appendix B for details. The parameter set is given by

$$\begin{aligned}\Theta = \{\ & a > 0,\ \sigma^2 > 0,\ R > 1,\ \beta > 0,\ 0 \leq v \leq 1,\ 0 < \mu < 1,\ \gamma > 0, \\ & \lambda > 0,\ 0 \leq \eta \leq 1,\ m^{fund} \geq 0,\ m^{ma} \geq 0,\ 0 \leq m^{fund} + m^{ma} \leq 1, \\ & C^{fund} \geq C^{ma} \geq 0\ \}.\end{aligned}$$

The difference in probability with which the fundamental and moving average belief are chosen is equal to

$$q_t^{fund} - q_t^{ma} = (m^{fund} - m^{ma}) + (1 - m^{fund} - m^{ma}) \tanh\left(\frac{\beta}{2}\left(\hat{F}_t^{fund} - \hat{F}_t^{ma}\right)\right).$$

As can be seen in the above formula, the higher the difference in fitness in favour of the fundamental belief, the higher the difference in probability in favour of the fundamental belief. The fraction of agents who choose the fundamental believe is restricted to be strictly positive $q_t^{fund} > 0$, since otherwise there is no solution for the equilibrium price. This condition will be automatically satisfied, even if $m^{fund} = 0$, because of the discrete choice model probabilities which for finite β are always strictly positive[2]. Furthermore, the following condition should hold for the fraction of total market wealth the moving average traders invest in the risky asset

$$q_t^{ma} y_t^{ma} < q_t^{fund} \frac{R}{a\sigma^2},$$

for otherwise there is also no solution for the equilibrium price.

Note that

$$\lim_{\sigma^2 \downarrow 0} P_{1,t} = \lim_{a \downarrow 0} P_{1,t} = \lim_{q_t^{ma} \downarrow 0} P_{1,t} = \lim_{y_t^{ma} \downarrow 0} P_{1,t} = \frac{1}{R} E_t^{fund}(P_{t+1} + D_{t+1}). \tag{6.39}$$

Hence, if the conditional variance or the risk aversion of the fundamental belief goes to zero, or if the fraction of wealth invested by the moving average belief goes to zero, then the equilibrium price is equal to the discounted value of the expectation of tomorrow's price and dividend of the fundamental belief.

[2]However, if $\hat{F}_t^{ma} - \hat{F}_t^{fund}$ becomes large which causes $q_t^{fund} \downarrow 0$, this can cause numerical problems in computing the market equilibrium price, because of floating point errors in the computer simulations. These problems are avoided by placing a lower bound $m^{fund} > 0$ on the probability with which the fundamental belief is chosen.

We define the vector variable

$$z_t = (P_{1,t}, P_{2,t}, P_{3,t}, \widehat{MA}_{1,t}, \widehat{MA}_{2,t}, \widehat{MA}_{1,t}, \widehat{F}_t^{fund}, \widehat{F}_t^{ma})'.$$

In the following we denote the dynamical system by Φ, where

$$z_t = \Phi(z_{t-1}).$$

Additive dynamic noise can be introduced into the system to obtain

$$z_t = \Phi(z_{t-1}) + \boldsymbol{\epsilon}_t,$$

where $\boldsymbol{\epsilon}_t = (\epsilon_t, 0, 0, 0, 0, 0, 0, 0)'$ are iid random variables representing the model approximation error in that our model can only be an approximation of the real world. Because we assumed for all beliefs

$$V_t^h(r_{t+1}^P) = V_t^h\left(\frac{P_{t+1} + D_{t+1} - P_t}{P_t}\right) = \sigma^2$$

and because P_{t+1} and D_{t+1} are independent, this implies

$$V_t^h(P_{t+1}) = P_t^2\sigma^2 - V_t^h(D_{t+1}) = P_t^2\sigma^2 - \sigma_\delta^2.$$

Therefore, when we add dynamic noise to the deterministic skeleton, we draw ϵ_t iid from a normal distribution with expectation 0 and variance

$$\sigma_{\epsilon_t}^2 = P_t^2\sigma^2 - \sigma_\delta^2.$$

6.4 Trading volume

In this section we describe a procedure to determine trading volume. The total number of short or long positions transferred from belief b to belief h at time t converges in probability to $z_{t-1}^b q_t^h$ as the number of agents, each having zero market power, converges to infinity. The total number of long and short positions transferred to belief h from the other beliefs converges then in probability to

$$\begin{aligned} &\#long_t(\rightarrow h) \xrightarrow{p} \textstyle\sum_{b=1}^H z_{t-1}^b\ q_t^h\ I(z_{t-1}^b \geq 0); \\ &\#short_t(\rightarrow h) \xrightarrow{p} |\ \textstyle\sum_{b=1}^H z_{t-1}^b\ q_t^h\ I(z_{t-1}^b < 0)\ |, \end{aligned} \tag{6.40}$$

where $I(.)$ is the indicator function. The demand for shares of each belief, under the equilibrium price which is set by the auctioneer, is equal to

$$z_t^h = \frac{y_t^h W_t^h}{P_t} \xrightarrow{p} \frac{y_t^h q_t^h W_t}{P_t}.$$

The turnover of shares in belief h we define to be equal to

$$\begin{aligned} &\text{if } z_t^h > 0 \text{ then } Vol_t^h = |z_t^h - \#long_t(\to h)| + |\#short_t(\to h)|; \\ &\text{if } z_t^h < 0 \text{ then } Vol_t^h = |z_t^h + \#short_t(\to h)| + |\#long_t(\to h)|; \\ &\text{if } z_t^h = 0 \text{ then } Vol_t^h = |\#long_t(\to h)| + |\#short_t(\to h)|. \end{aligned} \tag{6.41}$$

The total turnover of shares is equal to

$$Vol_t = \sum_{h=1}^{H} Vol_t^h,$$

doubly counted. For example, if belief h advises to hold a long position in the market at time t, then first it is determined how many long positions are transferred to belief h from the other beliefs at time t. The change in long positions is given by $|z_t^h - \#long_t(\to h)|$. This gives the (minimum) number of stock positions sold or bought to reach the new long position from the old long position. Because a long position in the market is held, the short positions transferred to belief h must be closed, which gives an extra volume of $|\#short_t(\to h)|$. Adding the two turnovers together yields the total trading volume in belief h, in the case $z_t^h > 0$. The other cases in (6.41) have a similar explanation.

6.5 Stability analysis

6.5.1 Steady state

For the system to be in the steady state it is required that the memory parameter is restricted to $0 \leq \eta < 1$, thus we assume finite memory. A variable x at its steady state will be denoted by $\bar{x}$. A steady state for the map Φ is a point $\bar{z}$ for which $\Phi(\bar{z}) = \bar{z}$. Hence in the steady state $\overline{MA} = \mu\overline{P} + (1-\mu)\overline{MA}$, implying $\overline{P} = \overline{MA}$. Furthermore, $\overline{P} = \overline{MA}$, implies $\overline{y}^{MA} = 0$ and hence $\overline{F}^{ma} = \frac{r^F - C^{ma}}{1-\eta}$. Thus the steady state price of the risky asset is equal to the steady state exponential moving average of the price. This relation implies that the steady state demand of the moving average belief is equal to zero.

The steady state price must satisfy $\overline{P} = \frac{1}{R}(P^* + v(\overline{P} - P^*) + \overline{D})$, where $P^* = \frac{\overline{D}}{r^f}$ is the fundamental price. This implies that $\overline{P} = P^*$, $\overline{y}^{fund} = 0$ and $\overline{F}^{fund} = \frac{r^F - C^{fund}}{1-\eta}$. As for the moving average belief, also the steady state demand of the fundamental belief is equal to zero.

In the steady state the difference in probability with which both beliefs are chosen is equal to

$$\bar{q}^{fund} - \bar{q}^{ma} = (m^{fund} - m^{ma}) + (1 - m^{fund} - m^{ma}) \tanh\left(\frac{-\beta}{2(1-\eta)}(C^{fund} - C^{ma})\right).$$

If $m^{fund} = m^{ma} = 0$, then because $C^{fund} \geq C^{ma} \geq 0$, we have that $\bar{q}^{fund} \leq \bar{q}^{ma}$. Thus, if no lower bound is imposed on the discrete choice probabilities, then at the steady state the fundamental belief is chosen with smaller probability than the moving average belief if the costs of the fundamental belief are higher than the costs of the moving average belief. Because $\bar{q}^{fund} + \bar{q}^{ma} = 1$, the steady state probabilities are equal to

$$\bar{q}^{fund} = \frac{1}{2}\left(1 + (m^{fund} - m^{ma}) + (1 - m^{fund} - m^{ma}) \tanh\left(\frac{-\beta}{2(1-\eta)}(C^{fund} - C^{ma})\right)\right),$$

$$\bar{q}^{ma} = 1 - \bar{q}^{fund}.$$

6.5.2 Local stability of the steady state

The local behavior of the dynamical system $z_t = \Phi(z_{t-1})$ around the steady state $\bar{z}$ is equivalent to the behavior of the linearized system

$$(z_t - \bar{z}) = \left.\frac{d\Phi(z_{t-1})}{dz_{t-1}}\right|_{z_{t-1}=\bar{z}} (z_{t-1} - \bar{z}) = \bar{J}\,(z_{t-1} - \bar{z}),$$

if none of the eigenvalues of the Jacobian matrix $\bar{J}$ lies on the unit circle. Hence we can study the dynamical behavior of the system for different parameter values by calculating the eigenvalues of $\bar{J}$. The steady state $\bar{z}$ is locally stable if all eigenvalues lie within the unit circle and becomes unstable if one of the eigenvalues crosses the unit circle. At this point a bifurcation, a qualitative change in dynamical behavior, occurs.

A straightforward computation shows that the Jacobian matrix of Φ at the steady state $\bar{z}$ is equal to

$$\bar{J} = \begin{bmatrix} \frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}} & 0 & 0 & \frac{-2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}} & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \mu & 0 & 0 & 1-\mu & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \eta & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \eta \end{bmatrix}.$$

The characteristic polynomial of $\bar{J}$ evaluated at the steady state is equal to

$$p(\xi) = |\bar{J} - \xi I| = \\ \xi^4(\eta - \xi)^2 \left(\xi^2 - (1 - \mu + \frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R} \frac{\bar{q}^{ma}}{\bar{q}^{fund}})\xi + (1-\mu)\frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R} \frac{\bar{q}^{ma}}{\bar{q}^{fund}} \right). \tag{6.42}$$

Thus the eigenvalues of $\bar{J}$ are 0 (with algebraic multiplicity 4), η (with algebraic multiplicity 2) and the roots ξ_1, ξ_2 of the quadratic polynomial in the last bracket. Note that these roots satisfy the relations

$$\xi_1 + \xi_2 = 1 - \mu + \frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R} \frac{\bar{q}^{ma}}{\bar{q}^{fund}} \quad \text{and} \quad \xi_1\xi_2 = (1-\mu)\frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R} \frac{\bar{q}^{ma}}{\bar{q}^{fund}}, \tag{6.43}$$

because

$$(\xi - \xi_1)(\xi - \xi_2) = \xi^2 - (\xi_1 + \xi_2)\xi + \xi_1\xi_2. \tag{6.44}$$

Also note that because memory cannot be infinite in the steady state (i.e. $0 \leq \eta < 1$), the stability of the steady state is entirely determined by the absolute values of ξ_1 and ξ_2. Furthermore, if there is no difference in costs between implementing the fundamental or moving-average strategy, that is $C^{ma} - C^{fund} = 0$, then $\bar{q}^{ma}$ and $\bar{q}^{fund}$ are independent of the intensity of choice parameter β and hence the local stability of the steady state of the heterogeneous agents model is independent of β.

We have seen in (6.39) that if the risk aversion, a, or if the expected dispersion of the return of the fundamental belief, σ^2, goes to zero, then the equilibrium price is entirely determined by the fundamental belief. Now, using (6.42), we find

$$\lim_{a \downarrow 0} p(\xi) = \lim_{\sigma^2 \downarrow 0} p(\xi) = \xi^4(\eta - \xi)^2(\xi - \frac{v}{R})(\xi - (1-\mu)), \tag{6.45}$$

so that the eigenvalues are equal to 0, η, $\frac{v}{R}$ and $(1-\mu)$. Because $R > v$ all eigenvalues lie within the unit circle. Hence, in this limiting case, the fundamental steady state is locally stable, because near the fundamental steady state fundamental traders exploit all profit opportunities, driving the price back to the fundamental value.

6.5.3 Bifurcations

A bifurcation is a qualitative change in the dynamical behavior of the system when varying the value of one of the parameters. Bifurcations occur for example, if one of the eigenvalues of the linearized system in the steady state crosses the unit circle. We are now going to investigate local bifurcations of the steady state.

Eigenvalue equal to 1

If one of the eigenvalues crosses the unit circle at 1, a saddle-node bifurcation may arise in which a pair of steady states, one stable and one saddle, is created. Another possibility is that a pitchfork bifurcation arises in which two additional steady states are created. The only possibility for an eigenvalue to be equal to one is that one of the solutions, ξ_j, of the quadratic polynomial in (6.44) is equal to 1, say $\xi_2 = 1$. Then it follows from (6.43) that

$$\xi_1 + 1 = 1 - \mu + \frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}} \quad \text{and} \quad \xi_1 = (1-\mu)\frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}}.$$

Eliminating ξ_1 from these equations leads to the condition

$$R = v.$$

However, since $0 \leq v \leq 1 < R$, this condition can never be satisfied. Hence eigenvalues equal to 1 can never occur.

Eigenvalue equal to -1

If one of the eigenvalues crosses the unit circle at -1, a period doubling or flip bifurcation may arise in which a 2-cycle is created. Under the assumption that $\xi_2 = -1$, equations (6.43) lead to the relations

$$\xi_1 - 1 = 1 - \mu + \frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}} \quad \text{and} \quad -\xi_1 = (1-\mu)\frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}}.$$

Eliminating ξ_1 leads to the condition

$$\lambda(\mu - 2)(R + v) = 4a\gamma\sigma^2\frac{\bar{q}^{ma}}{\bar{q}^{fund}}.$$

Since all parameters in the model are strictly positive and because $-2 < \mu - 2 < -1$, the left hand side of this condition is strictly negative. However the right hand side of the condition is strictly positive, so that this condition can never be satisfied. Hence eigenvalues equal to -1 and therefore period doubling bifurcations of the steady state can never occur.

Two complex conjugate eigenvalues of modulus 1

If a pair of complex conjugate eigenvalues crosses the unit circle in the complex plane, a Hopf or Neimark-Sacker bifurcation may arise in which an invariant circle with periodic or quasi-periodic dynamics is created. The roots ξ_1, ξ_2 of the characteristic equation are complex conjugate of modulus 1 if $\xi_1\xi_2 = 1$ and $|\xi_1 + \xi_2| < 2$. Using (6.43) this leads to the conditions

$$(1-\mu)\frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}} = 1 \quad \text{and} \quad |1-\mu+\frac{v}{R} + \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}}| < 2. \tag{6.46}$$

Substituting the first condition in the second yields

$$|2-\mu\left(1-\frac{v}{R}\right)| < 2.$$

For $0 < \mu < 1$ and $0 \leq v \leq 1 < R$ this condition is always satisfied. Hence for parameters satisfying the first condition a Hopf bifurcation should occur. However, when solving the first condition for β, η, v or μ it turns out that not always a Hopf bifurcation occurs when varying one of these four parameters while keeping the other parameters constant, because for these parameters additional restrictions apply.

When solving the first condition for the risk aversion parameter a a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash a$ if a_H satisfies

$$a_H = \left(1-(1-\mu)\frac{v}{R}\right)\frac{\lambda R}{2\gamma\sigma^2}\frac{\bar{q}^{fund}}{\bar{q}^{ma}} > 0.$$

When solving the first condition for the intensity of choice parameter β a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash\beta$ and $C^{fund} > C^{ma}$ if β_H satisfies

$$\beta_H = \frac{1-\eta}{C^{fund}-C^{ma}}\ln(c),$$

where c is defined as

$$c = \frac{b(1-m^{ma})-m^{ma}}{(1-m^{fund})-bm^{fund}}\text{ ,with } b = \left(\left(1-(1-\mu)\frac{v}{R}\right)\frac{\lambda R}{2a\gamma\sigma^2}\right) > 0.$$

However, because $\beta \geq 0$, there are possibly cases for which no Hopf bifurcation occurs, when varying β and keeping the other parameters constant if the logarithm $\ln(c)$ is taken over a value smaller than one.

When solving the first condition for the memory parameter η a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash\eta$ if η_H satisfies

$$\eta_H = 1 - \frac{\beta(C^{fund}-C^{ma})}{\ln(c)}.$$

However, because $0 \leq \eta < 1$, there are cases for which no Hopf bifurcation occurs, when varying η and keeping the other parameters constant.

When solving for the expected dispersion in return parameter σ^2 a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash\sigma^2$ if σ^2_H satisfies

$$\sigma^2_H = \left(1-(1-\mu)\frac{v}{R}\right)\frac{\lambda R}{2a\gamma}\frac{\bar{q}^{fund}}{\bar{q}^{ma}} > 0.$$

When solving for the gross risk-free interest rate parameter R a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash R$ if R_H satisfies

$$R_H = \frac{2a\gamma\sigma^2}{\lambda\left(1-(1-\mu)\frac{v}{R}\right)}\frac{\bar{q}^{ma}}{\bar{q}^{fund}}.$$

Because $R > 1$, there are possibly cases for which no Hopf bifurcation occurs, when varying R and keeping the other parameters constant.

When solving the first condition for the fundamental belief parameter v a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash v$ if v_H satisfies

$$v_H = \frac{R}{1-\mu}\left(1-\frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}}\right).$$

Again however, because $0 \leq v \leq 1$, there are cases for which no Hopf bifurcation occurs, when varying v and keeping the other parameters constant.

When solving the first condition for the exponential moving average parameter μ a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash\mu$ and $v > 0$ if μ_H satisfies

$$\mu_H = 1-\frac{R}{v}+\frac{2a\gamma\sigma^2}{\lambda v}\frac{\bar{q}^{ma}}{\bar{q}^{fund}},$$

and where v should additionally satisfy $0 < v \leq 1$. Now also, because $0 < \mu < 1$, there are cases for which no Hopf bifurcation occurs, when varying μ and keeping the other parameters constant.

When solving for the moving average belief parameter γ a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash\gamma$ if γ_H satisfies

$$\gamma_H = \left(1-(1-\mu)\frac{v}{R}\right)\frac{\lambda R}{2a\sigma^2}\frac{\bar{q}^{fund}}{\bar{q}^{ma}} > 0.$$

When solving for the moving average belief parameter λ a Hopf bifurcation occurs given the parameter set $\{\Theta\}\backslash\lambda$ if λ_H satisfies

$$\lambda_H = \frac{2a\gamma\sigma^2}{R\left(1-(1-\mu)\frac{v}{R}\right)}\frac{\bar{q}^{ma}}{\bar{q}^{fund}} > 0.$$

Hence when one of the parameters a, σ^2, γ or λ is varied while keeping the other parameters constant, a Hopf bifurcation always arises for some parameter value.

If the Jacobian matrix of Φ at the steady state $\bar{z}$ has two complex conjugate eigenvalues, $\xi_1 = c + di$ and $\xi_2 = c - di$, then the price series, and therefore also the exponential moving average series, follows a wavelike pattern. For fluctuation close to the steady state the period of the wave is approximately equal to

$$\frac{2\pi}{\theta}, \text{ where } \tan(\theta) = \frac{d}{c}, \text{ with } c > 0,$$

if the two complex conjugate eigenvalues are near the unit circle. Solving $p(\xi) = 0$ under the conditions in (6.46) yields

$$\frac{d}{c} = \sqrt{\frac{4 - (1 - \mu + \frac{v}{R} + K)^2}{(1 - \mu + \frac{v}{R} + K)^2}}, \text{ with } K = \frac{2a\gamma\sigma^2}{\lambda R}\frac{\bar{q}^{ma}}{\bar{q}^{fund}}.$$

For $0 < \mu < 1$ this is an increasing function of μ and hence θ is an increasing function of μ. Thus the period of the wave of the price fluctuation close to the unstable steady state is a decreasing function of μ. Recall that in the computation of the exponential moving average, the larger μ, the more weight is placed on current prices, the more closely the moving average follows the price series, and the more earlier a change in direction of the price series is detected. Thus, a larger μ causes price to return to the fundamental value with a higher frequency than a smaller μ.

6.6 Numerical analysis

In the last section we studied the local stability of the steady state analytically. We determined what kind of bifurcations can occur if the value of one of the model parameters is varied. In this section we study the global dynamical behavior numerically, especially when the steady state is unstable, with the aid of time series plots, phase diagrams, delay plots, bifurcation diagrams and the computation of Lyapunov exponents.

6.6.1 Lyapunov characteristic exponents

The Lyapunov characteristic exponents (LCEs) measure the average rate of divergence (or convergence) of nearby initial states, along an attractor in several directions. Consider the dynamical model $z_{t+1} = \Phi(z_t)$, where Φ is a k-dimensional map. After n periods the distance between two nearby initial state vectors z_0 and $z_0 + v_0$ has grown approximately to

$$\|\Phi^n(z_0 + v_0) - \Phi^n(z_0)\| \approx \|D\Phi^n(z_0)v_0\|,$$

where v_0 is the initial perturbation vector, $D\Phi^n(z_0)$ is the Jacobian matrix of the n-th iterate of Φ evaluated at z_0 and $\|.\|$ denotes the Euclidean distance. The exponent $\lambda(z_0, v_0)$ measuring the exponential rate of divergence has to satisfy

$$\|\Phi^n(z_0 + v_0) - \Phi^n(z_0)\| \approx \|D\Phi^n(z_0)v_0\| = e^{n\lambda(z_0,v_0)}\|v_0\|.$$

For a k dimensional system there exist k distinct LCEs, ordered as $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_k$, each measuring the average expansion or contraction along an orbit in the different directions.

The largest LCE can be defined as

$$\lambda(z_0, v_0) = \lim_{n\to\infty} \frac{1}{n} \ln(\|D\Phi^n(z_0)v_0\|). \tag{6.47}$$

To calculate the largest LCE we thus have to determine $\|D\Phi^n(z_0)v_0\|$. We set the initial perturbation vector v_0 with $\|v_0\| = \epsilon$, where ϵ is some small number. We define

$$\Phi(z_i + v_i) - \Phi(z_i) \approx D\Phi(z_i)v_i = v'_{i+1} = f_{i+1}v_{i+1}, \tag{6.48}$$

where v_i is a perturbation vector on the i-th iterate of Φ (i.e. $z_i = \Phi^i(z_0)$) and f_{i+1} is a scalar. We define

$$v_{i+1} = \frac{v'_{i+1}}{\|v'_{i+1}\|}\epsilon, \text{ so that } \|v_{i+1}\| = \|v_i\| = ... = \|v_0\| = \epsilon. \tag{6.49}$$

Using the chain rule for $D\Phi^n(z_0)$ we get

$$D\Phi^n(z_0)\ v_0 = D\Phi(z_{n-1})...D\Phi(z_1)\ D\Phi(z_0)\ v_0.$$

Using (6.48) recursively this relation transforms to

$$D\Phi^n(z_0)\ v_0 = f_n...f_2\ f_1 v_n.$$

Because

$$\lim_{n\to\infty} \frac{1}{n} \ln(\|v_n\|) = 0,$$

the LCE in equation (6.47) can be written as

$$\lambda(z_0, v_0) = \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} \ln(f_i). \tag{6.50}$$

Hence we can confine ourselves to the calculation of

$$f_i = \frac{\|v'_i\|}{\|v_i\|} = \frac{\|v'_i\|}{\epsilon}, \text{ for } i = 1...n \tag{6.51}$$

to determine the largest LCE.

Numerically we compute the largest LCE as follows. Given an initial perturbation vector v_0, the approximation in (6.48) is used to determine v'_{i+1} for $i \geq 0$, that is $\Phi(z_i + v_i) - \Phi(z_i) \approx v'_{i+1}$. Next we compute the perturbation vector for the $i+1$-th iterate by using (6.49). The factor f_{i+1} is computed by using (6.51). Finally, for large n, the largest LCE is computed by using (6.50).

Attractors may be characterized by their Lyapunov spectrum. For a stable steady state or a stable cycle all LCEs are negative. For a quasi-periodic attractor the largest LCE is equal to zero, while all other LCEs are negative. An attractor is called a strange or a chaotic attractor if the corresponding largest LCE is positive, implying sensitive dependence on initial conditions.

6.6.2 Parameter values

In our numerical analysis of the heterogeneous agents model with evolutionary learning we want to choose values for the model parameters which are economically sensible. We assume that there are 250 trading days in one year. The trading interval in our model is 1 day. If we are talking about daily frequencies, then the order of magnitude of percentage price changes is in basis points (1/100 of 1%).

We set the risk-free interest rate to 5% at a yearly basis with daily compounding. Thus $r^f = 0.05/250 = 0.0002$, that is 2 basis points daily. The daily standard deviation of the Dow-Jones Industrial Average during the twentieth century is equal to 1.0830%, which translates to a yearly standard deviation of, if we assume that returns are independently distributed, $1.0830 * \sqrt{250} \approx 17\%$. We take this number as the standard deviation of the returns, that is $\sigma = 0.010830$. Dividends are assumed to be iid and the mean dividend is set to 50 yearly, paid daily. Hence the fundamental value of the risky asset under the iid assumption is equal to $50/0.05 = 1000$. The standard deviation of the dividend process is set equal to 10 yearly.

We choose the exponential moving average parameter μ to be equal to 0.18. The maximum fraction of individual wealth a moving average trader can go long or can go short in the risky asset we choose to be equal to $\gamma = 1.25$ and occurs when the price deviates from the moving average with 7 basis points ($\lambda = 0.0007$).

The fundamental value expectations parameter v we choose to be equal to 0.99. Because

$$E_t^{fund}(P_{t+1}) = P^* + v(P_{t-1} - P^*),$$

the expected two-day return of the stock price, not corrected for dividends, is equal to

$$\frac{E_t^{fund}(P_{t+1}) - P_{t-1}}{P_{t-1}} = (1-v)\frac{P^* - P_{t-1}}{P_{t-1}}.$$

Thus, if the price should decline by 2% to return to the fundamental value P^*, then for $v = 0.99$ the fundamental trader expects that the two-day price return is equal to 2 basis points, which corresponds with a one-day price return of 1 basis point.

A broad range of studies, taking into account the full range of available assets, places the degree of risk aversion a for the representative investor in the range of 2 to 4, see for example Friend and Blume (1975), Grossman and Shiller (1981). We set a initially to 4.

Costs for implementing the strategy with fundamental beliefs are higher than the costs for implementing the exponential moving-average strategy. We set the costs of determining the fundamentals to 1 basis point daily ($C^{fund} = 0.0001$), which is 2.5% yearly. The costs of the moving-average strategy we set to zero.

The discrete choice model determines on the basis of the fitnesses of the beliefs with which probabilities the moving average and fundamental beliefs are chosen by the agents. The memory parameter, η, we choose to be equal to 0.25. We choose the intensity of choice parameter, β, to be equal to 250. The minimum probabilities with which the fundamental belief, m^{fund}, and the moving average belief, m^{ma} are chosen, we set equal to 0.01.

6.6.3 Model simulations

Bifurcations

We have seen in equation (6.45) that in the case of risk neutrality of the fundamental traders, i.e. $a = 0$, there is locally always convergence to the fundamental steady state. If $a = 4$, then for $\beta = 0$ the dynamical system exhibits quasi periodic behavior and no change in the dynamics occurs by increasing β. Only for $a < 0.456$ changes in the dynamical behavior can be observed by varying β. Therefore we set the risk aversion parameter a initially low (0.42), so that the local dynamics around the steady state is dependent on the intensity of choice parameter β.

For $a = 0.42$ figure 6.3a shows the bifurcation diagram with respect to β. A Hopf bifurcation occurs at $\beta_H = 635$. Figure 6.3b shows the corresponding largest LCE plot. Before the Hopf bifurcation occurs the largest LCE is clearly smaller than zero, indicating convergence to the steady state. After the Hopf bifurcation occurred, the largest LCE is close to zero, indicating quasi periodic dynamical behavior. Thus for costs and low risk aversion for the fundamental traders and low intensity of choice for all traders, the price locally converges to the fundamental value. However for high intensity of choice, traders quickly change to the most profitable strategy and the moving-average trading strategy can survive in the market even for low risk aversion of the fundamental traders. Price fluctuations are then driven by the evolutionary dynamics between the two different beliefs.

If the costs for the fundamental traders decrease to zero, then locally when varying β there is always convergence to the fundamental steady state, for low risk aversion. Fundamental expectations then dominate the moving-average strategy. Hence, costs can cause the fundamental steady state to become unstable, even if the risk aversion of fundamental traders is low. In the case of no costs and $\beta = 250$, figure 6.4a shows the bifurcation diagram with respect to the parameter a, when a is varied between 0.1 and 5. Figure 6.4b shows the corresponding largest LCE plot. At $a_H = 0.456$ a Hopf bifurcation occurs and the dynamics shows quasi periodic behavior after the Hopf bifurcation. Hence, if fundamental traders become more risk averse, then even in the no cost case, moving average traders can survive in the market and affect the price by their actions.

We set a equal to 4 and study the local dynamical behavior when varying the exponential moving average parameter μ. To observe a change in the dynamical behavior for the parameter μ we double the parameter λ to 14 basis points and we decrease the intensity of choice parameter β to 125. Figure 6.5a shows the bifurcation diagram with respect to μ, if μ is varied between 0.04 and 0.98. Figure 6.5b shows the corresponding largest LCE plot. Remember that by increasing the parameter μ the moving average follows the price series more closely and generates earlier a trading signal when the directional trend in prices changes direction. From the bifurcation diagram and the LCE plot it can be seen that the fundamental steady state becomes locally stable if the technical traders use a very fast moving average ($\mu > 0.82$), that is if the technical traders quickly change their trading position if the directional trend in prices changes direction. For lower values of μ the LCE plot is close to zero and thus the dynamical system exhibits quasi periodic behavior.

Price simulations

Figures 6.6a, b, c and d show, given the parameter values in section 6.6.2, the time series plots of the price, return, fraction of fundamental traders and trading volume. The price series plot shows that there is a slow movement away from the fundamental value and a quick movement back. In figure 6.6a price starts below the fundamental value of 1000 and slowly increases with a declining positive return, or stated differently, the price sequence is concave. As price is increasing further and further above the fundamental value of 1000, the fundamental traders go short a larger fraction of their wealth, causing volume to increase as can be seen in figure 6.6d. The fraction of fundamental traders starts below 0.50 and is slowly increasing until the point that stock returns become smaller than the risk-free interest rate. Then the moving average forecasting rule is not profitable anymore and the fraction of fundamental traders increases sharply until approximately 0.56. These fundamental traders cause the price to turn back in the direction of the fundamental value. This change in trend is picked up by the moving average traders and they reinforce the downtrend by holding also short positions in the risky asset. Because as well the fundamental traders as the moving average traders are expecting price to decline, price falls quickly back to the fundamental value in a convex way. However, because the moving average traders are doing better than the fundamental traders, the fraction of fundamental traders declines sharply. Thus, the fundamentalists change the direction of the trend, but the chartists push prices back to the fundamental value. Because a majority of the agents was following the fundamental forecasting rule and already had short positions before the turn in price direction, volume drops sharply after the change of direction in the price trend. As price returns to the fundamental value, agents following the fundamental belief are closing their short positions, while traders following the moving average belief are holding more and more short positions, causing volume to increase. After prices dropped back to the fundamental value, prices keep on declining due to the moving average traders, with negative but increasing returns, so that the price sequence is convex. Volume increases, because traders following the fundamental belief are now holding more and more long positions as price moves below the fundamental value. Then, if the short position held by the moving average traders is not profitable anymore, the fraction of fundamental traders increases sharply turning the downward trend in price to an upward trend in price. The moving average traders detect the change in trend and will change their short position to a long position in the risky asset, causing price to increase back to the fundamental value. Because a majority of the agents was following the fundamental forecasting rule and already had long positions, volume drops sharply after the change of direction in the price trend. The price cycle is thus characterized by a period of small price changes when moving average traders dominate the market and periods of rapid decrease or increase of prices when fundamental traders temporarily dominate the market. Furthermore, volume goes by the prevailing trend as can be seen in figure 6.6d. That is, if the primary trend is upwards, then volume increases. Volume drops during a change in directional trend. Then, if the primary trend is downwards, volume also increases. This is a very important concept in technical analysis and the relation has been shown in many price charts.

Adding dynamic noise to the deterministic skeleton leads to irregular price behavior as can be seen in figure 6.7a. Clearly periods with trending behavior can be identified. Figure 6.7c shows that the fraction of fundamental traders is switching irregular between its lower- and upperbound. Because little autocorrelation, volatility clustering and fat tails are important characteristics of real financial time series, we check our return series for these features. Figures 6.8b and 6.8c show the autocorrelation function plots of the returns and the squared returns up to order 36. Figure 6.8b shows that the return series does not exhibit any serial autocorrelation, which means that price changes are linearly independent. Further, according to figure 6.8c the squared return series does not exhibit any serial autocorrelation, which means that there is no volatility clustering present in the data. The return distribution does show excess kurtosis relatively to the normal distribution (see figure 6.8a). Thus our theoretical heterogeneous agents model only fails in mimicking the feature of volatility clustering.

6.7 Conclusion

In this chapter we have built a financial market model with heterogeneous adaptively learning agents, fundamentalists and technical traders. The model is an extension of the Brock and Hommes (1998) model in that it extends the set of trading techniques the agents can independently choose from with a realistic moving-average technical trading rule. Moving averages are well known and one of the mostly used technical indicators in financial practice and therefore they deserve to be implemented in heterogeneous agents modeling. Furthermore, the model is derived under the assumption of relative risk aversion, instead of absolute risk aversion as in the Brock and Hommes (1998) case.

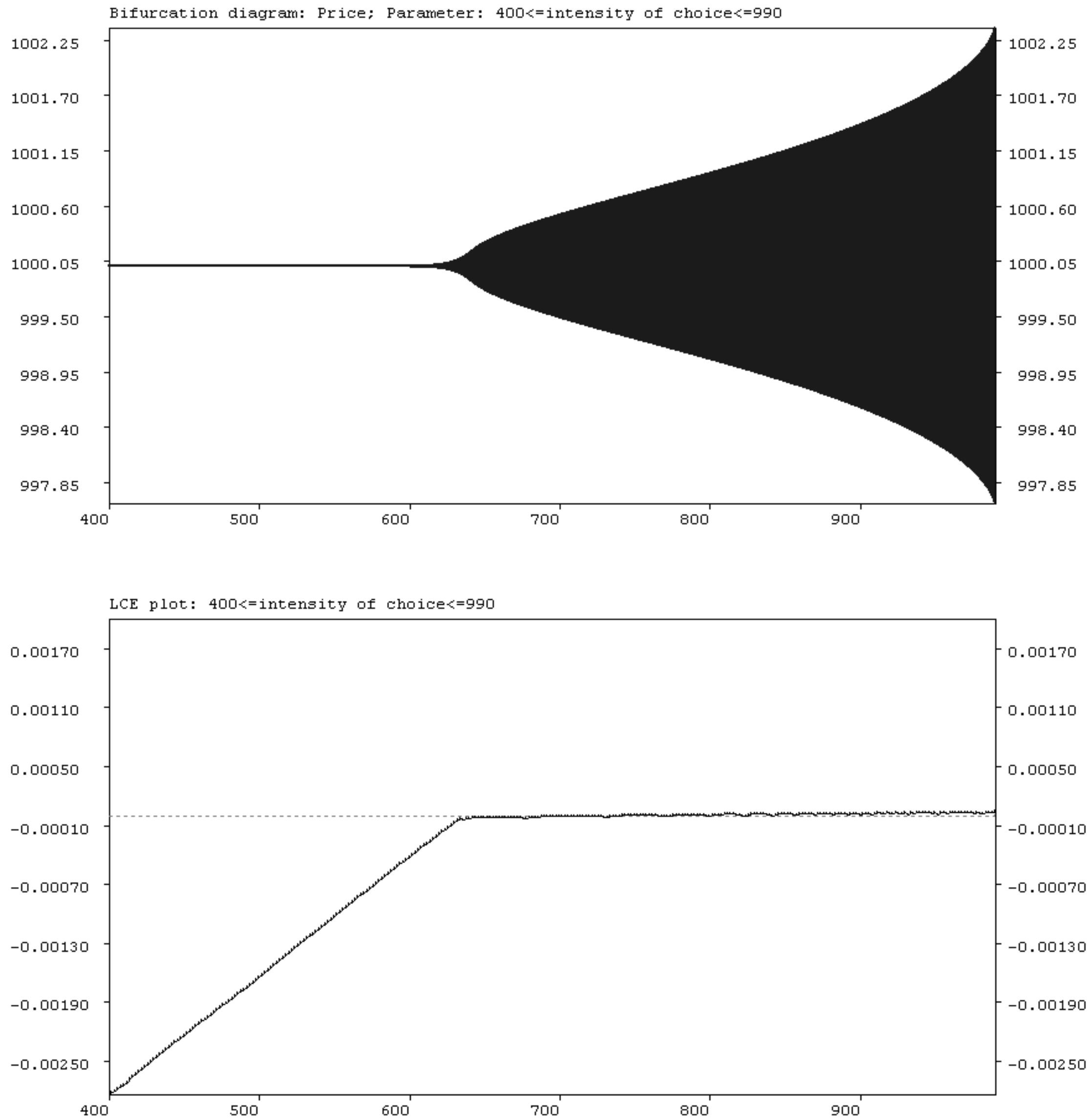
The model is derived under the assumption of infinitely many agents, who only differ in the forecasting rule they select each period. Under the assumption that each agent has zero market power at each date, that is his individual investment decision will not influence the equilibrium price, it is shown that the fraction of total market wealth invested by all agents according to a certain belief converges in probability to the probability that the belief is chosen by the agents. Under the assumption of zero supply of outside stocks and the use of certain beliefs types it turns out that the price equilibrium formula is exactly the same as in Brock and Hommes (1998), namely that the price is equal to the discounted value of the average expected price and dividends by all agents. Moreover if the moving-average technical trading rule is added to the model, then also risk aversion and expected dispersion of future returns play a role in our model.

In the end, our financial market model is an eight dimensional nonlinear dynamical system. The steady state price is equal to the fundamental value, which is the discounted value of all future dividends. Analytically we derive the eigenvalues of the linearized system and we examine for which parameter values bifurcations occur. It is shown that the system only can exhibit a Hopf bifurcation. We use numerical tools such as delay, phase and bifurcation diagrams, and computation of Lyapunov characteristic exponents to study the local stability around the fundamental steady state. If there is no difference in costs of applying the fundamental or moving-average strategy, then it is found that the intensity of choice parameter, measuring how quickly traders switch beliefs, has no influence on the dynamical behavior. In the presence of costs, if the risk aversion parameter of the fundamental traders is low enough, then these traders always drive prices back to the fundamental steady state for the case the intensity of choice parameter is sufficiently low. For high values of the intensity of choice parameter, even for low risk aversion, quasi periodic price behavior can occur as a consequence of a Hopf bifurcation. If costs of all trader types are set to zero and if more realistic values for the risk aversion parameter are chosen, then fundamental traders are too risk averse to drive prices to the fundamental steady state and the price exhibits quasi periodic behavior. However, if the risk aversion parameter is high and the technical traders use a very fast moving average, which follows the price closely, then the price does converge to the fundamental value.

We study a case in which we choose parameter values that are economically sensible. The solution of the dynamical system is quasi periodic price behavior. Interaction between fundamentalists and technical analysts may thus destabilize the market and lead to persistent price fluctuations around an unstable fundamental steady state. It turns out that fundamental traders change the direction of a prevailing price trend, but that once the direction has changed, the technical traders push prices back to the fundamental value. Moreover it is found that volume goes by the prevailing trend, that is if the primary trend is upwards or downwards, then volume increases, only dropping if a change in the direction of the trend occurs. This is an important concept in technical analysis. Dynamic noise to the deterministic skeleton is added and leads to irregular price behavior. The features of the return distribution of the dynamical system are examined, but it is concluded that although the model generates returns series which show zero autocorrelation and fat tails, the model fails in mimicking the important characteristic of volatility clustering.

Appendix

A. Figures



(a)

(b)

Figure 6.3: (a) Bifurcation diagram for the intensity of choice parameter β with a Hopf bifurcation leading to quasi-periodic dynamics; (b) largest LCE plot.

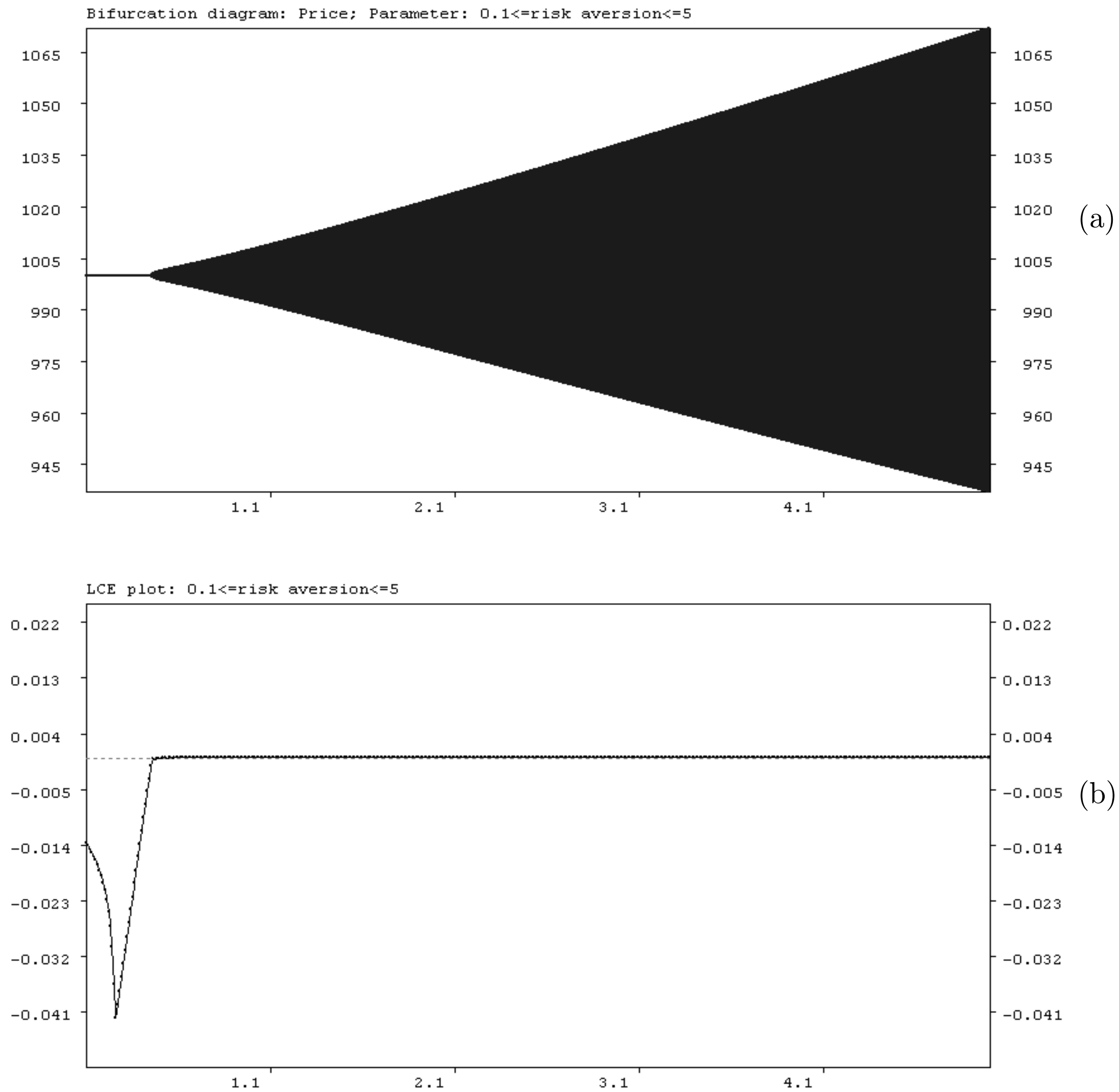
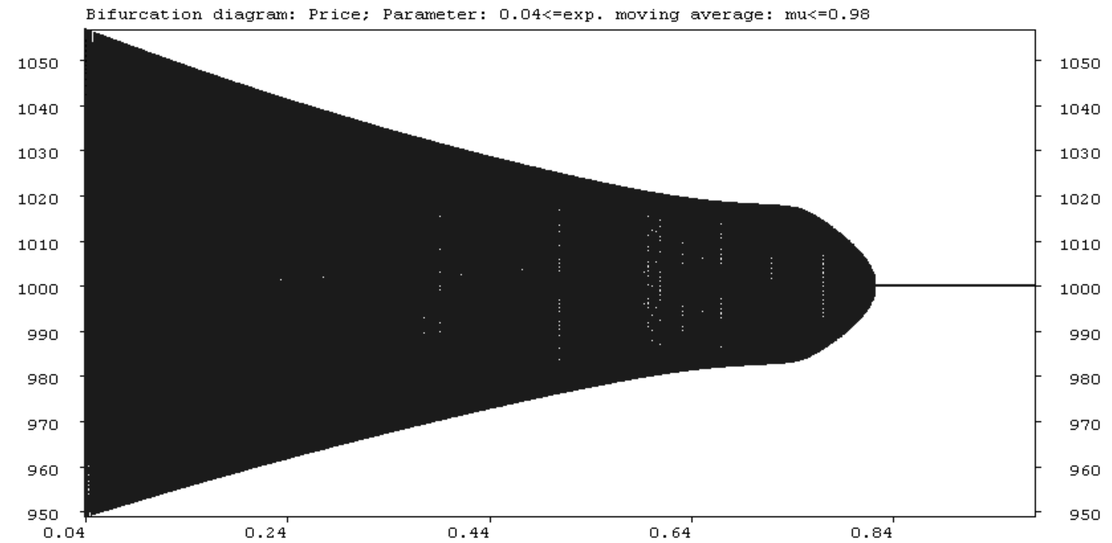
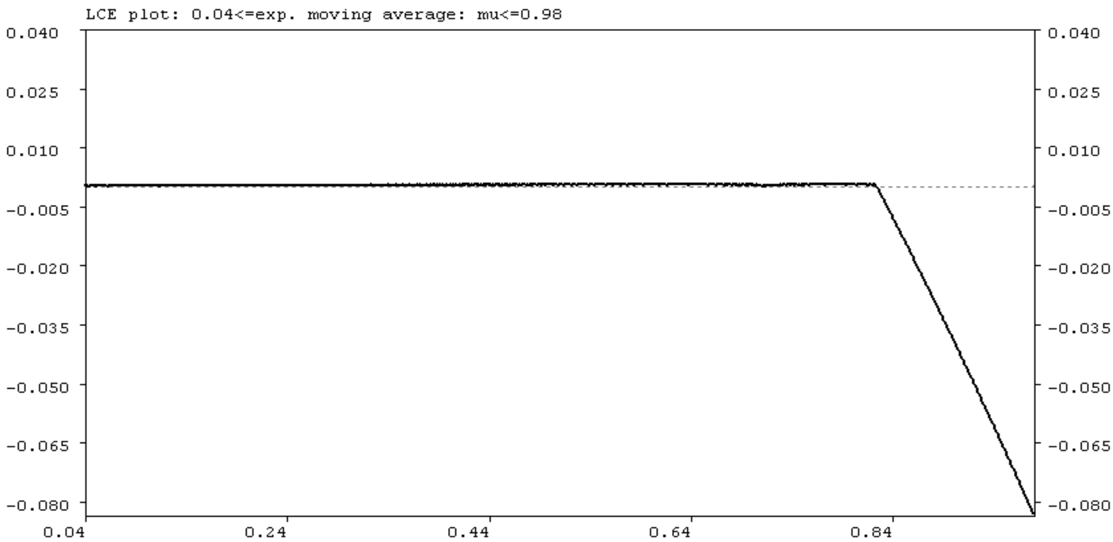


Figure 6.4: (a) Bifurcation diagram for the risk aversion parameter a with a Hopf bifurcation leading to quasi-periodic dynamics; (b) largest LCE plot.



(a)



(b)

Figure 6.5: (a) Bifurcation diagram for the exponential moving average parameter μ with a Hopf bifurcation leading to quasi-periodic dynamics; (b) largest LCE plot.

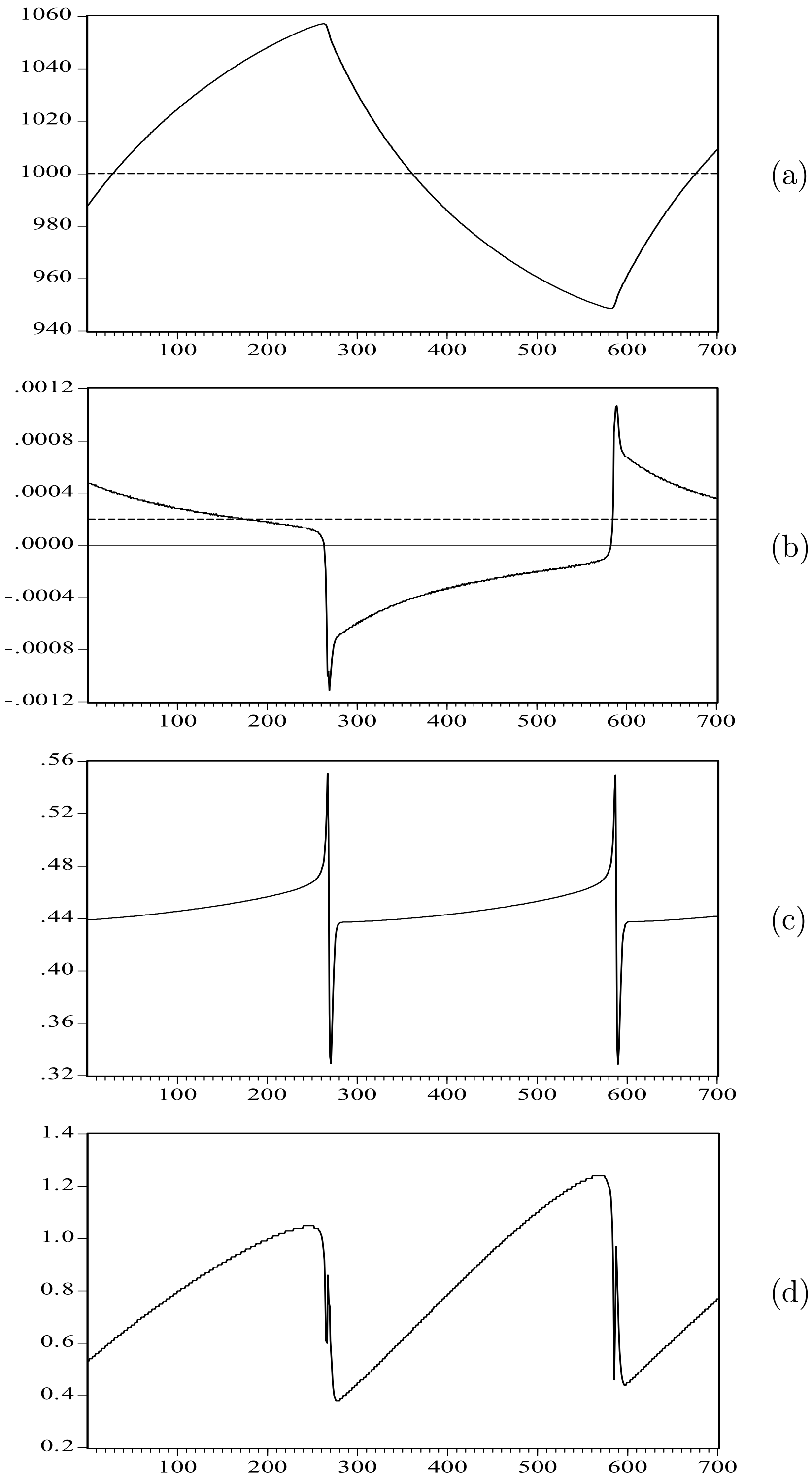


Figure 6.6: $r_f = 0.05/250$, $\overline{D} = 50/250$, $a = 4$, $\mu = 0.18$, $\gamma = 1.25$, $\lambda = 0.0007$, $v = 0.99$, $\eta = 0.25$, $\beta = 250$, $m^{fund} = m^{ma} = 0.01$, $C^{fund} = 0.0001$, $C^{ma} = 0$. (a) Price plot. Dotted line is the fundamental value; (b) Return plot. Dotted line is the risk-free interest rate; (c) Fraction of fundamental traders; (d) Trading volume.

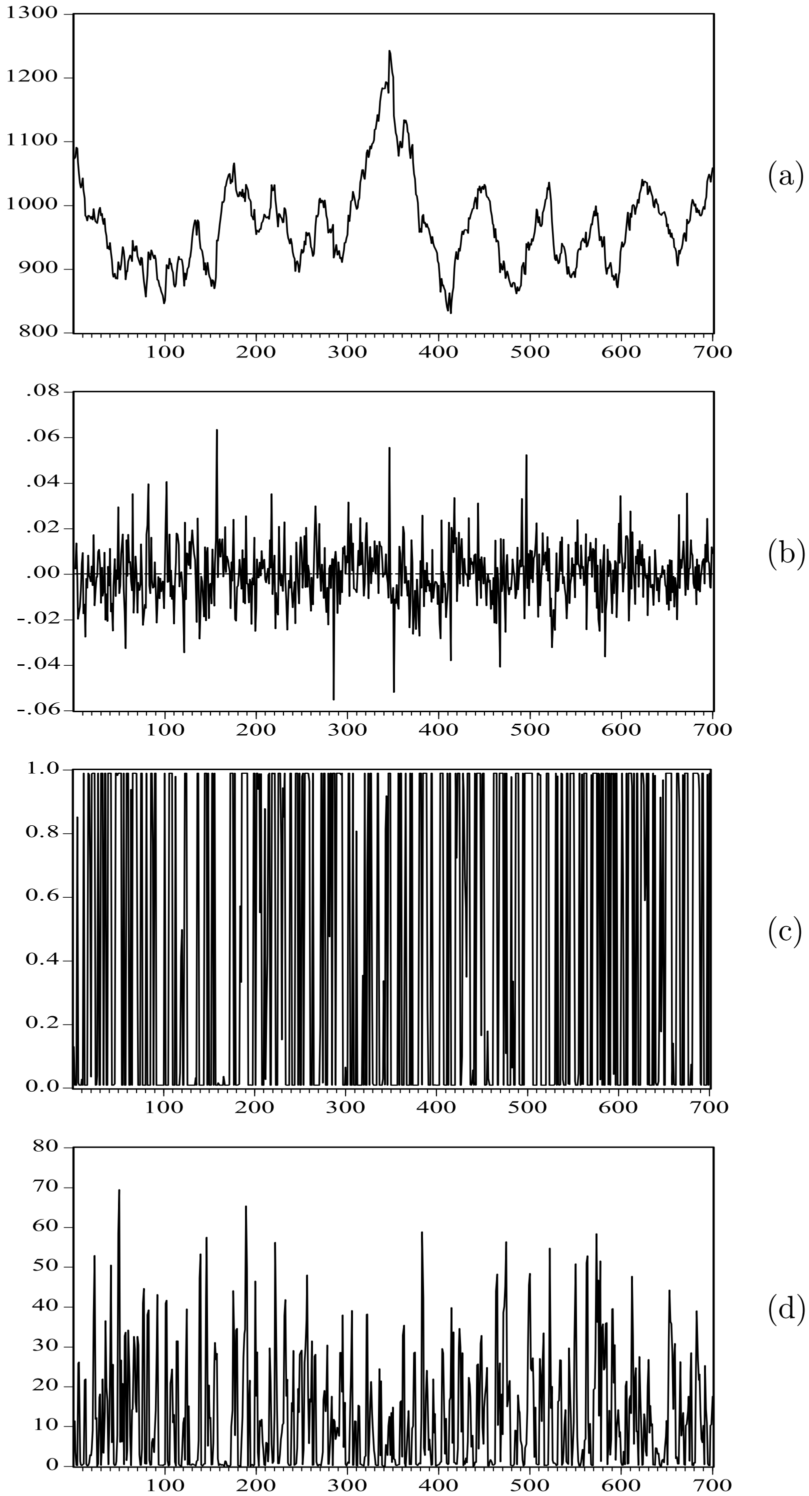


Figure 6.7: Adding dynamic noise to the deterministic skeleton of the nonlinear financial market model with fundamentalists versus moving average traders: $\sigma^2 = 0.17/\sqrt{250}$, $\sigma_\delta^2 = 10/\sqrt{250}$. (a) Price plot; (b) Return plot. Dotted line is the risk-free interest rate; (c) Fraction of fundamental traders; (d) Trading volume.

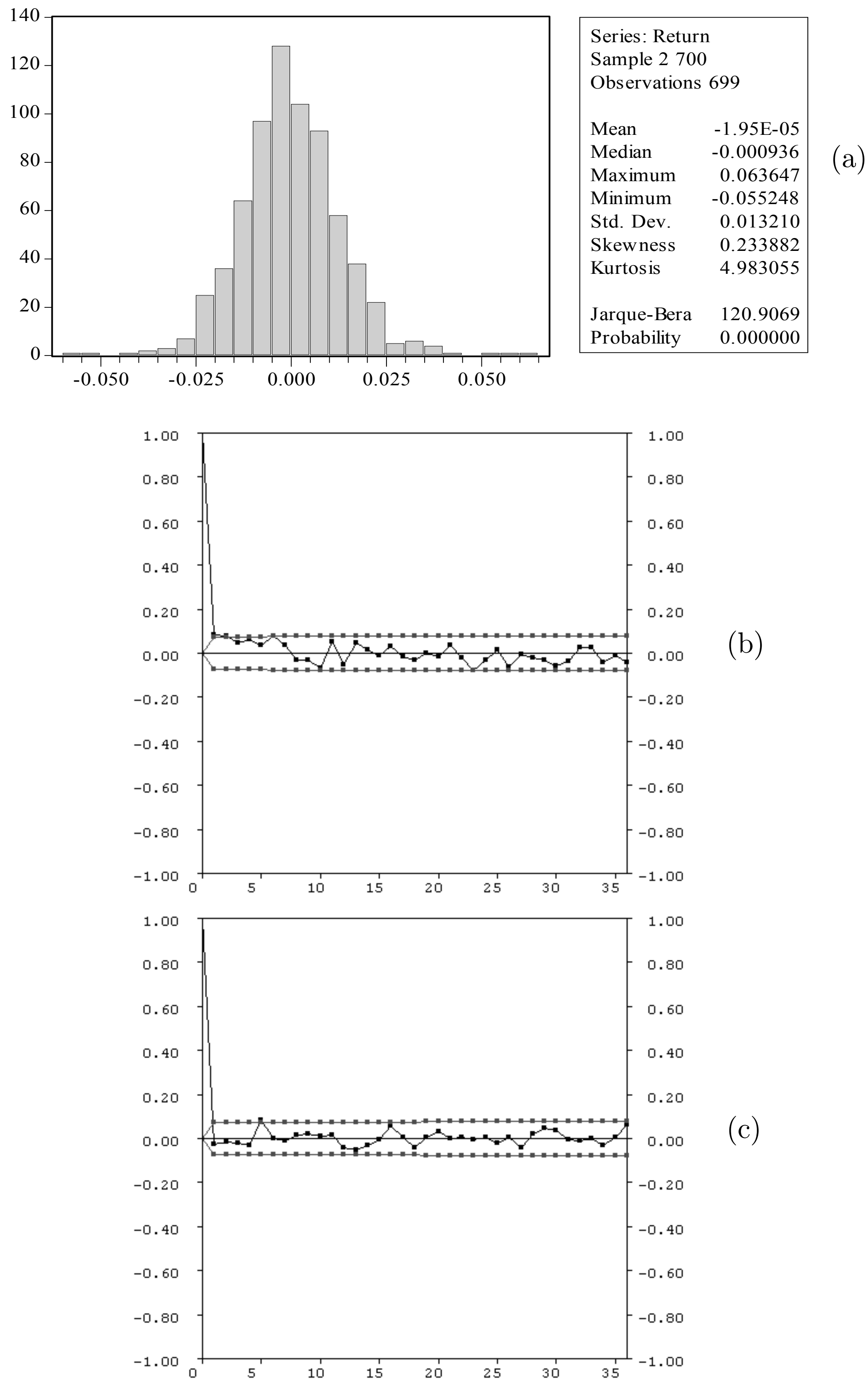


Figure 6.8: (a) Histogram and summary statistics; (b) Autocorrelation function of the returns; (c) Autocorrelation function of the squared returns.

B. Wealth invested according to belief h

Choice probability

The probability that agent j chooses belief h is determined by the discrete choice model in (6.15). The return of belief h in period t is equal to: $r^F + y^h_{t-1}(r^P_t - r^F)$. Therefore the fitness measure is defined as

$$F^h_{j,t} = r^F + y^h_{t-1}(r^P_t - r^F) - C^h_j + \eta_j F^h_{j,t-1}; \tag{6.52}$$

As in the BH model it is assumed that for all agents $\beta_j = \beta$, $\eta_j = \eta$ and $C^h_j = C^h$. However, we adjust the probabilities with which each belief is chosen by introducing a lower bound m^h on the probabilities as motivated by Westerhoff (2002):

$$\widetilde{q}^h_t = \frac{\exp(\beta F^h_{t-1})}{\sum_{k=1}^{H} \exp(\beta F^k_{t-1})};$$

$$q^h_t = m^h + (1 - \textstyle\sum_{h=1}^{H} m^h)\ \widetilde{q}^h_t,$$

where $m^h \geq 0\ \forall h$ and $0 \leq \sum_{h=1}^{H} m^h \leq 1$. For example, Taylor and Allen (1990, 1992) found in questionnaire surveys that a small group of traders always uses technical or fundamental analysis and do not switch beliefs[3]. We define $X^h_{j,t} = 1$ if agent j chooses belief h at time t and $X^h_{j,t} = 0$ if agent j chooses a belief other than belief h. Because $X^h_{1,t}, ..., X^h_{N,t}$ are iid with $E(X^h_{j,t}) = q^h_t$ and limited variance $V(X^h_{j,t}) = q^h_t(1 - q^h_t)$, the fraction of agents who choose belief h converges in probability to q^h_t:

$$\frac{1}{N}\sum_{j=1}^{N} X^h_{j,t} \xrightarrow{p} q^h_t,$$

as the number of agents goes to infinity. Furthermore we did assume that all agents have the same risk aversion parameter $a_j = a$, so that agents who follow the same belief have the same demand. Hence in the end we assume that agents are only heterogeneous in the beliefs they can choose from.

Wealth assigned to belief h by agent j

The wealth invested according to belief h by agent j at time t is equal to $W^h_{j,t} = X^h_{j,t} W_{j,t}$. From this it follows that the total wealth assigned to belief h by all agents is equal to

[3]Moreover, especially in our final two type trader model, by placing a lower bound on the probabilities, we can avoid numerical problems in computing the market equilibrium price, because of floating point errors in the computer simulations.

$W_t^h = \sum_{j=1}^N W_{j,t}^h$. Finally, total market wealth is equal to $W_t = \sum_{h=1}^H W_t^h$. The expected wealth transferred from agent j to belief h conditioned on the wealth of agent j and the information set $I_t = \{P_{t-i}, D_{t-i}; i \geq 0\}$ is equal to:

$$E(W_{j,t}^h|I_t, W_{j,t}) = W_{j,t}E(X_{j,t}^h|I_t) = W_{j,t}(q_t^h\ 1 + (1 - q_t^h)\ 0) = q_t^h W_{j,t}.$$

The expectation of wealth transferred from agent j to belief h conditioned only on I_t is equal to:

$$E(W_{j,t}^h|I_t) = E(E(W_{j,t}^h|I_t, W_{j,t})|I_t) = q_t^h E(W_{j,t}|I_t).$$

According to (6.28) the wealth of agent j at time t depends on the fraction of the wealth invested at time $t-1$ and this chosen fraction depends on the agent's belief at time $t-1$. Hence the expected wealth of agent j at time t conditioned on his wealth at time $t-1$ is equal to:

$$E(W_{j,t}|I_t, W_{j,t-1}) = \sum_{h=1}^{H} \left(\left(RW_{j,t-1} + (P_t + D_t - RP_{t-1}) \frac{y_{t-1}^h W_{j,t-1}}{P_{t-1}} \right)\ q_{t-1}^h \right) =$$

$$RW_{j,t-1} + (P_t + D_t - RP_{t-1}) \frac{E(y_{t-1}) W_{j,t-1}}{P_{t-1}},$$

where $E(y_{t-1}) = \sum_{h=1}^H y_{t-1}^h q_{t-1}^h$. The expected wealth of agent j at time t only conditioned on I_t is equal to:

$$E(W_{j,t}|I_t) = E_{W_{j,t-1}}(E(W_{j,t}|I_t, W_{j,t-1})|I_t) = \sum_{\{W_{j,t-1}\}} E(W_{j,t}|I_t, W_{j,t-1}) P(W_{j,t-1}) =$$

$$R\ E(W_{j,t-1}|I_{t-1}) + (P_t + D_t - RP_{t-1}) \frac{E(y_{t-1}) E(W_{j,t-1}|I_{t-1})}{P_{t-1}}. \tag{6.53}$$

In the end:

$$E(W_{j,t}|I_t) = \left(R + \frac{(P_t + D_t - RP_{t-1})}{P_{t-1}} E(y_{t-1}) \right) E(W_{j,t-1}|I_{t-1}) =$$

$$(1 + r^F + (r_t^P - r^F) E(y_{t-1})) E(W_{j,t-1}|I_{t-1}),$$

which is a recursive formula for the expected wealth of agent j at time t given the dividends paid and given the equilibrium prices $\{P_{t-i} : i \geq 0\}$ the auctioneer did set. Given the wealth of agent j at time 0, the expected wealth of agent j at time t is equal to:

$$E(W_{j,t}|I_t) = W_{j,0} \prod_{i=0}^{t-1} \left(1 + r^F + (r_{t-i}^P - r^F) E(y_{t-1-i})\right).$$

Assume that at time 0, all agents have equal initial wealth. Thus for all j we have $W_{j,0} = \omega_0$ and

$$E(W_{j,t}|I_t) = \omega_0 \prod_{i=0}^{t-1} \left(1 + r^F + (r^P_{t-i} - r^F)E(y_{t-1-i})\right). \tag{6.54}$$

According to (6.54) the expectation is equal for all agents at time t, $E(W_{j,t}|I_t) = \omega_t$, under the assumption that all agents have the same wealth at time 0. Finally we now have found that $E(W^h_{j,t}|I_t) = q^h_t \omega_t \; \forall j$. The variance of $W^h_{j,t}$ conditioned on I_t is equal to:

$$\begin{aligned} V(W^h_{j,t}|I_t) &= E((W^h_{j,t})^2|I_t) - E^2(W^h_{j,t}|I_t) \\ &= q^h_t E(W^2_{j,t}|I_t) - (q^h_t)^2 E^2(W_{j,t}|I_t) \\ &= q^h_t V(W_{j,t}|I_t) + q^h_t(1 - q^h_t)E^2(W_{j,t}|I_t). \end{aligned} \tag{6.55}$$

The expectation of the squared value of the wealth of agent j at time t conditioned on I_t and his wealth at $t-1$ is equal to:

$$E(W^2_{j,t}|I_t, W_{j,t-1}) = R^2 W^2_{j,t-1} + 2RW^2_{j,t-1}(r^P_t - r^F)E(y_{t-1}) + W^2_{j,t-1}(r^P_t - r^F)^2 E(y^2_{t-1}),$$

and the expectation only conditioned on I_t is equal to:

$$E(W^2_{j,t}|I_t) = [R^2 + 2R(r^P_t - r^F)E(y_{t-1}) + (r^P_t - r^F)^2 E(y^2_{t-1})]E(W^2_{j,t-1}|I_{t-1}),$$

which iterates to:

$$E(W^2_{j,t}|I_t) = W^2_{j,0} \prod_{i=0}^{t-1} [R^2 + 2R(r^P_{t-i} - r^F)E(y_{t-1-i}) + (r^P_{t-i} - r^F)^2 E(y^2_{t-1-i})], \tag{6.56}$$

where $W_{j,0}$ is the initial wealth of investor j. The square of the expectation of the wealth of agent j at time t is equal to:

$$E^2(W_{j,t}|I_t) = [R^2 + 2R(r^P_t - r^F)E(y_{t-1}) + (r^P_t - r^F)^2 E^2(y_{t-1})]E^2(W_{j,t-1}|I_{t-1}),$$

which iterates to:

$$E^2(W_{j,t}|I_t) = W^2_{j,0} \prod_{i=0}^{t-1} [R^2 + 2R(r^P_{t-i} - r^F)E(y_{t-1-i}) + (r^P_{t-i} - r^F)^2 E^2(y_{t-1-i})]. \tag{6.57}$$

Substituting (6.56) and (6.57) in (6.55) gives the variance of the wealth of agent j assigned to belief h at time t conditioned on I_t. If $W_{j,0} = \omega_0$ for all agents, then the variance is equal for all agents, $V(W^h_{j,t}|I_t) = \sigma^2_{h,t}$ for all j. As a simple example we can take the return of the risky asset to be equal to the risk free rate for $t = 1, ..., T$. Then

$$E(W^h_{j,T}|I_T) = q^h_T R^T \omega_0,$$

$$V(W^h_{j,T}|I_T) = q^h_T(1 - q^h_T)(R^T \omega_0)^2.$$

Hence in this simple example expected wealth and variance of wealth transferred by agent j to belief h both increase in time.

Fraction of total market wealth assigned to belief h by all agents

We define

$$\widetilde{W}^h_{j,t} = \frac{W^h_{j,t}}{W_t}$$

as the individual wealth assigned by agent j to belief h as a fraction of total market wealth W_t. The choices agents make at time t are dependent on the performances of the different beliefs until and including time $t-1$, hence the choices are independent of the price and wealth at time t. However, the price set at time t, which influences the wealth of each agent at time t and thus total wealth, is dependent on the choice of each agent at time t. Thus $\widetilde{W}^h_{1,t}$, ... , $\widetilde{W}^h_{N,t}$ given I_t are dependent. However, if an agent is very small relative to the market, his choice will have a negligible effect on the eventual price set at time t. Hence if we assume that the market power of each agent is zero, that is

$$\forall t \wedge \forall j: \lim_{N\to\infty} \frac{W_{j,t}}{W_t} \to 0, \tag{6.58}$$

then the law of large numbers still holds. Thus $\widetilde{W}^h_{1,t}$, ... , $\widetilde{W}^h_{N,t}$ given I_t are dependent but identically distributed with mean $E(\widetilde{W}^h_{j,t}|I_t) = q^h_t \frac{\omega_t}{W_t}$ and finite (under assumption 6.58) variance $V(\widetilde{W}^h_{j,t}|I_t)$, so that

$$\frac{1}{N}\sum_{j=1}^{N}(\widetilde{W}^h_{j,t}) = \frac{1}{N}\frac{W^h_t}{W_t} \xrightarrow{p} q^h_t \frac{\omega_t}{W_t}. \tag{6.59}$$

This means that the average wealth per agent which is assigned to belief h as a fraction of total market wealth converges in probability to $q^h_t \frac{\omega_t}{W_t}$ as the number of agents goes to infinity. Average wealth per agent as a fraction of total wealth converges to:

$$\frac{\overline{W_t}}{W_t} = \sum_{h=1}^{H}\frac{1}{N}\frac{W^h_t}{W_t} \xrightarrow{p} \sum_{h=1}^{H} q^h_t \frac{\omega_t}{W_t} = \frac{\omega_t}{W_t}. \tag{6.60}$$

If we divide (6.59) by (6.60) we find that the fraction of total wealth invested according to belief h at time t converges to:

$$\frac{W_t^h}{W_t} \xrightarrow{p} q_t^h.$$

C. Equilibrium price for $s > 0$

If $s > 0$, then the derivation of the equilibrium price becomes more complex. By substituting (6.24) and (6.29) in (6.35) we can rewrite (6.35) as the solution to a quadratic equation of P_t. The formulas for the equilibrium price P_t are:

$$\begin{aligned}
c_1 &= \frac{1}{R} \sum_{h \in B_1} \frac{q_t^h}{c_3} E_t^h(P_{t+1} + D_{t+1}); \\
c_2 &= R(W_{t-1} - sP_{t-1}) + sD_t; \\
c_3 &= \textstyle\sum_{h \in B_1} q_t^h; \\
c_4 &= \textstyle\sum_{h \in B_2} q_t^h y_t^h; \\
Discr &= (c_1 c_3 Rs + c_2 c_3 R - a c_2 c_4 \sigma^2)^2 + 4 a c_1 c_2 c_3 R s \sigma^2; \\
P_t &= \frac{(c_1 c_3 Rs - c_2 c_3 R + a c_2 c_4 \sigma^2) + \sqrt{Discr}}{2s(c_3 R + a(1 - c_4)\sigma^2)}.
\end{aligned} \tag{6.61}$$

Here c_1 is the net present value of the average of the expected future price plus dividend by all agents in belief group B_1, c_2 is the total amount of money invested in the risk free asset by all agents, c_3 is the total fraction of market wealth assigned to beliefs in group B_1 and c_4 is the fraction of market wealth invested in the risky asset by agents in belief group B_2 at time t. For the equilibrium equation to be solvable for P_t it is necessary that there is a belief $h \in B_1$ for which $q_t^h > 0$. If for all beliefs $h \in B_1 : q_t^h = 0$, then there is no solution for P_t. Further, an upperbound should be imposed on the fraction of total market wealth traders in group B_2 can go long in the market. If $s > 0$, then the fraction of total market wealth invested in the risky asset lies between 0 and 1, that is

$$0 \leq \sum_{h \in B_1} q_t^h y_t^h + \sum_{h \in B_2} q_t^h y_t^h < 1,$$

or equivalently

$$-\sum_{h \in B_1} q_t^h y_t^h \leq \sum_{h \in B_2} q_t^h y_t^h < 1 - \sum_{h \in B_1} q_t^h y_t^h.$$

Because of the characteristics of the demand function (6.24) for the risky asset, traders in belief group B_1 are restricted in the fraction of individual wealth they can go short, that is

$$-\frac{R}{a\sigma^2} < y_t^h < \infty$$

This implies that there is an upperbound on the fraction of total wealth traders in belief group B_2 can go long, that is

$$\sum_{h \in B_2} q_t^h y_t^h < 1 + \frac{R}{a\sigma^2} \sum_{h \in B_1} q_t^h, \text{ or equivalently } c_4 < 1 + c_3 \frac{R}{a\sigma^2}$$

Thus the denominator in (6.61) is positive. Now the question is whether the nominator of (6.61) is also positive, so that there is a unique positive equilibrium price. It is clear that $c_1 \geq 0$. If the initial wealth invested in the risk free asset is positive, then according to (6.30) the total wealth at time t should be at least be equal to the value of the total number of shares: $W_t = c_2 + sP_t \geq sP_t$, implying $c_2 \geq 0$. Because for all beliefs h: $q_t^h \geq 0$ it is also true that $c_3 \geq 0$. $c_4 \in \mathbb{R}$ and can be of either sign. Hence under these relationships the nominator of (6.61) is positive, because:

$$\begin{aligned}
&(c_1 c_3 R s - c_2 c_3 R + a c_2 c_4 \sigma^2) + \sqrt{Discr} > \\
&(c_1 c_3 R s - c_2 c_3 R + a c_2 c_4 \sigma^2) + \sqrt{(c_1 c_3 R s + c_2 c_3 R - a c_2 c_4 \sigma^2)^2} = 2 c_1 c_3 R s > 0.
\end{aligned}$$

We have shown that the nominator and denominator of (6.61) are both positive, so that we have proven that for $s > 0$ the model yields a unique positive equilibrium price.

References

Achelis, S.B. (1995), *Technical Analysis from A to Z*, McGraw-Hill, New York.

Adriaanse, G. (2002), Technical Indicators, master thesis, University of Amsterdam.

Alexander, S.S. (1961), Price Movements in Speculative Markets: Trends or Random Walks, *Industrial Management Review* 2, 7-26.

Alexander, S.S. (1964), Price movements in speculative markets: Trends or random walks, Number 2, *Industrial Management Review* 5, 25-46.

Allen, H., Taylor, M.P. (1990), Charts, Noise and Fundamentalists in the London Foreign Exchange Market, *The Economic Journal* 100, 49-59.

Arditti, F.D., McCollough, W.A. (1978), Can Analysts Distinguish Between Real and Randomly Generated Stock Prices? *Financial Analysts Journal*, 70-74.

Arthur, W.B., Holland, J.H., LeBaron, B., Palmer, R., Taylor, P. (1997), Asset pricing under endogenous expectations in an artificial stock market. In: Arthur, W.B., Durlauf, S.N., and Lane, D.A., eds., The economy as an evolving complex system II, Redwood City, Addison-Wesley.

Bartlett, M.S. (1946), On the Theoretical Specification of Sampling properties of Autocorrelated Time Series, *Journal of the Royal Statistical Society*, Series B, 8, 27-41.

Bass, A.B. (1999), *The Predictors: How a band of maverick physicists set out to beat Wall Street*, Penguin Books Ltd, London.

Bera, A.K., Higgins, M.L. (1993), Arch Models: Properties, Estimation and Testing, *Journal of Economic Surveys* 7, 305-366.

Bernstein, P.L. (1996), *Against the Gods: the remarkable story of risk*, John Wiley & Sons, Inc.

Bessembinder, H., Chan, K. (1995), The profitability of technical trading strategies in the Asian stock markets, *Pacific-Basin Finance Journal* 3, 257-284.

Bessembinder, H., Chan, K. (1998), Market Efficiency and the Returns to Technical Analysis, *Financial Management* 27, 5-17.

Bodie, Z., Kane, A., Marcus, A.J. (1996), *Investments*, Irwin.

Bollerslev, T., Wooldridge, J.M. (1992), Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances, *Econometric Reviews* 11, 143-172.

Boswijk, H.P. (1998), *Unit Roots and Cointegration*, University of Amsterdam, Lecture notes.

Bouman, S., Jacobsen, B. (1997), The Halloween Indicator: Sell in May and go away, Chapter in thesis: *Time Series Properties of Stock Returns*, 86-106, University of Amsterdam.

Box, G., Pierce, D. (1970), Distribution of Autocorrelations in Autoregressive Moving Average Time Series Models, *Journal of the American Statistical Association* 65, 1509-1526.

Brock, W.A., Hommes, C.H. (1997), A rational route to randomness, *Econometrica* 65, 1059-1095.

Brock, W.A., Hommes, C.H. (1997), Models of complexity in economics and finance, *System Dynamics in Economic and Financial Models*, ed C. Hey et al (New York: Wiley), 3-41.

Brock, W.A., Hommes, C.H. (1998), Heterogeneous beliefs and routes to chaos in a simple asset pricing model, *Journal of Economic Dynamics and Control* 22, 1235-1274.

Brock, W.A., Lakonishok, J., LeBaron, B. (1992), Simple Technical Trading Rules and the Stochastic Properties of Stock Returns, *The Journal of Finance* 47, 1731-1764.

Campbell J.Y., Lo, A.W., MacKinlay, A.C. (1997), *The Econometrics of Financial Markets*, Princeton University Press, New Jersey.

Chan, L.K.C., Lakonishok, J. (1993), Institutional Trades and Intraday Stock Price Behavior, *Journal of Financial Economics*, 173-199.

Cheung, Y., Chinn, M.D. (1999), Macroeconomic Implications of the Beliefs and Behavior of Foreign Exchange Traders, NBER working paper 7417.

Cheung, Y., Chinn, M.D., Marsh, I.W. (2000), How Do UK-Based Foreign Exchange Dealers Think Their Market Operates? NBER working paper 7524.

Cootner, P. (ed.) (1964), *The Random Character of Stock Market Prices*, MIT Press, Cambridge. Reprint in 2000 by Risk Publications, London.

Coutts, J.A., Cheung, K.C. (2000), Trading rules and stock returns: some preliminary short run evidence from the Hang Seng 1985-1997, *Applied Financial Economics* 10, 579-586.

Cowles, A. (1933), Can Stock Market Forecasters Forecast?, *Econometrica* 1, 309-324.

Cowles, A. (1944), Stock Market Forecasting, *Econometrica*, 206-214.

Curcio, R., Goodhart, G. Guillaume, D., Payne, R. (1997), Do Technical Trading Rules Generate Profits? Conclusions from the Intra-Day Foreign Exchange Market, *International Journal of Finance and Economics* 2, 267-280.

Cuthbertson, K. (1996), *Quantitative Financial Economics: Stocks, Bonds and Foreign Exchange*, John Wiley & Sons Ltd., London.

Dacorogna, M.M., Müller, U.A., Pictet, O.V. (1991), A Measure of Trading Model Performance with a Risk Component, *A discussion paper by the O&A Research Group,* MMD.1991-05-24.

Dash, M. (1999), *Tulipomania: The Story of the World's Most Coveted Flower and the Extraordinary Passions It Aroused*, Victor Gollancz, London.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J. (1989), The size and incidence of the losses of noise trading, *Journal of Finance* 44, 681-696.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J. (1990), Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

Detry, P.J., Gregoire, P. (2001), Other Evidences of the Predictive Power of Technical Analysis: the Moving-Average Rules on European Indices, working paper, European Financial Management Association.

Diebold, F.X. (1986), Testing for Serial Correlation in the Presence of ARCH, *Proceedings of the American Statistical Association, Business and Economic Statistics Section*, 323-328.

Diebold, F.X., Mariano, R.S. (1995), Comparing predictive accuracy, *Journal of Business and Economic Statistics* 13, 253-265.

Dooley, M.P., Shafer, J.R. (1976), Analysis of Short-Run Exchange Rate Behavior: March 1973 to September 1975, International Finance Discussion Paper 123, Federal Reserve Board, Washington, D.C.

Dooley, M.P., Shafer, J.R. (1983), Analysis of Short-Run Exchange Rate Behavior: March 1973 to November 1981, 43-69, Exchange Rate and Trade Instability: Causes, Consequences and Remedies, in D. Bigman and T.Taya eds., Ballinger, Cambridge, MA.

Dudewicz, E.J., Mishra, S.N. (1988), *Modern Mathematical Statistics*, John Wiley & Sons, Inc.

Edwards, R.D., Magee, J. (1998), *Technical Analysis of Stock Trends.* Seventh Edition, second printing, John Magee, Inc.

Efron, B. (1979), Bootstrap methods: Another look at the jackknife, *The Annals of Statistics* 7, 1-26.

Efron, B., Tibshirani, R. (1986), Bootstrap methods for standard errors, confidence intervals and other measures of statistical accuracy, *Statistical Science* 1, 54-77.

Enders, W. (1995), *Applied Econometric Time Series*, John Wiley & Sons, Inc.

Fama, E.F. (1965a), The behavior of stock market prices, *Journal of Business* 38, 34-105.

Fama, E.F. (1965b), Tomorrow on the New York Stock Exchange, *Journal of Business* 38, 285-299.

Fama, E.F. (1970), Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance* 25, 383-417.

Fama, E.F., Blume, M.E. (1966), Filter Rules and Stock-Market Trading, *Journal of Business* 39, 226-241.

Fama, E.F, French, K.R (1988), Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3-25.

Farmer, J.D. (1998), Market force, ecology, and evolution, Santa Fe Institute working paper 98-12-117.

Fernández-Rodríguez, F., Sosvilla-Rivero, S., Andrada-Félix, J. (2001), Technical Analysis in the Madrid Stock Exchange, *Moneda y Crédito* 213, 11-37.

Frankel, J.A., Froot, K.A. (1988), Chartists, fundamentalists and the demand for dollars, *Greek Economic Review* 10, 49-102.

Franses, P.H., Dijk, D. van (2000), *Non-linear time series models in empirical finance*, Cambridge University Press, New York.

Freedman, D. (1984), On bootstrapping two-stage least squares estimates in stationary linear models, *Annals of Statistics* 12, 827-842.

Freedman, D., Peters, S. (1984a), Bootstrapping a regression equation: Some empirical results, *Journal of the American Statistical Society* 79, 97-106.

Freedman, D., Peters, S. (1984b), Bootstrapping an econometric model: Some empirical results, *Journal of Business and Economic Statistics* 2, 150-158.

Friedman, M. (1953), The case of flexible exchange rates, In: *Essays in Positive Economics*, University of Chicago Press, Chicago.

Friend, I., Blume, M.E. (1975), The Demand for Risky Assets, *The American Economic Review* 65, 900-922.

Gaunersdorfer, A. (2000), Endogenous fluctuations in a simple asset pricing model with heterogeneous agents, *Journal of Economic Dynamics and Control* 24, 799-831.

Gaunersdorfer, A., Hommes, C.H. (2000), A nonlinear structural model for volatility clustering, CeNDEF Working Paper 00-02, University of Amsterdam.

Gaunersdorfer, A., Hommes, C.H., Wagener, F.O.O. (2000), Bifurcation Routes to Volatility Clustering, CeNDEF Working Paper 00-09, University of Amsterdam.

Giersbergen, N.P.A. van (1998), Bootstrapping Dynamic Econometric Models, Thesis, University of Amsterdam.

Graham, B. (1949), *The Intelligent Investor*, Fourth revised edition (1973), Harper & Row, Publishers, Inc., New York.

Grandia, V. (2002), The Search for the Golden Rule: A Reality Check of Technical Analysis in the Dutch Stock Market, master thesis, University of Amsterdam.

Grossman, S.J., Shiller, R.J. (1981), The Determinants of the Variability of Stock Market Prices, *The American Economic Review*, 222-227.

Hamilton, W.P. (1922), *The Stock Market Barometer*, Harper & Brothers, New York. Reprint in 1998 by John Wiley & Sons, Inc., New York.

Hansen, P.R. (2001), An Unbiased and Powerful Test for Superior Predictive Ability, Brown University, Department of Economics, working paper no.01-06.

Hommes, C.H. (1997), Nonlinear Economic Dynamics, University of Amsterdam, Lecture notes.

Hommes, C.H. (2001), Financial markets as nonlinear adaptive evolutionary systems, *Quantitative Finance* 1, 149-167.

Hong, H., Stein, J.C. (1999), A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hsieh, D.A. (1988), The Statistical Properties of Daily Foreign Exchange Rates: 1974-1983, *Journal of International Economics* 24, 129-145.

Hudson, R., Dempsey, M., Keasey, K. (1996), A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices - 1935 to 1994, *Journal of Banking and Finance* 20, 1121-1132.

Hull, J.C. (1991), *Futures and Options Markets*, Prentice-Hall, Inc., New Jersey.

Isakov D., Hollistein, M. (1999), Application of simple technical trading rules to Swiss stock prices: Is it profitable?, *Financial Markets and Portfolio Management* 13, 9-26.

James, F.E. (1968), Monthly Moving Averages: An Effective Investment Tool?, *Journal of Financial and Quantitative Analysis*, 315-326.

Jensen, M.C. (1967), Random Walks: Reality or Myth - Comment, *Financial Analysts Journal*, 77-85.

Jensen, M.C., Benington, G.A. (1969), Random Walks and Technical Theories: Some Additional Evidence, *Journal of Finance* 25, 469-482.

Kendall, M.G. (1953), The Analysis of Economic Time-Series, *Journal of the Royal Statistical Society* 96, 11-25.

Keynes, J.M. (1936), *The General Theory of Unemployment, Interest and Money*, Harcourt Brace, London.

Kho, B.C. (1996), Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets, *Journal of Financial Economics* 41, 249-290.

Kirman, A. (1991), Epidemics of opinion and speculative bubbles in financial markets, In: M. Taylor (ed.), Money and financial markets, Macmillan, London.

Knez, P., Ready, M. (1996), Estimating the Profits from Trading Strategies, *Review of Financial Studies*, 1121-1164.

Langedijk, N. (2001), The Predictability of Technical Trading Rules on the Foreign Exchange Market: A Bootstrap Approach, master thesis, University of Amsterdam.

LeBaron, B. (1993), Practical Comparisons of Foreign Exchange Forecasts, *Neural Network World* 6, 779-790.

LeBaron, B. (2000a), The Stability of Moving-Average Technical Trading Rules on the Dow-Jones Index, *Derivatives Use, Trading and Regulation* 5, 324-338.

LeBaron, B. (2000b), Technical Trading Profitability in Foreign Exchange Market's in the 1990's, Brandeis University, working paper.

LeBaron, B., Arthur, W.B., Palmer, R. (1999), Time series properties of an artificial stock market, *Journal of Economic Dynamics and Control* 23, 1487-1516.

Lee, C.I., Mathur, I. (1995), Trading rule profits in European currency spot cross rates, *Journal of Banking and Finance* 20, 949-962.

Leeson, N. (1996), *Rogue Trader*, Time Warner Paperbacks.

Levich, R.M., Thomas L.R. (1993), The significance of technical trading-rule profits in the foreign exchange market: A bootstrap approach, *Journal of International Money and Finance* 12, 451-474.

Levy, R.A. (1967), Relative Strength as a Criterion for Investment Selection, *Journal of Finance* 22, 595-610.

Levy, R.A. (1971), The Predictive Significance of Five-Point Chart Patterns, *The Journal of Business* 44, 316-323.

Lintner, J. (1965), The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, Review of Economics and Statistics 47, 13-37.

Ljung, G., Box, G. (1978), On a Measure of Lack of Fit in Time Series Models, *Biometrika* 65, 297-303.

Lo, A.W., MacKinlay, A.C. (1988), Stock market prices do not follow random walks: evidence from a simple specification test, *Review of Financial Studies* 1, 41-66.

Lo, A.W., MacKinlay, A.C., (1997), Maximizing predictability in the stock and bond markets, *Macroeconomic Dynamics* 1, 102-134.

Lo, A.W., MacKinlay, A.C. (1999), A non-random walk down Wall Street, Princeton University Press, Princeton.

Lo, A.W., Mamaysky, H., Wang, J. (2000), Foundations of technical analysis: computational algorithms, statistical inference and empirical implementation, *Journal of Finance* 55, 1705-1722.

Lux, T. (1995) Herd Behavior, Bubbles and Crashes, *The Economic Journal* 105, 881-896.

Malkiel, B.G. (1996), *A Random Walk down Wall Street*, W.W. Norton & Company, Inc, New York.

Mandelbrot, B. (1963), The Variation of Certain Speculative Prices, *Journal of Business* 36, 394-419.

Markowitz, H.M. (1952), Portfolio Selection, *Journal of Finance* 7, 77-91.

Markowitz, H.M. (1959), *Portfolio Selection: Efficient Diversification of Investments*, John Wiley, New York.

Marquering, W., Verbeek, M. (2000), The Economic Value of Predicting Stock Index Returns and Volatility, Tilburg University, Center for Economic Research, Discussion paper 78.

Menkhoff, L. (1998), The noise trading approach - questionnaire evidence from foreign exchange, *Journal of International Money and Finance* 17, 547-564.

Mills, T.C. (1990), *Time series techniques for economists*, Cambridge University Press.

Mills, T.C. (1997), Technical Analysis and the London Stock Exchange: Testing Trading Rules Using the FT30, *International Journal of Finance and Economics* 2, 319-331.

Ming Ming, L., Mat Nor, F., Krishnan Guru, B. (2000), Technical Analysis in the Malaysian Stock Market: An Empirical Evidence, working paper, Universiti Kebangsaan Malaysia.

Murphy J.J. (1986), *Technical Analysis of the Futures Markets*, New York institute of finance.

Neftci, S.N. (1991), Naive Trading Rules in Financial Markets and Wiener-Kolmogorov Prediction Theory: A Study of "Technical Analysis", *Journal of Business* 64, 549-571.

Nelson, D.B. (1995), Conditional heteroskedasticity in asset returns: a new approach, *Econometrica* 59, 347-370.

Nelson, S.A. (1903), The ABC of Stock Speculation. Reprint in 1999 by Fraser Publishing Company, Burlington.

Newey, W., West, K. (1987), A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

O'Hara, M. (1995), *Market Microstructure Theory*, Blackwell Publishers, Inc., Massachusettes.

Osler, C.L., Chang, P.H.K. (1995), Head and Shoulders: Not Just a Flaky Pattern, Staff Reports No. 4, Federal Reserve Bank of New York.

Pesaran, M.H., Timmermann, A. (1995), Predictability of Stock Returns: Robustness and Economic Significance, *The Journal of Finance* 50, 1201-1228.

Pesaran, M.H., Timmermann, A. (2000), A Recursive Modeling Approach to Predicting UK Stock Returns, *Economic Journal* 110, 159-191.

Phillips, P.C.B. (1986), Understanding Spurious Regressions in Econometrics, *Journal of Econometrics* 33, 311-340.

Politis, D., Romano, J. (1994), The Stationary Bootstrap, *Journal of the American Statistical Association* 89, 1303-1313.

Prestbo, J.A. (1999), *The Market's Measure*, Dow Jones & Company, Inc., New York.

Pring, M. (1998), *Introduction to Technical Analysis*, McGraw-Hill, New York.

Ratner, M., Leal, R.P.C. (1999), Tests of technical trading strategies in the emerging equity markets of Latin America and Asia, *Journal of Banking and Finance* 23, 1887-1905.

Ready, M.J. (1997), Profits from Technical Trading Rules, working paper, University of Wisconsin-Madison.

Rhea, R. (1932), *The Dow Theory*, Barron's, New York. Reprint in 1993 by Fraser Publishing Company, Burlington.

Roberts, H.V. (1959), Stock-Market "Patterns" and Financial Analysis: Methodological Suggestions, *Journal of Finance* 14, 1-10.

Samuelson, P. (1965), Proof that Properly Anticipated Prices Fluctuate Randomly, *Industrial Management Review* 6, 41-49.

Satterthwhaite, R.E. (1946), *Biom. Bull. 2* :110.

Schulmeister, S. (1988), Currency Speculation and Dollar Fluctuations, *Quarterly Review Banca Nazionale del Lavoro*, 343-365.

Sharpe, W. (1964), Capital Asset Prices: A Theory of Market Equilibrium, Journal of Finance 19, 425-442.

Shiller, R.J. (2000), *Irrational Exuberance*, Princeton University Press, New Jersey.

Snedecor, G.W., Cochran, W.G. (1989), *Statistical Methods (8)*, Iowa: Stek University Press, Ames.

Sullivan, R., Timmermann, A., White, H. (1999), Data-snooping, Technical Trading Rule Performance, and the Bootstrap, *Journal of Finance* 54, 1647-1691.

Sullivan, R., Timmermann A., White, H. (2001), Dangers of data mining: The case of calendar effects in stock returns, *Journal of Econometrics* 105, 249-286.

Sweeney, R.J. (1986), Beating the Foreign Exchange Market, *The Journal of Finance* 61, 163-182.

Sweeney, R.J. (1988), Some New Filter Rule Tests: Methods and Results, *Journal of Financial and Quantitative Analysis* 23, 285-300.

Taylor, M.P., Allen, H. (1992), The use of technical analysis in the foreign exchange market, *Journal of International Money and Finance* 11, 304-314.

Theil, H., Leenders, C.T. (1965), Tomorrow on the Amsterdam Stock Exchange, *Journal of Business* 38, 277-284.

Thomson, R. (1998), *Apocalypse Roulette*, Pan Macmillan, London.

Wang, J. (1994), A model of competitive stock trading volume, *Journal of Political Economy* 102, 127-168.

West, K.D. (1996), Asymptotic Inference about Predictive Ability, *Econometrica* 64, 1067-1084.

Westerhoff, F.H. (2002), Expectations driven distortions in the foreign exchange market, *Journal of Economic Behavior and Organization* 1502, 1-24.

White, H. (1980), A Heteroskedasticity-Consistent Covariance Matrix and a Direct Test for Heteroskedasticity, *Econometrica* 48, 817-838.

White, H. (2000), A Reality Check for Data Snooping, *Econometrica* 68, 1097-1126.

Williams, J.B. (1938), *The Theory of Investment Value*, Harvard University Press.

Working, H. (1934), A Random Difference Series for Use in the Analysis of Time Series, *American Statistical Association Journal* 29, 11-24.

Samenvatting (Summary in Dutch)

Financiële analisten gebruiken "fundamentele" en "technische" analyse om de toekomstige prijsontwikkeling van een financiële waarde, zoals een aandeel, termijncontract, valuta etc., te kunnen voorspellen. Bij fundamentele analyse wordt er onderzoek gedaan naar allerlei economische factoren die de inkomsten van een financiële waarde, zoals dividenden, kunnen beïnvloeden. Deze economische factoren worden ook wel de fundamentele variabelen genoemd. De fundamentele variabelen meten macro-economische omstandigheden, zoals bijvoorbeeld de olieprijs, inflatie, rente, werkloosheid, etc., bedrijfstak specifieke omstandigheden, zoals bijvoorbeeld concurrentie, technologische veranderingen, vraag/aanbod, etc., en bedrijfsspecifieke omstandigheden, zoals bijvoorbeeld dividend, groei, inkomsten, rechtszaken, stakingen, etc. Op basis van alle verzamelde fundamentele informatie wordt de fundamentele of intrinsieke waarde berekend. Vervolgens wordt bepaald of de marktprijs van de financiële waarde lager of hoger is dan de fundamentele waarde en wordt de financiële waarde gekocht of verkocht.

Technische analyse is de bestudering van koerspatronen aan de hand van grafieken met als doel het voorspellen van de toekomstige koersontwikkeling. De filosofie achter technische analyse is dat alle informatie geleidelijk wordt verwerkt in de prijs van een financiële waarde. Hierdoor bewegen koersen zich voort in min of meer regelmatige patronen, die herhaaldelijk zijn waar te nemen in de koersgrafieken. Technische analisten claimen dat zij die patronen kunnen herkennen en daarop winstgevend kunnen handelen. Samengevat kan dus gezegd worden dat de technische analist het effect van een prijsverandering op de toekomstige koersontwikkeling bestudeert, terwijl de fundamentele analist altijd op zoek is naar een economische oorzaak voor een prijsverandering.

In de huidige wetenschappelijke literatuur over financiële markten staat de efficiënte markthypothese (EMH) nog steeds centraal. Een financiële markt heet zwak efficiënt als het onmogelijk is om een handelsstrategie te ontwikkelen die op basis van de koershistorie van een financiële waarde de toekomstige koersontwikkeling van die financiële waarde kan voorspellen. Een financiële markt heet semi-stringent efficiënt als het onmogelijk is om een handelsstrategie te ontwikkelen die op basis van alle publieke informatie de toekomstige koersontwikkeling van een financiële waarde kan voorspellen. Tenslotte heet een financiële markt sterk efficiënt als het onmogelijk is om op basis van alle denkbare beschikbare informatie, dus ook insider informatie, de toekomstige koersontwikkeling van een financiële waarde te voorspellen. Bovendien geldt voor elk van de drie efficiëntie hypothesen dat de handelsstrategie niet continu een bovengemiddeld rendement kan opleveren als er wordt gecorrigeerd voor risico en transactiekosten. Semi-stringente efficiëntie impliceert zwakke efficiëntie en sterke efficiëntie impliceert semi-stringente en zwakke efficiëntie. Als de zwakke vorm van de EMH verworpen kan worden, dan kan ook de semi-stringente en de sterke vorm van de EMH verworpen worden.

Een bovengemiddeld rendement van technische handelsstrategieën is dus in strijd met de zwakke vorm van de EMH. In dit proefschrift wordt de zwakke vorm van de EMH getest door het toepassen van vele verschillende trend-volgende technische handelsstrategieën op een groot aantal financiële datareeksen. Na correctie voor transactiekosten, risico en de zoektocht naar de beste strategie zal statistisch getoetst worden of de voorspelbaarheid en de winsten gegenereerd door technische handelsregels echt zijn of slechts schijn.

In hoofdstuk 2 wordt een verzameling van 5350 technische handelsstrategieën toegepast op de koersen van cacao goederen termijncontracten verhandeld op de *London International Financial Futures Exchange* (LIFFE) en op de *New York Coffee, Sugar and Cocoa Exchange* (CSCE) in de periode van januari 1983 tot en met juni 1997. Voor diezelfde periode wordt de verzameling van strategieën ook toegepast op de Pond-Dollar wisselkoers. Als de verzameling van handelsstrategieën wordt toegepast op de prijzen van de LIFFE cacao termijncontracten, dan wordt er gevonden dat 58% van de technische handelsregels een strikt positief bovenmatig gemiddeld rendement oplevert, zelfs als er een correctie wordt gemaakt voor transactiekosten. Bovendien laat een groot percentage van de technische strategieën een statistische significante voorspellende kracht zien. Echter, als dezelfde strategieverzameling wordt toegepast op de prijzen van de CSCE cacao termijncontracten, dan worden er veel slechtere resultaten gevonden. Nu levert slechts 12% van de handelsstrategieën een bovenmatig gemiddeld rendement op. Verder wordt er nauwelijks nog enige statistische significante voorspellende kracht gevonden. Bootstrap technieken onthullen dat de goede resultaten die gevonden zijn voor de LIFFE cacao termijncontracten niet verklaard kunnen worden door enkele populaire econometrische tijdreeksmodellen, zoals het *random walk*, het autoregressieve, en het GARCH model. Echter, de resultaten lijken wel verklaard te kunnen worden door een model met een structurele verandering in de trend. Het grote verschil in de gevonden resultaten voor de LIFFE en CSCE cacao termijncontracten kan worden toegeschreven aan het vraag/aanbod mechanisme in de cacaomarkt in combinatie met een toevallige invloed van de Pond-Dollar wisselkoers.

De trends in de cacaoreeksen vallen toevallig samen met de trends in de Pond-Dollar wisselkoers, waardoor de prijstrends in de LIFFE termijncontracten worden versterkt, maar de prijstrends in de CSCE cacao termijncontracten worden afgezwakt. Verder suggereert deze casestudie een verband tussen het succes of falen van technische handelsregels en de relatieve grootte van een trend en de beweeglijkheid van een financiële tijdreeks.

In de hoofdstukken 3, 4 en 5 wordt een verzameling van trend volgende technische handelsstrategieën toegepast op de koersen van verscheidene aandelen en op de indices van internationale aandelenmarkten. Twee verschillende maatstaven worden gebruikt om het resultaat van een strategie te beoordelen, namelijk het gemiddelde rendement en de Sharpe ratio. In de berekeningen wordt er gecorrigeerd voor transactiekosten. Als technische handelsregels winstgevend blijken te zijn, dan kan het zijn dat die winsten de beloning zijn voor het dragen van risico. Daarom worden er Sharpe-Lintner *capital asset pricing* modellen (CAPMs) geschat om deze hypothese te toetsen. Als technische handelsregels een economische significante winst opleveren na correctie voor risico en transactiekosten, dan bestaat het gevaar dat dit het resultaat is van een te uitgebreide zoektocht naar de best strategie ("data snooping"). Daarom wordt er de nul hypothese getoetst of de beste technische handelsregel daadwerkelijk superieur is ten opzichte van een passieve strategie van eenmaal kopen en niet meer verkopen, nadat er een correctie is uitgevoerd voor de zoektocht naar de beste handelsregel. Om deze hypothese te toetsen wordt er gebruik gemaakt van twee recentelijk ontwikkelde toetsen, zoals White's (2000) *Reality Check* (RC) en Hansen's (2001) test voor *Superior Predictive Ability* (SPA). Tenslotte wordt er met een recursieve methode van optimaliseren en toepassen getest of technische handelsregels daadwerkelijk een *out-of-sample* voorspellende kracht hebben. Bijvoorbeeld, aan het begin van elke maand wordt de technische handelsregel geselecteerd die de beste resultaten opleverde in het afgelopen half jaar en vervolgens wordt die strategie gebruikt om handelssignalen te genereren gedurende die maand.

In hoofdstuk 3 wordt een verzameling van 787 trend volgende technische handelsstrategieën toegepast op de Dow-Jones Industrial Index en op alle aandelen genoteerd in de Dow-Jones Industrial Index in de periode van januari 1974 tot en met juni 2001. Omdat uit verschillende wetenschappelijke artikelen naar de voorspelbaarheid van speculatieve prijsreeksen is gebleken dat technische handelsregels een statistische significante voorspellende kracht vertonen tot het jaar 1987, maar niet in de periode daarna, wordt de steekproef opgedeeld in de twee subperioden 1973-1986 en 1987-2002. In alle perioden wordt er zowel voor het gemiddeld rendement als voor het Sharpe ratio selectiecriterium gevonden dat voor elke datareeks een technische handelsregel kan worden geselecteerd die in staat is de passieve strategie van eenmaal kopen en vasthouden te verslaan, ook als er wordt gecorrigeerd voor transactiekosten. Bovendien wordt er, wanneer er geen transactiekosten worden opgevoerd, met behulp van het regresseren van Sharpe-Lintner CAPMs voor de meeste datareeksen gevonden dat technische handelsregels een statistisch significant bovengemiddeld rendement opleveren, zelfs na correctie voor risico. Echter, als de transactiekosten toenemen dan wordt de nul hypothese dat door technische handelsregels gegenereerde winsten een beloning zijn voor het dragen van risico, voor steeds meer datareeksen niet verworpen. Tevens wordt bij 0.25% transactiekosten voor vrijwel alle onderzochte datareeksen de nul hypothese dat de beste technische handelsstrategie niet superieur is ten opzichte van de strategie van eenmaal kopen en vasthouden, nadat een correctie is uitgevoerd voor de zoektocht naar die beste strategie, niet verworpen door de RC en de SPA-test. Tenslotte vertoont de recursieve methode van optimaliseren en toepassen van handelsregels geen voor risico gecorrigeerde *out-of-sample* voorspellende kracht van technische analyse. Er kan dus worden geconcludeerd dat trend-volgende technische handelsregels, na correctie voor transactiekosten, risico en de zoektocht naar de beste strategie, geen economische en statistische significante voorspellende kracht vertonen voor zowel de Dow-Jones Industrial Index als de aandelen genoteerd in de Dow-Jones Industrial Index.

In hoofdstuk 4 wordt de strategieverzameling van hoofdstuk 3 toegepast op de AEX-index en op 50 aandelen genoteerd in de AEX-index in de periode van januari 1983 tot en met mei 2002. Voor zowel het gemiddeld rendement als het Sharpe ratio selectiecriterium wordt er gevonden dat voor elke datareeks een technische handelsstrategie kan worden geselecteerd die in staat is om de strategie van eenmaal kopen en vasthouden te verslaan, zelfs na correctie voor transactiekosten. Bovendien wordt er voor ongeveer de helft van de onderzochte datareeksen gevonden dat de beste strategie een statistische significante voorspellende kracht heeft, ook na correctie voor risico. Vervolgens wordt er een correctie gemaakt voor de zoektocht naar de beste technische handelsregel met behulp van de RC en de SPA-test. Als het gemiddeld rendement criterium wordt gebruikt om de beste strategie te selecteren, dan leiden beide toets procedures tot dezelfde conclusie als minstens 0.10% transactiekosten worden opgevoerd: de beste geselecteerde technische handelsregel is niet statistisch significant superieur aan de strategie van eenmaal kopen en vasthouden. Echter, als het Sharpe ratio criterium wordt toegepast, dan wordt voor ongeveer één derde van de aandelen de nul hypothese van geen superieure voorspellende kracht na correctie voor de zoektocht naar de beste strategie wel verworpen, zelfs als 1% transactiekosten worden opgevoerd. In tegenstelling tot de resultaten gevonden in hoofdstuk 3 vinden we in hoofdstuk 4 dat technische analyse toekomstige koersontwikkelingen kan voorspellen, na correctie voor transactiekosten, risico en *data snooping*, als het Sharpe ratio criterium wordt gebruikt om de beste strategie te selecteren. Tenslotte toont de recursieve methode van optimaliseren en toepassen van handelsregels aan dat technische analyse een *out-of-sample* voorspellende kracht heeft. Bovendien toont het schatten van Sharpe-Lintner CAPMs aan dat de beste recursieve methode van optimaliseren en toepassen van technische handelsstrategieën een statistische significante voor risico gecorrigeerde voorspelkracht heeft voor ongeveer 40% van de onderzochte datareeksen, na correctie voor 0.10% transactiekosten. Echter, als de kosten toenemen tot 0.50% per order, dan heeft de recursieve procedure van optimaliseren en toepassen van handelsregels geen statistische significante voorspellende kracht meer voor bijna alle onderzochte datareeksen. Er kan dus worden geconcludeerd dat technische analyse winstgevend is en een statistische significante voorspellende kracht heeft voor een groep van aandelen genoteerd in de AEX-index, alleen als de transactiekosten voldoende laag zijn.

In hoofdstuk 5 wordt de verzameling van 787 technische handelsstrategieën uit hoofdstuk 3 toegepast op 50 indices van aandelenmarkten in Afrika, Azië, Europa, het Midden Oosten, Noord en Zuid Amerika en Oceanië, en op de MSCI Wereld Index in de periode van januari 1981 tot en met juni 2002. Alhoewel de helft van de indices een continue investering tegen een rentevoet niet kon verslaan, wordt er net als in de hoofdstukken 3 en 4 voor beide selectiecriteria gevonden dat voor elke index een technische handelsregel kan worden geselecteerd die de passieve strategie van eenmaal kopen en vasthouden kan verslaan, ook als er gecorrigeerd wordt voor transactiekosten. Bovendien wordt er voor de helft van de indices gevonden dat de beste strategie een statistische significante voor risico gecorrigeerde voorspellende kracht heeft, zelfs na correctie voor 1% transactiekosten. Echter, als er tevens wordt gecorrigeerd voor de zoektocht naar de beste strategie, dan verwerpen zowel de RC als de SPA-test bij 0.25% transactiekosten voor de meeste aandelenindices niet de nul hypothese dat de beste strategie geselecteerd door het gemiddeld rendement criterium geen superieure voorspellende kracht heeft. Net als in hoofdstuk 4 worden er andere resultaten gevonden voor het Sharpe ratio criterium: voor een kwart van de indices, voornamelijk die in Azië, wordt de nul hypothese van geen superieure voorspellende kracht dan wel verworpen. Ook de recursieve methode van optimaliseren en toepassen van technische handelsregels toont aan dat technische analyse *out-of-sample* voorspelwinsten kan genereren, voornamelijk voor aandelenindices in Azië, Latijns Amerika, het Midden Oosten en Rusland, zelfs na implementatie van transactiekosten. Echter, voor aandelenindices in de VS, Japan en de meeste West Europese landen is de recursieve methode van optimaliseren en toepassen van technische handelsregels niet winstgevend als er een klein beetje transactiekosten worden opgevoerd. Tenslotte, zodra er CAPMs worden geschat, wordt er voor voldoende hoge transactiekosten gevonden dat de trend-volgende handelsstrategieën geen statistische significante voor risico gecorrigeerde *out-of-sample* voorspellende kracht vertonen voor bijna alle indices. Alleen voor voldoende lage transactiekosten ($\leq 0.25\%$ per order) wordt er een economische en statistische significante voor risico gecorrigeerde *out-of-sample* voorspellende kracht gevonden voor trend-volgende technische handelsstrategieën toegepast op de indices van de aandelenmarkten in Azië, Latijns Amerika, het Midden Oosten en Rusland.

Uit de resultaten van hoofdstuk 2 kan worden geconcludeerd dat een toevallig samenspel van economische factoren er voor kan zorgen dat technische analyse een schijnbaar voorspellende kracht kan vertonen. Uit de resultaten van hoofdstuk 3 blijkt dat met het toepassen van technische analyse op de Amerikaanse aandelenmarkt geen statistisch significant bovengemiddeld rendement kan worden behaald. Aandelen op de Nederlandse aandelenmarkt lijken wel enigszins voorspelbaar te zijn, zo blijkt uit hoofdstuk 4, maar transactiekosten doen de meeste positieve resultaten teniet. Na correctie voor transactiekosten, risico en de zoektocht naar de beste strategie, wordt in hoofdstuk 5 aangetoond dat technische analyse winstgevend is en een statistische significante voor risico gecorrigeerde *out-of-sample* voorspellende kracht heeft in de opkomende markten in Azië, het Midden Oosten, Rusland en Zuid Amerika. Echter, dit geldt alleen voor voldoende lage transactiekosten. Namelijk, voor transactiekosten groter dan of gelijk aan 0.50% per order worden er geen tot weinig significante resultaten gevonden. De conclusie van dit proefschrift is dan ook dat voor alle onderzochte financiële datareeksen de zwakke vorm van de EMH niet zondermeer verworpen kan worden door het toepassen van trend-volgende technische handelsstrategieën, nadat er is gecorrigeerd voor voldoende transactiekosten, risico, de zoektocht naar de beste strategie en *out-of-sample* voorspellen.

In hoofdstuk 6 wordt een theoretisch financieel markt model ontwikkeld met heterogeen adaptief lerende beleggers. De beleggers kunnen kiezen uit een fundamentele en een technische handelsregel. De fundamentele regel voorspelt dat de koers met een bepaalde snelheid terugkeert naar de fundamentele of intrinsieke waarde, terwijl de technische handelsregel is gebaseerd op voortschrijdende gemiddelden. Het model in hoofdstuk 6 is een uitbreiding van het Brock en Hommes (1998) heterogene agenten model, omdat het aan de verzameling van voorspelregels waaruit de agenten kunnen kiezen een realistische technische handelsregel gebaseerd op voortschrijdende gemiddelden toevoegt. Het model wijkt af door de aanname van relatieve risico aversie, zodat beleggers die dezelfde voorspelregel kiezen hetzelfde percentage van hun vermogen investeren in het risicovolle goed. Het lokale dynamische gedrag van het model rond het fundamentele evenwicht wordt bestudeerd door het variëren van de waarden van de modelparameters. Een mix van theoretische en numerieke methoden wordt gebruikt om de dynamica te analyseren.

In het bijzonder wordt aangetoond dat het fundamentele evenwicht instabiel kan worden als gevolg van een Hopf bifurcatie. De interactie tussen fundamentalisten en technische analisten kan er dus toe leiden dat de koers afwijkt van de fundamentele waarde en grote schommelingen vertoont. In deze heterogene wereld zijn fundamentalisten niet in staat om technische analisten uit de markt te drijven, maar fundamentalisten en technische analisten blijven voor altijd naast elkaar bestaan en hun relatieve invloed varieert door de tijd.

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