Market Efficiency in The Swedish Market

- Study on technical trading rules 1987-2008

Fredrik Schulz-Jänisch[a]
Major in Finance
Stockholm School of Economics

ABSTRACT

I investigate market efficiency in the Swedish market by analyzing the informational value and profitability of a set of technical indicators and trading systems, many of which have received little attention in previous research. I determine that technical analysis has informational value, as the distributions of the conditional returns differ greatly from that of the unconditional returns and the normal distribution. Regarding the profitability of technical trading rules, I find that the risk-adjusted daily returns are slightly negative overall for the standalone indicators. However, profitability increases greatly when indicators are combined. In addition, I find that technical analysis has larger predictive powers when based on weekly instead of daily data and that technical returns have decreased over the sample period. These results determine that markets are inefficient, but have become more efficient over the studied period. This suggests that technical traders have to use increasingly sophisticated technical trading rules in order to earn profits in future markets.

[a]19454@student.hhs.se

Master's thesis in Finance
Tutor: Stefan Engström
Dissertation: 12 June 2009, 10.15-12.00
Venue: Room 550
Discussant: Johanna Eklund

I would like to thank Stefan Engström for his support and valuable guidance.

TABLE OF CONTENTS

1. Introduction

If markets are efficient, all available information is known to investors. Firms are then valued at their true values at all times. However, previous research has pointed out several signs of market inefficiency. Dennis and Weston (2001) find evidence of information asymmetries in markets, where some investors have more information than others. Furthermore, this superior information is only slowly diffused in the market, allowing the informed investors to reap profits for as long as a year (Hong, Lim and Stein, 2000). Moreover, market participants buy disproportionately large stakes in previous star performers (Cai and Zheng, 2004) and they tend to buy and sell firms in the same industries (Choi and Sias, 2008). These factors of stake and information imbalances lead to temporary excessive demand in periods of intense institutional buying (and selling), driving prices away from their fundamental values. After these periods of institutional repositioning, prices return to their true values, resulting in excessive negative (positive) returns instead (Cai and Zheng, 2004).

One area of market efficiency that has received increased interest in the last few decades is technical analysis. Technical trading rules suggest trades based on past data. As all information is available to investors in efficient markets, past information is reflected in prices. Hence these trades cannot be profitable. Moreover, since technical rules do not possess information that is not already incorporated in prices in efficient markets, they should not alter the distribution of unconditional returns in efficient markets. If trades are profitable and the conditional and unconditional distributions differ, markets are inefficient.

The aim of this thesis is to provide additional insights into market efficiency by examining the forecasting ability of technical indicators and trading systems that have so far received little interest in research. This study thus supplements previous research and contributes to a fuller picture of the prevalence of market discrepancies.

Based on the discussion above, the main purpose of the thesis is to answer the following questions:

Does technical analysis have informational value? That is, do technical rules alter return distributions?

Are returns positive after accounting for transaction costs and risk?

Apart from the main purpose, this thesis also addresses four additional issues: *i) do trading systems perform better than standalone indicators? ii) do different types of trading systems perform differently? iii) do technical rules perform differently when using weekly instead of daily data? iv) have technical returns changed over the years?* The first two questions seek to answer whether the forecasting ability of technical analysis can be increased by combining standalone indicators. The third issue investigates if collecting data in larger time units improves results, as these technical trade signals will be based on more data. The last question examines whether markets have become less or more efficient over time.

In order to study the existence of market discrepancies, data on securities included in the Swedish OMX 30 index with complete data series from 1987 to the first quarter of 2008 will be used. These securities are studied as these are the most traded and thus the amount of data will be enough in order to test the predictive powers of technical rules.

Two types of standalone indicators will be investigated: mathematical indicators and various bar chart patterns known as guerrilla indicators. They all look for trend shifts, but guerrilla indicators are usually more short-term. In order to explore whether combinations of indicators increase performance, indicators included in the trading systems are added one by one. During this process, trade signals sequences where the already added indicators are not concordant are disregarded.

The results show that the distribution of the conditional technical returns differs from the distribution of the unconditional returns. This implies that technical analysis has informational value. Furthermore, the standalone indicators have weak profitability, whereas the trading systems are profitable. Hence, combining indicators substantially improves profitability and investors should therefore focus on utilizing these techniques, especially by combining different types of indicators. The results further show that returns increase by about 6 percentage units when technical analysis is based on weekly data instead. Finally, returns decrease by 2.4 percentage units over time, illustrating the need for more elaborate trading techniques in the future.

1.1. Outline

The thesis will start by giving a detailed description of the examined indicators and trading systems (section 2). Next, having introduced technical trading terms, past research in the field will be presented and discussed along with other studies in market efficiency (section 3). Thereafter, the hypotheses will presented (section 4), which will be followed by an overview of the dataset and a description of the computational methods used (section 5). Section 6 will present and analyse the results. I conclude with a summary of the main findings (section 7).

2. Description of Technical Indicators and Systems

As mentioned above, the field of technical analysis is made up of various techniques. The most used methods to display chart data are bar-, line-, point & figure and candlestick charts. I will use bar charts in my analysis, as the method is very common and straightforward. In a bar chart, there is one vertical bar for every trading day (assuming daily data is used). The vertical length of the bar is determined by price volatility (assuming price, and not for example volume, is the input) during the day, where the greater the difference between the highest and lowest price, the longer the bar. Furthermore, there are tick marks on the left and right sides of the bar, showing the opening and closing price respectively. Hence, a bar gives a wealth of information. Apart from displaying the daily volatility, it also tells the user whether the day was a bull or bear day and if the security ended strongly (close to the top of the bar) or weakly (vice versa).

The indicators studied are of two different types: mathematical and guerrilla indicators. Guerrilla indicators are, as their umbrella term suggests, short-term indicators that quickly take position in securities where there are signs of change and then shortly afterwards pull out again. These indicators base their trading decisions on the above mentioned multitude of information given by the bar charts. Furthermore, guerrilla indicators can be studied by looking at bar charts directly as they trade based on bar patterns. However the second type, mathematical indicators, cannot. They are produced by mathematical formulas and hence one has to generate graphs based on the output of these formulas in order to be able to study them. Another important distinction is that the mathematical indicators are always long or short in markets, in contrast to the temporary market presence of guerrilla indicators. Below follows a detailed description of the indicators and systems studied in this thesis.

2.1. Mathematical Indicators

The mathematical indicators that I study can themselves be divided into four categories: trend, momentum, volume and volatility. The trend indicators will be studied separately and in conjunction with each other (trend trading systems), while the other three indicator types will be used in conjunction with trend (combination trading systems). Trend indicators naturally look for trends in the security price. The trend indicators investigated in this thesis are: Dual Moving Average Crossover, The Directional System, Linear Regression and Moving Average Convergence Divergence. These, along with the other indicators, are explained more carefully below. Momentum indicators, on the other hand, are used to study securities that are not trending in the chosen time window. In this state, the price exhibits a wave pattern, where it oscillates around a certain level. Momentum indicators spot when prices are at the bottom or top of a price wave and trade accordingly. Thus, they signal the trade status in a shorter time period. The Slow Stochastics indicator will be used in this way. By being able to detect short-term trend shifts, it further means that momentum indicators have the potential to detect more long-term trend shifts early. They can hence also be categorized as trend indicators (Torssell and Nilsson, 2000b). Thus, one momentum indicator (Moving Average Convergence Divergence) is listed as a trend indicator. Volume indicators look for trends in volume. The volume pattern should confirm the trend pattern. This means that in a positive trend, volume should increase as the price goes up and decrease when the price goes down. Hence, in a negative trend, volume should increase as the price goes down and decrease when the price goes up (Torssell and Nilsson, 2000a). As volume is more volatile than price, I add a modified volume-based moving average indicator to facilitate the analysis. Finally, Chaikin Volatility Indicator is investigated as changes in volatility affect returns (Torssell and Nilsson, 2003)

As mentioned earlier, two different types of trading systems will be studied; a trading system based on trend indicators and another based on indicators from all four categories. Due to the fact that the trend indicators are of the same type, they should be rather highly correlated. Thus, it has been suggested that combining trend indicators does not substantially increase technical returns (Torssell and Nilsson, 2000b). Hence, combination systems are also studied. Both systems will use the Dual Moving Average Crossover indicator trend as their base indicator. Then, indicators will be added one-by-one in order to study the gradual changes in forecasting ability. The indicators are added in order of decreasing similarity of type. This results in the following trading systems:

- Trend 1 (Trend 1): Dual Moving Average Crossover and the Directional System.
- Trend 2 (Trend 2): Trend 1 indicators and Linear Regression.
- Trend 3 (Trend 3): Trend 2 indicators and Moving Average Convergence Divergence.

- Combination 1 (Comb. 1): Dual Moving Average Crossover and Slow Stochastic.
- Combination 2 (Comb. 2): Comb. 1 indicators and Volume.
- Combination 3 (Comb. 3): Comb. 2 and Chaikin Volatility Indicator.

Trend:

Dual Moving Average Crossover (DMAC):

This indicator consists of two Simple Moving Averages (SMA) with different lengths. The shorter SMA is added to the longer SMA to better time trend shifts. To illustrate how a SMA is calculated, a 10-day SMA is computed as follows: The first value of the SMA is an arithmetic mean based on values on days 1-10, the second value is based on days 2-11 and so on. This indicator follows the saying "let the trend be your friend". That is, if the trend is positive, it is likely that a security will continue to go up. I have chosen a short 20-day SMA and a long 50-day SMA. SMAs with these parameter lengths make trading decisions based on the medium trend (a few weeks to a few months). I deem this trading horizon to be the most relevant to study. When prices are not trending, the two curves in the trend crossover indicators (hence all trend indicators except Linear Regression, as this indicator has a single curve) are at times intertwined. This behaviour results in many false signals. These signals are therefore removed (for more information see section 5.2).

Trading rules:

- Buy when the short SMA crosses the long SMA from below.
- Sell when the short SMA crosses the long SMA from above.

The Directional System (DS):

This indicator is more complex and unintuitive. In short, it compares the average relative size of bar gains and bar losses during a period of x days in order to determine the trend direction and thus generate buy and sell signals. I use the standard value of x equal to 13 days. Standard values are preferred as this reduces data mining issues. Its calculation steps below provide further insight.

Calculation steps:

1. Calculate positive and negative Directional Movement (DM). DM is the part of today's range, which is outside yesterday's range (the difference between a bar's high and low). DM is denoted DM+ if today's high is greater than yesterday's high and denoted DM- if today's low is lower than yesterday's low. DM is always a positive

value. An outside day (today's bar exceeds yesterday's bar at both ends) is the maximum of DM+ and DM-. An inside day (today's range does not exceed yesterday's at either end) has a DM of zero.

2. Calculate True Range. It is the largest value of 1) today's range 2) today's high minus yesterday's close 3) today's low minus yesterday's close. True Range is always a positive value as well.
3. Calculate DI+ and DI-. DI+ = DM+ / True Range and DI- = DM- / True Range.
4. Smooth DI+ and DI- by calculating 13-day SMAs based on their values.

Trading rules:

- Buy when the smoothed DI+ crosses the smoothed DI- from below.
- Sell when the smoothed DI+ crosses the smoothed DI- from above.

- **Note:** When the following mathematical indicators (and the DS indicator) are not evaluated as standalone indicators but as part of trading systems, their buy (and sell) rules are simplified. It is not important when they turn positive (buy) or negative (sell). What is important is whether they are positive or negative at the same time as the previously added indicators in the trading system. For example, a positive DMAC indicator is reinforced by a positive DS indicator, but if the DS indicator is negative, it disagrees with the positive DMAC indicator, thus the security is sold. When the DS signal starts or ends is irrelevant. Hence, when part of a trading system, the above trading rules are (and the reasoning for the other indicators in the systems is the same):
    - Positive indicator (the smoothed DI+ is above the smoothed DI-)
        - Long trading system positions: Do NOT terminate the trading system position.
        - Short trading system positions: discrepancy in signal type – terminate trade
    - Negative indicator (the smoothed DI+ is below the smoothed DI-)
        - Long trading system positions: discrepancy in signal type – terminate trade
        - Short trading system positions: do NOT terminate trade

Linear Regression (LR):

This method calculates the line that best fits the closing prices N days back. Even though it is computationally different from DMAC, it looks similar. I have chosen N equal to 35 days. Thus, signals will be generated based on the medium trend (the same as DMAC).

The equation for the line is of the familiar form $y = a + b \cdot x$.

Calculation steps:

1. $$b = \frac{N \cdot \sum_{i=1}^{35} x_i \cdot y_i - \sum_{i=1}^{35} x_i \cdot \sum_{i=1}^{35} y_i}{N \cdot \sum_{i=1}^{35} x_i^{\,2} - \left(\sum_{i=1}^{35} x_i \right)^2},$$

   where x is a weight, (for example x=1 for the closing price 35 days back, thus recent prices have greater weight), and y denotes the closing price. Furthermore,

   $$a = \frac{1}{N} \cdot \left(\sum y - b \cdot \sum x \right)$$

2. Insert values for b and a in the line equation above.

Trading rules:

- Buy when the slope of the line becomes positive.
- Sell when the slope becomes negative.

Moving Average Convergence Divergence (MACD):

MACD measures the difference between two Exponential Moving Averages (EMA). The standard values are 12 and 25. The interpretation is the same as for the DMAC indicator. The difference between the two indicators is that MACD uses exponential moving averages, which react faster to price changes than simple moving averages. MACD is known as a *leading indicator*, i.e. it may turn around before the price curve. A negative aspect of its faster reaction times is that the accuracy of its predictions is diminished. Hence, it should be combined with indicators that can confirm whether the indicator's early predictions are correct (Torssell and Nilsson, 2000b).

Steps:

1. The MACD Line = 12-day EMA - 25-day EMA, where

   $EMA = \frac{2}{1+N} \cdot \left(C_t - EMA_{t-1} \right) + EMA_{t-1}$, C denotes closing price and N days (12 or 25)

2. The MACD Signal Line = 9-day EMA on the MACD line

Trading rules:

- Buy when the MACD line crosses the signal line from below.
- Sell when the MACD line crosses the signal line from above.

Momentum:

Slow Stochastic:

As described earlier, the idea behind momentum indicators is that security prices oscillate around a mean. The indicators identify when securities are oversold and overbought, i.e. at levels far away from the mean. Stochastic is based on the fact that prices usually end closer to the highs (lows) than the lows (highs) for the day in a positive (negative) trend. Because Fast Stochastic is very volatile, I have opted for the smoothed version of the indicator, Slow Stochastic. The indicator is limited to values between 0 and 100, where below 20 means that a security is oversold and above 80 signals that a security is overbought. It consists of two curves (the %K and the %D curve) and signals are generated when the faster reacting curve crosses the slower adapting curve. I use standard values.

Steps:

1. The Fast Stochastic curve: 5-period %K = (today's closing price – lowest closing price in the last 5 days) / (highest closing price in the last 5 days – the lowest closing price in the last 5 days)
2. Smoothing the curve: 3-period %D = 3-day SMA of %K
3. The Slow Stochastic curve: %K (slow stochastic) = %D (fast stochastic)
4. Smoothing the curve once again to improve accuracy: %D (slow stochastic) = 3-day SMA of %K (slow stochastic)

Trading rules:

- Positive indicator (both slopes are positive):
  - Long trading system positions: Do NOT terminate the trading system position.
  - Short trading system positions: discrepancy in signal type – terminate trade
- Negative indicator (both slopes are negative):
  - Long trading system positions: discrepancy in signal type – terminate trade
  - Short trading system positions: do NOT terminate trade.

Volume:

Volume uses the same trade criteria as DMAC above but with two exceptions. Firstly, volume data is used as input rather than price data. Secondly, due to the volume-confirms-price criterion, a positive (negative) volume trend confirms (does not confirm) both a positive and a negative price trend. Thus the trading rules are simpler than previous ones:

<u>Trading rules:</u>

- Do NOT terminate the trade when the short volume SMA is above the long volume SMA.
- Terminate trade when the short volume SMA is below the long volume SMA.

Volatility:

Chaikin Volatility Indicator (CVI):

Periods of low volatility is followed by periods of high volatility. Low volatility is hence an indication of that there will be subsequent large moves in the stock price (Torssell and Nilsson, 2003). Thus, volatility is a useful addition to trading systems. Chaikin indicator identifies volatility by examining the average spread between highs and lows over a period of 10 days (the standard period). Then the percentage increase of the average is calculated to produce the indicator.

<u>Steps:</u>

1. High-Low Average = 10-day EMA of (High – Low)
2. $$\left(\frac{(\text{H - L Average}) - (\text{H - L Average N days ago})}{(\text{H - L Average N days ago})}\right)\cdot 100$$

To exclude signals generated during periods of high volatility, I only take volatility signals activated during periods of below average volatility into account. Furthermore, a positive slope of the Chaikin indicator (which is a moving average of volatility) increases the probability that there will be a shift in the more long-term volatility in the near future. As was previously the case with the volume indicator, these trading rules are simpler due to the fact that the rules are the same for long and short transactions:

<u>Trading rules:</u>

- Do NOT terminate the trade when:
  - The slope of the indicator is positive.
  - If volatility is in the low 50 percent of the volatility readings during the past 100 days.

- Terminate the trade when:
  - The slope is negative.
  - If volatility is in the high 50 percent of the volatility readings during the past 100 days.

2.2. Guerrilla-Trading

Guerrilla-trading is a set of strategies that act on certain bar patterns. The trades are often very short-term (usually less than two-three weeks). However, guerrilla-trading can also be used to find the start of a trend. The guerrilla pattern might hence be the starting point in a long-term trade as well. Many of the indicators are seen as unreliable on their own (Torssell and Nilsson, 2000b). I will therefore test their predictive powers with and without a trend filter. The filter is a moving average system with 10- and 50-day or 20- and 50-day moving averages depending on trend strength requirements. The position is terminated when there is a “big range day” (i.e. a bar that is seen as large compared to the previous bars). This is because such a trading day is seen as an indication of a subsequent end of the current trend or shift in trend (Torssell and Nilsson, 2000b). The rule descriptions are vice versa for short trades.

Key Reversal Day (KR):
Key Reversal Day can be categorized as a turnaround signal. After reaching a new low, the security closes above the high of the previous bar. Thus, the signal often occurs when new positive information about a company has been released (Torssell and Nilsson, 2000b).

<u>Trading rules:</u>

1. The price must have decreased at least one unit of time.
2. A Key Reversal Day is formed when the security reaches a new low, but turns around and closes above the high of the previous bar the same day.
3. *Trend filter: The close (in the Key Reversal Day bar) must be above both the 20- and 50-day moving averages (hence both the short- and medium-term trend are positive).*
4. If the security reaches a new high during the next time unit (after the key reversal bar), the security is purchased.
5. The security is sold on the next “big range day”. I choose to define it as a bar, which length is at least 50 percent longer than the previous three bars.

Reversal Day (RD):

This signal is similar to the Key Reversal Day. The difference is that the Reversal Day signal only requires the security to close above the previous bar's closing price instead of above its high. Hence, this signal is weaker than the Key Reversal Day. But due to its less stringent conditions it is more common and hence there are more trading opportunities.

Steps and trading rule:

1. The price must have decreased at least one unit of time.
2. A reversal day is formed when the security reaches a new low, but turns around and closes above the closing price of the previous bar the same day.
3. *Trend filter: The close (in the reversal day bar) must be above both the 20- and 50-day moving averages.*
4. If the security reaches a new high during the next time unit, the security is purchased.
5. The security is sold on the next "big range day" with the same definition as above.

Two Day Reversal (TDR):

This signal can be categorized as a three-day turnaround signal. The trend filter is stricter in this case as this is a weaker turn-around signal and hence regarded as less reliable than the previous two trading strategies (Torssell and Nilsson, 2000b). Its main use is to take advantage of short pauses in trends and thus buy the security at a "discount" (Torssell and Nilsson, 2000b).

Steps and trading rule:

1. In the first time unit, the closing price must be in the lower 20 percent of the bar.
2. In the next time unit, the closing price must be in the higher 20 percent of the bar.
3. *Trend filter: The close (in the second bar) must be above both the 10- and 50-day moving averages.*
4. If the security reaches a new high during the following time unit, the security is purchased.
5. The security is sold on the next "big range day".

One Day Reversal (ODR):

A one day reversal is comparable to the first two strategies as there is a significant turnaround during a time unit. A security both starts and ends close at the top of the bar but reaches a new low in-between.

Steps and trading rule:

1. The price must have decreased at least one unit of time.
2. The security opens and closes in the top 20 percent of the bar, and reaches a new low in between.
3. *Trend filter: The close must be above both the 20- and 50-day moving averages.*
4. If the security reaches a new high during the following time unit, the security is purchased.
5. The security is sold on the next “big range day”.

Pattern Gap (PG):

A pattern gap must fulfil a series of requirements. Its most noticeable feature is that the low of the current bar is higher than the preceding bar’s close. Hence, this signal usually occurs in relation to new information being released between trading sessions (Torssell and Nilsson, 2000b).

<u>Steps and trading rule:</u>

1. The price must have decreased at least one unit of time.
2. The lowest price of the time unit is above the previous bar’s close.
3. The close must at least be higher than the middle of the bar.
4. The close must be above the preceding bar’s high.
5. The close price must be above the two previous bars’ closing prices.
6. *Trend filter: The close must be above both the 20- and 50-day moving averages.*
7. If the security reaches a new high during the following time unit, the security is purchased.
8. The security is sold on the next “big range day”.

Reversal Gap (RG):

A reversal gap is formed when the entire bar is above the previous bar. Hence, the signal is stronger than the pattern gap and consequently it too appears in connection with new information (Torssell and Nilsson, 2000b).

<u>Steps and trading rule:</u>

1. The price must have decreased at least one unit of time.
2. The low of the bar is above the high of the preceding bar.
3. The close must be above the preceding bar’s high.
4. The close must at least be higher than the middle of the bar.
5. The close must be above the two previous bars’ closing prices.

6. *Trend filter: The close must be above both the 20- and 50-day moving averages.*
7. If the security reaches a new high during the following time unit, the security is purchased.
8. The security is sold on the next "big range day".

1-2-3-4-Signal:

According to the late trader W.D. Gann, a common pattern in a strong trend is that a security trades against the trend for three days; thereafter the trend run is continued. A stricter trend filter is applied as the signal is used in strong trends (Torssell and Nilsson, 2000b).

Steps and trading rule:

1. The security must have traded against the trend for three time units. Either the security has had three consecutive lower lows or there has been a combination of an inside day and two lower lows. An inside day is a bar, which high is as high or lower as the previous bar's high and which low is as low or higher than the previous bar's low. Hence, the bar is inside the preceding bar.
2. *Trend filter: The close must be above both the 10- and 50-day moving averages.*
3. If the security reaches a new high during the fourth time unit, the security is purchased.
4. The security is sold at the next "big range day".

3. Literature Review

In the introduction, I gave examples of various types of market inefficiencies. Due to the large amount of literature in the field, this section will focus on research closely related to my investigation. A significant part of the review will also concentrate on papers specifically exploring technical analysis.

3.1. Market Efficiency Studies

In the last few decades, large institutional investors have greatly increased their discretionary control in equity market firms. For example, institutions control a majority of the US equity market. Furthermore, large institutional investors have become the most influential institutions (Gompers and Metrick, 2001). Thus, it is essential to examine the price impact of large institutional investors in the market.

The question is whether institutional trading pushes away prices from their true values. Two theories are of special interest: i) positive-feedback trading; institutions buy (sell) past winners (losers) and ii) institutional herding; institutions trade in the same direction in the same period in certain securities or industries.

Cai and Zheng (2004) study quarterly data on institutional holdings in the US market. The authors find that there is a run-up (run-down) in returns for purchased (sold) securities before the quarter with the most intense trading, while securities exhibit mean-reversion after the trading quarter. The trading quarter itself, has the highest (lowest) returns, where the portfolios with the most intense institutional buying (selling) generate the highest (lowest) returns. This price pattern suggests positive-feedback trading as prices are unsustainable and there is a positive correlation between changes in institutional ownership and returns. Sias, Starks and Titman (2001), Burch and Swaminathan (2003) and Shu (2008) examine quarterly data as well and report significant evidence of positive-feedback trading. Grinblatt, Titman and Wermers (1995) investigate mutual funds and finds some support, while Lakonishok, Shleifer and Vishnu (1992) in their study of pension funds document positive-feedback trading and low levels of herding only in the smallest securities. Wermers (1999) finds evidence of herding in small securities among mutual funds. However, Wylie (2005) documents that the herding results in Lakonishok, Shleifer and Vishnu (1992) and Wermers (1999) are positively biased as they exempt short-sale restrictions. When accounting for these constraints, he reports no evidence of herding in U.K. data. Badrinath and Wahal (2002) analyze the trading behaviour among different types of investors and find, in line with Burch and Swaminathan (2003) and Dennis and Strickland (2002), that investment advisors and mutual funds are more active traders than other groups.

Nofsinger and Sias (1999) study daily trader-identified transaction data (US institutions only have to report changes in their holdings quarterly) and find a positive relation between returns and changes in institutional ownership. Chakravarty (2001) reports similar results. Dennis and Strickland (2002) study the trading behaviour of institutional investors during volatile sessions (defined as the absolute value of the market's return exceeding two percent) and document that both turnover and security returns are positively related to the fraction of institutional ownership. Thus, the authors find evidence of that institutional herding contributes to market volatility, especially the subsample with mutual funds. However, using the same definition of volatility as Dennis and Strickland (2002), Lipson and Pucket (2006) study mutual funds and pension plan sponsors and find them to be contrarian traders, where bullish and bearish days are seen as opportunities to execute previously determined trades.

Nofsinger and Sias (1999) also investigate the relation between changes in institutional ownership and returns on an annual basis and report a positive correlation. However, the returns do not exhibit mean-reversion after the trading period. Hence, positive-feedback trading only partially explains results. The results are consistent with the informed trading hypothesis, where some traders have superior information. Sias, Starks and Titman (2001) support the hypothesis since they find that, apart from the absence of mean-reversion, returns are more related to the number of institutions entering or exiting securities than the fraction of securities held by institutions. Hence, returns cannot be attributed to price pressure caused by increasing institutional ownership. Bennett, Sias and Starks (2003) report that greater informational advantages for institutional investors in small firms than large firms result in larger post-herding returns in the former group. Cohen, Gompers and Vuolteenaho (2002) find that institutions only pursue strategies related to changes in cash flow and their trades are contrarian to price movements caused by other factors. Finally, Gompers and Metrick (2001) document that the small-company security premium has disappeared due to increased demand for large liquid securities among institutional investors. Thus, the imbalance is driven by demand rather than trading strategies.

A few studies focus their attention on institutional behaviour during the dotcom bubble. Brunnermeier and Nagel (2004) find that funds invested mainly in the technology sector during the bubble and began reducing their positions when the bubble started bursting. Thus, they deliberately rode the bubble and contributed to pushing away prices from their fundamental levels. Griffin, Harris and Topaloglu (2003) study the bubble as well and report that the best performing securities during the previous session were more likely to be purchased by institutions than the worst performing ones. Thus, the institutions engaged in positive-feedback trading. Ofek and Richardson (2003) argue that significant short-sale restrictions prohibited institutions from pushing back prices to fundamental values. Jones and Lamont (2002) study the impact of short-sale constraints between 1926-1933 and report similar results.

Evidence outside US markets, is mixed as well. Rouwenhorst (1998) report that a rebalanced European portfolio consisting of past winners outperforms a portfolio of past losers by about one percent a month between 1980 and 1995, thus contradicting the market efficiency hypothesis. This effect is present in all 12 markets in the sample. Grinblatt and Keloharju (2001) study the Finnish security market and document that domestic sophisticated investors are contrarian investors (i.e. they trade against the trend) while foreign investors are momentum investors. Mei, Scheinkman and Xiong (2004) study the A-B share premia in Chinese markets, where class A and B shares can only be held by domestic and foreign investors respectively. The two classes of shares have identical rights, yet the prices of class A shares were on average 420% higher than class B shares. After controlling for liquidity and several other factors, they find that the average price difference between class A and B shares is due to speculation among domestic investors. This evidence is in line with the results found in Brunnermeier and Nagel (2004) and other papers, which assert that prices can be affected by non-fundamental factors. Finally, Choe, Kho and Stulz (1999) find daily positive-feedback trading among institutional investors in Korea, while Kim and Nofsinger (2005) only report evidence of investigative herding (herding based on some investors having superior information) in the Japanese market.

3.1.1. Papers on Technical Analysis

Filter rules:

Alexander (1961) was the first major paper about technical analysis. He introduced filter rules[1]. The three smallest filters produce substantial profits. Thus, the filters are likely to generate positive returns after accounting for commissions as well. The existence of trading profits shows that the rules have informational value. This contradicts the random walk hypothesis, suggesting market inefficiency. However, Mandelbrot (1963) documents that Alexander’s calculations are biased, as they underestimate the purchase price and overestimates the selling price. After revising the rule, the profits diminish (Alexander, 1964). Furthermore, Fama and Blume (1966) report that Alexander’s papers do not take dividends into account, thus exaggerating short sale profits. After adding dividends, the filter rules underperform a buy-and-hold portfolio. However, Logue and Sweeney (1977) and Cornell and Dietrich (1978) test filter rules in the European spot currency market and find that they outperform the buy-and-hold strategy, though, Raj (2000) report negative results for his currency sample. Studies of other markets include Stevenson and Bear (1970) and Solt and Swanson (1981) who receive poor results in the futures market (corn and soybean) and precious metals market (gold and silver)

[1] These trading rules filter out small movements. A buy (sell) signal is produced when today’s closing price is x percent above (below) yesterday’s low (high).

Moving average rules:

In the last decades, the papers on technical analysis have changed their focus from studying filter rules to moving averages and other indicators and techniques. Brock, Lakonishok and LeBaron (1992) test a number of moving averages on the Dow Jones Industrial Average. The authors find that all buy (sell) signals outperform (underperform) the unconditional returns before transaction costs. Similar return discrepancies are reported by Fama and Blume (1966) for filter rules. A possible explanation is the existence of greater volatility after sell signals Brock et al. (1992). The authors conclude that the return and volatility discrepancies are inconsistent with random walk models. Bessembinder and Chan (1995) use the same trading rules as Brock et al. (1992) and show that round-trip transaction costs have to be 1.57% to eliminate technical trading profits in Asian markets. However, results are less pronounced in developed markets, although informational inefficiency can only explain the gains partially. Adjusted for transaction costs as well, Hudson, Dempsey and Keasey (1996) report negative returns for U.K. data. Bessembinder and Chan (1998) adjust Brock et al's (1992) results for dividends and find that break-even costs have decreased over time to 0.22% for the last sub period (1976-1991), while actual trading costs are estimated at 0.25%. Parisi and Vasquez (2000) confirm the conclusions in the two previous papers. Papers using other moving average rules, arrive at mixed conclusions. Day and Wang (2002) find that the technical profits turn negative in the last subsample (1987-96), thus supporting the evidence in Bessembinder and Chan (1998). Gunasekarage and Power (2001) report similar results to Bessembinder and Chan (1995) as they find substantially larger returns than the benchmark strategy in emerging markets.

Trading Systems:

Stevenson and Bear (1970) test four trading systems, which combine filter rules and stop-loss techniques[2]. Overall the combination system are profitable and perform well compared to the benchmark. Lukac, Brorsen and Irwin (1988) test a combination of Directional Movement[3] (DRM) and the Parabolic Time/Price System[4] (PAR) on various types of futures. The DRM acts as a trade filter and PAR is the trigger to take position. The returns are strongly positive 5

[2] A stop-loss places a limit of z percent below (or above when short) the position. The position is terminated when the limit is reached.

[3] DRM calculates two moving averages; the first is an average based on days with up ticks and the second on days with down ticks.

[4] The PAR-indicator starts a chosen z percent below (above for sell signals) the price curve and accelerates upwards (downwards), the speed of which is set by the user. When the indicator hits the price curve, the trade is terminated and the opposite position, sell (buy), in the security is taken.

out of 7 years (net returns between 30% and 90%). This supports the disequilibrium hypothesis, which state that the trading profits arise due to the market being slow to respond to informational shocks (Lukac et al. (1988). Fang and Xu (2003) use a combination of moving averages and time series models and find that the combination systems yields significantly greater returns than the moving average strategies alone (an average monthly return of 1.6% compared to 0.75%). Several studies have been performed on the CRISMA[5] combination system. Goodacre, Bosher and Dove (1999) and Goodacre and Kohn-Spreyer (2001) find negative results, while Pruitt, Tse and White (1992) arrive at the opposite conclusion.

Bar chart patterns:

Regarding bar chart patterns, Lo, Mamaysky and Wang (2000) perform goodness-of-fit tests and find that return distributions from 10 chart patterns differ from unconditional distributions. Thus, they conclude that technical analysis has informational value, even though it might not produce profits. Dawson and Steeley (2003) find similar results for U.K. data. Chang and Osler (1999) investigate the head-and-shoulders strategy[6] and find poor results. The outcome is confirmed by Lo et al. (2000). Caginalp and Laurent (1998) examine candlestick (another type of price chart than the bar chart) reversal patterns and find strong evidence in favour of technical analysis. Leigh, Paz and Purvis (2002) examine the performance of bull flag[7] patterns. The results show that the trading rule average return was more than twice that of the market for the 10-, 20- and 40-day forecast horizons and 1.5 times as large for the 80-day horizon before transaction costs. Leigh, Modani, Purvis and Roberts (2002) test a combination of a bull flag signal and volume. When combining the bull flag signal with volume, the returns of the long and short transactions increased from 11.5% to 14% and 7.8% to 8.6% respectively.

[5] Cumulative volume, RelatIve Strength, Moving Average (50/200) Cumulative volume measures the cumulative sum of the volume on up tick days minus the volume down tick days. Relative Strength compares a security's performance relative, for example, an index.

[6] A buy (sell) formation consists of a low (high), followed buy a lower (higher) low (high), which is followed by a third higher (lower) low (high). A line is drawn, connecting the first two highs (lows), which follows the lows (highs). When the price pushes through this line, a buy (sell) signal is triggered.

[7] A bull flag constitutes of a short period, usually in the middle of an uptrend, during which the security takes a break in the trend and moves sideways (or recedes slightly) before continuing to trend upwards. Thus, the pattern looks a bit like a flagpole.

3.2. Summary of Previous Research

In table 3.1 below, I list the papers whose results will be the basis for my hypotheses.

Table 3.1 **Summary of previous results.**

Authors *Year*	**Markets studied**[8]	**Sample period**	**Relevant findings**
Fama and Blume (1966)	30 DJIA securities	1956-62	• Longs significantly outperform shorts.
Lakonishok and LeBaron (1992)	DJIA	1897-1986	• Return and volatility discrepancies between longs and shorts suggest that the random walk hypothesis is untrue.
Bessembinder and Chan (1998)	DJIA	1926-91	• Technical returns have decreased over time and are less than the transaction costs for the last subperiod (1976-1991).
Lukac, Brorsen and Irwin (1988)	Futures (agricultural, metals, currencies, interest rates)	1975-83	• The combination system greatly outperforms the benchmark and the standalone indicators and the returns are above risk. • The disequilibrium model is favoured.
Lo, Mamaysky and Wang (2000)	NYSE/AMEX and Nasdaq securities	1962-96	• Technical analysis has informational value.
Leigh, Paz, Purvis and Roberts (2002)	NYSE	1980-1999	• Bull flag signals are profitable. • Combining bull flag signals with volume increases returns by 2.5 percentage units for longs and 0.8 percentage units for shorts.

4. Hypotheses

My hypotheses aim to explore market efficiency by examining how informative and profitable technical trading is from various angles. Firstly, I will investigate the distributional properties of the standalone indicators in order to study whether the distribution of the conditional returns (based on the trading rules) differ from the unconditional returns and the normal distribution. If so, technical analysis is informative. Secondly, I will compute returns before

[8] DJIA: Dow Jones Industrial Average, NYSE: New York Security Exchange, AMEX: American Security Exchange

and after transaction costs and adjust for risk, thus arriving at returns that increasingly better reflect the true performance of the indicators. Thirdly, I will examine if trading systems perform better than standalone indicators and whether combining different types of indicators (combination systems) yield better results than combining indicators of the same kind (trend systems). Thereafter, I will study if time unit length impacts results (by comparing daily and weekly data). Finally, the data is split into three subsamples to examine whether the profitability of technical analysis has changed over time.

Table 4.1 **Hypotheses**

H1:	*Technical analysis is informative.*
H2:	*The indicators outperform the market before transaction costs.*
H3:	*The indicators outperform the market after transaction costs.*
H4:	*The indicators outperform the market after risk.*
H5:	*Trading systems improve returns.*
H6:	*Combination systems outperform trend systems.*
H7:	*Returns increase when using weekly data instead of daily data.*
H8:	*Technical returns have decreased over time.*

Hypothesis 1: *Technical analysis is informative.*

According to the weak form of the efficient-market hypothesis, technical analysis is of no use, as the hypothesis claims that current prices take past market data fully into account. Today's security performance is thus independent of yesterday's, which means that there are no significant trends in the price series. Hence, prices should exhibit a random walk. However, it is not uncommon that markets go up (down) several days in a row. According to disequilibrium pricing models (Lukac, Brorsen and Irwin, 1988), markets are efficient (in equilibrium) most of the time. However, when "informational shocks" hit the market, investors' perceptions of the true value of a security change. During the time it takes for investors to evaluate the incoming news and change their portfolios accordingly, there will be confusion about the true value and thus the security price will be in disequilibrium. The disequilibrium theorists claim, that profits can be earned by exploiting the price trends during this state of market inefficiency.

By comparing the distributional characteristics of the conditional and unconditional returns one can find out whether or not technical analysis is informative. If the technical rules are informative, they will alter return distributions. Hence, if conditional and unconditional return distributions differ, technical analysis is informative. I will complement with the Kolmogorov-Smirnov test, in order to compare conditional distributions to the normal distribution. If the market follows a random walk, technical returns should be normally distributed. Previous research above showed that technical returns differ from unconditional returns. This hypothesis tests whether this is true for this sample of indicators as well.

Hypothesis 2-4: *The indicators outperform the market before transaction costs, after transaction costs and after adjusting for both transaction costs and risk respectively.*

The disequilibrium models give reason to believe that there might be technical profits. Furthermore, as important news flashes that either direct or indirect affect firms are frequent in today's global economy, there should be recurring periods of disequilibrium. The information shocks will alter firm risk. However, many other factors affect returns as well. Risk thus only partly explains returns and therefore conditional and unconditional returns should still differ after adjusted for transaction costs and risk.

Hypothesis 5: *Trading systems improve returns.*

This hypothesis examines whether trading systems generate better results than standalone indicators. The claim is that indicators look for different signs in the data. As two or more indicators signal a buy (or sell) at the same time, this increase the likelihood that the trading decision is correct. Hence, trading systems should improve technical returns.

Hypothesis 6: *Combination systems outperform trend systems.*

The idea that some trading systems yield better results than others is based on the argument in the previous hypothesis that indicators look for different signs in the data. While trend indicators look for the same patterns in price data, trends, synergy trading utilizes indicators that all search for different types of patterns (trend, oscillation, volume, volatility etc.). Correlation between indicators of the same type is considerable (Torssell and Nilsson, 2000b). Thus, combination systems should generate larger returns than trend systems.

Hypothesis 7: *Returns increase when using weekly data instead of daily data.*

Technical analysis should yield higher returns when using weekly instead of daily data. The reason is that one bar now contains a week of price information instead of only a day. Hence, whereas a daily up- or down move could be due to a market rebound or an equilibrium random walk, it is more likely that a weekly price change is due to firm- or market specific factors, as more news has been able affect the security price during this longer time period.

Hypothesis 8: *Technical returns have decreased over time.*

Bessembinder and Chan (1998) and Olson (2004) show that technical returns have decreased over time, which is due to greater market efficiency (Olson, 2004). Possible explanations for the improvement in efficiency include lower overall transaction costs, a larger fraction of sophisticated investors in markets and easier and faster access to news and market data. Thus, trading returns should decrease in the latter part of the sample.

5. Method and Data

Most of this section has already been covered, as the computational steps and trading rules for the indicators and systems were described in section 2. This section will present the dataset along with describing how returns are calculated after the trading rules have generated the trading signals. As the formulas for calculating returns before risk are quite complex, I provide the explicit formulas in a separate section (section 5.3). In addition, the inclusion or exclusion of outliers will be discussed.

5.1. The dataset

The dataset consists of price data on 11 securities[9] in the Swedish OMX Stockholm 30 index (OMXS30) for the period 1Q 1987 until the end of 1Q 2008. These are the only securities in the index on which there is data for the whole period. Furthermore, it includes price data on the index itself (in order to have a benchmark strategy). The starting point was chosen as 1987 as this is the starting point of Reuters' Datalink database. Reuters was chosen as the database contains opening quotes, is reliable and it is linked to the technical analysis software Metastock where the accuracy of the signals can be checked graphically.

[9] Electrolux B, Ericsson B, Hennes and Mauritz B, Investor B, Sandvik, SCA B, SEB A, Skanska B, SKF B, Trelleborg B, Volvo B

5.2. Computational issues

Cleaning of data:

In section 2, the trading signals were generated. However, some signals have to be adjusted before proceeding to calculating the returns. This concerns the trend crossover systems (DMAC, DS and MACD). The reason is that when securities are not trending, the two crossover curves tend to be intertwined. Hence, trading signals are activated and deactivated constantly. This behaviour affects the rest of the data. Hence, in order to be able to make conclusions regarding the indicators' forecasting ability, these signals are removed from the data. This is done by visually searching for these patterns in Metastock, in order to reduce errors.

Outliers:

Another issue is whether to remove return outliers or not. These indicator returns are generated in markets that trend strongly for a prolonged period of time, i.e. the creation or deflation of a bubble. However, as these events are recurrent[10], rather than once-in-a-lifetime events, I have chosen to include these outliers.

Transaction costs:

When calculating transaction costs, brokerage fees of 0.035 percent[11] are included. In addition, a so called order friction cost (0.40 percent) is included in the transaction costs. The reason for including order frictions is twofold. Firstly, the bid-ask spread imposes a cost on investors as they enter and exit a security. Secondly, due to market volatility, investors cannot always buy at the desired price.

The risk-free rate:

Another issue is which interest rate to use as the risk-free rate. I have chosen the rate on one month Swedish treasury bills, obtained from The Riksbank. Since they are short-term and issued by the Swedish National Debt Office, they should be a good proxy for the true risk-free interest rate. However, due to high inflation (Statistics Sweden, 2006), the rates were very high between 1987 and 1992 in the sample. I compute the median rate (4.51 percent) of the

[10] Crises during the sample: Black Monday (1987), the Swedish crisis (beginning of the 90s), the Asian financial crisis (1997), the Dot-com bubble (1998-2001), 9/11 terrorist attack (2001-2002); after the sample: the US financial crises (2008-2009)

[11] a typical fee for an active trader at an internet broker in 2008

yearly t-bill rates in order reduce the positive bias of the mentioned years on results. The calculated median rate is hence defined as the risk-free rate for the whole sample. I assume there are 250 trading days per year.

How returns before and after transaction costs are calculated:
The method used for calculating returns before risk differs between the mathematical indicators and the guerrilla indicators. The reason is that mathematical indicators (when short trades are enabled, which is the focus of this investigation) are always in the market (except for the short periods of time when the bands are intertwined), while many of the guerrilla indicators are dormant most of the time. The computing of mathematical returns is, disregarding transaction costs, hence straightforward. However, the frequent periods of inactivity among guerrilla indicators raises two major issues. Firstly, the greater amount of inactivity makes it impossible to compare mathematical and guerrilla returns, as the accumulated guerrilla portfolio value for each security would largely (for most indicators) be based on risk-free rate returns. Secondly, it would be difficult to separate the effects of the interest rate from that of the technical trading rules. I therefore annualize the guerrilla trade returns in order to be able to disregard periods of inactivity. This results in returns that better reflect the performance of the guerrilla indicator and in addition it is easier to compare them with returns from the mathematical indicators. Below follows a more detailed description of the calculation methods.

The value of the trading portfolio for a particular strategy using mathematical trading rules is calculated as follows:

- For each individual security in the sample:
    - Calculate the accumulated portfolio value generated from the technical trades for the whole sample period, using the risk-free interest rate in the brief periods of inactivity. See section 5.3 for explicit formulas.
    - Annualize the return.
- Compute the average annualized return across all securities in the sample.

The value of the trading portfolio for a particular strategy using guerrilla trading rules is calculated as follows:

- For each individual security in the sample:
    - Calculate the accumulated portfolio value generated from the technical trades for each individual trade. As guerrilla trades are initiated during the trading

day, the return on the first day of trading is the return between the time of the signal activation and the end of the trading session. See section 5.3 for explicit formulas.
    - Annualize the return.
    - Compute the average annualized return.
- Compute the average annualized return across all securities.

How returns after transaction costs and risk are calculated:
The Capital Asset Pricing Model (CAPM) states that a security's expected individual risk premium, R_i[12], is linearly related to its sensitivity to the market return, β, times the market's risk premium, R_M[13] or in mathematical terms, $E[R_i] = \alpha_i + \beta_{i;r_M} \cdot E[R_M]$, where α is the difference between the fair[14] and the actual expected return.

In order to adjust returns for risk, I perform a regression based on the above model. Since the returns thus will be realized instead of expected, the equation and its interpretation changes. Apart from the fact that returns are actual returns instead of expected, α is now the difference between the actual and the theoretical return. Hence, since the CAPM model takes risk into account, a positive α implies that the return is above risk. The equation is now: $R_i = \alpha_i + \beta_{i;r_M} \cdot R_M$. In order to increase the amount of regression data and to make it comparable with the previous results, I compute the annual (or annualized) return for each year and security.

5.3. Formulas for accumulated portfolio value for each security or trade

The Portfolio Value (PV) denotes the accumulated value of the trading portfolio at each point in time (per security or trade depending whether mathematical or guerrilla indicators are studied). The dummy variables, $\delta_{y,}$ in the formulas below function as follows, where the denotation of the indices differs between mathematical and guerrilla indicators for computational reasons:

- The dummy variables have two states:
    - If active, they have value 1

[12] R_i is the expected return above the risk-free rate (the difference between the expected market return, the return on the OMXS30 index, and the risk-free rate
[13] R_M is the difference between the expected market return, the return on the OMXS30 index, and the risk-free rate
[14] what an investor personally believes will be the expected return

  - If inactive, they have value 0
- Their index y denotes in which scenario they are active:

  Mathematical indicators:
  - y = 1 – active signal
  - y = 2 – first or last trading session of an active signal
  - y = 3, no active signal

  Guerrilla indicators:
  - y = 1 – active signal (except the first or last trading session of an active signal)
  - y = 2 – first trading session of an active signal
  - y = 3 – last trading session of an active signal

The formulas for the indicators are the following:

Mathematical indicators:

Without transaction costs:

$PV_t = \delta_1 \cdot PV_{t-1} \cdot [1 + r_i] + \delta_3 \cdot PV_{t-1} \cdot (1 + r_f)$, where r_f is the risk-free rate.

With transaction costs:

$PV_t = \delta_1 \cdot PV_{t-1} \cdot [1 + r_i - \delta_2 \cdot (\theta - \varphi)] + \delta_3 \cdot PV_{t-1} \cdot (1 + r_f)$, where θ denotes the order friction cost, and φ denotes the cost of brokerage fees.

Guerrilla indicators:

The same formulas can be used for guerrilla indicators with a few adjustments. Firstly, there is no need for a dummy denoting "no active signal" as the interest rate is not a factor due to the fact that inactive periods are disregarded. Thus, the latter part of the formulas above is removed. Secondly, as guerrilla signals are initiated during the trading day, the return on the first trading day is the return between when the trade is initiated and the end of the trading session. Hence,

Without transaction costs:

$PV_t = \delta_2 \cdot PV_{t-1} \cdot [1 + r_{Guerrilla}] + \delta_1 \cdot PV_{t-1} \cdot [1 + r_i] + \delta_3 \cdot PV_{t-1} \cdot [1 + r_i]$, where $r_{Guerilla}$ is the return between signal activation and the end of the trading session on the signal's first trading day, as explained above.

With transaction costs:

$$PV_t = \delta_2 \cdot PV_{t-1} \cdot [1 + r_{Guerrilla} - \delta_2 \cdot (\theta - \varphi)] + \delta_1 \cdot PV_{t-1} \cdot [1 + r_i] + \delta_3 \cdot PV_{t-1} \cdot [1 + r_i - \delta_3 \cdot (\theta - \varphi)]$$

6. Results and Analysis

6.1. Results and analysis from hypothesis 1

Technical analysis is informative.

Studying the four moments in table 6.1, it is obvious that the conditional and unconditional return distributions differ. Hence, the standalone indicators are informative. Furthermore, the majority of the mathematical indicators have higher means than the underlying security data (securities), suggesting that these indicators are able to take position when the market is favourable, while the evidence is weaker for the guerrilla indicators. The latter result is in line with the claim that some guerrilla indicators have weak predictive powers (Torssell and Nilsson, 2000b).

Table 6.1 **Distribution of daily returns**

Indicators[a]	**Mean**	**Std. Deviation**	**Skewness**	**Kurtosis**
Securities	0.000241	0.006393	-0.119	4.316
Trend Indicators				
DMAC (LS)	0.000687	0.006118	-0.463	5.725
DS (LS)	0.000610	0.006202	-0.287	6.263
LR (LS)	0.001476	0.005774	-0.665	7.980
MACD (LS)	-0.000336	0.006609	0.516	3.674
Guerrilla Indicators				
KR (NF;LS)	0.001062	0.006085	-0.524	7.247
RD (NF;LS)	0.000103	0.006459	-0.161	5.985
TDR (NF;LS)	0.000069	0.006521	-0.255	3.841
ODR (NF;LS)	-0.000303	0.006415	0.476	5.214
PG (NF;LS)	-0.000123	0.006573	0.104	6.172
RG (NF;LS)	0.001670	0.006054	-0.685	7.689
1234 (NF;LS)	0.000711	0.006286	-0.520	6.261

[a]Securities is an average based on data of all securities in the sample. LS denotes that both long and short trades are allowed. NF (No Filter) means that no filter has been added to the guerilla indicator in question.

As can be seen in table 6.2, the Kolmogorov-Smirnov test rejects normality for all indicators. Hence, this test arrives at the same conclusion.

Table 6.2 **Kolmogorov-Smirnov test for normality**

Indicator	Test Statistic[a]	Indicator	Test Statistic
DMAC (LS)	6.652	**TDR (NF;LS)**	3.654
DS (LS)	4.361	**ODR (NF;LS)**	3.975
LR (LS)	8.210	**PG (NF;LS)**	5.607
MACD (LS)	9.517	**RG (NF;LS)**	9.391
KR (NF;LS)	6.320	**1234 (NF;LS)**	5.271
RD (NF;LS)	5.610		

[a]All indicators are significant at the 0.025 level or less.

6.2. Results and analysis from hypothesis 2

The indicators outperform the market before transaction costs.

The results in table 6.3 on page 30 confirm the previous data, where some guerrilla indicators had poor forecasting abilities. This is due to the fact that these indicator signals are too easily activated because of low activation requirements. Many of the signals are thus false (Torssell and Nilsson, 2000b). A subsequent hypothesis will test whether adding filters will improve the profitability of these guerrilla indicators. However, Key Reversal, Reversal Gap and to some extent the 1-2-3-4 indicator, all significantly outperform the market. The first two indicators signal considerable informational shocks as they require large shifts in market sentiment during the day and overnight respectively in order to arise. The positive performance of the 1-2-3-4 indicator suggests that the pattern mostly arises in up-trending markets as it merely signals the end of a short security pullback rather than new important news.

The trend indicators are strongly positive overall, except for the MACD indicator which performs poorly. The trend indicators lag behind the trend (except for the MACD indicator). Hence, when they are activated, the security has already trended for some time. This increases the likelihood that that the security is in the disequilibrium state rather than in a random walk. Hence, these indicators have greater predictive powers in general than the guerrilla indicators. As three out of four of the indicators are generating decidedly better returns than the buy-and-hold strategy, periods of market inefficiency seem to be prevalent. The MACD indicator returns deviate from the others. This is due to the fact that, even though it is sorted under trend indicators as an aid for spotting trends early, it is an oscillator. Thus, even though it might be helpful in localising beginning trends, it does not know whether the beginning trend will last or not. Overall, the results support the hypothesis.

As noted by Fama and Blume (1966) and Brock et al. (1992) among others, there is a clear discrepancy between long and short returns for both types of indicators. The cause of this divergence is not examined in this thesis, but as mentioned above, Brock et al. (1992) finds significantly larger amount of volatility after short than long trading signals, which could impede indicators' ability to terminate trades at the right time.

6.3. Results and analysis from hypothesis 3

The indicators outperform the market after transaction costs.

As seen in table 6.4 below, the mathematical indicators' returns decrease by about 6.5 percentage units on average after transaction costs. The size of the decrease is dependent on how often an indicator changes from buy to sell or vice versa. As more long term indicators shift position less frequently, they incur fewer transaction costs. Thus, as returns are aggregated over time, the impact of these costs can vary substantially among the indicators. Furthermore, enabling both long and short positions leads of course to more transactions and hence larger transaction costs. These two effects can clearly be seen by comparing tables 6.3 and 6.4 below. However, most indicators still perform better than the benchmark strategy and hence the hypothesis is true for the mathematical indicators. The hypothesis holds for guerrilla indicators as well, since their returns decrease by less than 1 percent. The small decrease in returns is due to the fact that the guerrilla indicators are short-lived and because transaction costs are not propagated throughout the sample.

6.4. Results and analysis from hypothesis 4

The indicators outperform the market after risk.

In table 6.5 and the full table A1 in the appendix, it is clear that returns have decreased substantially after taking risk into account. Regarding the mathematical indicators, one notes

Table 6.3 **Daily returns for individual indicators before transaction costs.**

Indicator	Ret.	Indicator	Ret.	Indicator	Ret.	Indicator	Ret.	Indicator	Ret.
DMAC (L)	0.203	**LR (S)**	0.228	**KR (NF:LS)**	0.283	**ODR (NF;L)**	-0.043	**RG (NF;S)**	0.375
DMAC (S)	0.065	**LR (LS)**	0.519	**RD (NF;L)**	0.074	**ODR (NF;S)**	-0.106	**RG (NF;LS)**	0.442
DMAC (LS)	0.239	**MACD (L)**	-0.014	**RD (NF;S)**	-0.004	**ODR (NF;LS)**	-0.079	**1234 (NF;L)**	0.258
DS (L)	0.187	**MACD (S)**	-0.044	**RD (NF;LS)**	0.027	**PG (NF;L)**	-0.053	**1234 (NF;S)**	0.103
DS (S)	0.050	**MACD (LS)**	-0.117	**TDR (NF;L)**	0.040	**PG (NF;S)**	-0.016	**1234 (NF;LS)**	0.190
DS (LS)	0.225	**KR (NF;L)**	0.242	**TDR (NF;S)**	-0.007	**PG (NF;LS)**	-0.033		
LR (L)	0.380	**KR (NF;S)**	0.332	**TDR (NF;LS)**	0.018	**RG (NF;L)**	0.505		

Table 6.4 **Daily returns for individual indicators after transaction costs.**

Indicator	Ret.	Indicator	Ret.	Indicator	Ret.	Indicator	Ret.	Indicator	Ret.
DMAC (L)	0.176	**LR (S)**	0.178	**KR (NF:LS)**	0.274	**ODR (NF;L)**	-0.052	**RG (NF;S)**	0.366
DMAC (S)	0.042	**LR (LS)**	0.388	**RD (NF;L)**	0.065	**ODR (NF;S)**	-0.115	**RG (NF;LS)**	0.432
DMAC (LS)	0.192	**MACD (L)**	-0.069	**RD (NF;S)**	-0.014	**ODR (NF;LS)**	-0.088	**1234 (NF;L)**	0.249
DS (L)	0.132	**MACD (S)**	-0.114	**RD (NF;LS)**	0.018	**PG (NF;L)**	-0.062	**1234 (NF;S)**	0.093
DS (S)	-0.013	**MACD (LS)**	-0.240	**TDR (NF;L)**	0.031	**PG (NF;S)**	-0.025	**1234 (NF;LS)**	0.181
DS (LS)	0.128	**KR (NF;L)**	0.234	**TDR (NF;S)**	-0.016	**PG (NF;LS)**	-0.042		
LR (L)	0.339	**KR (NF;S)**	0.323	**TDR (NF;LS)**	0.009	**RG (NF;L)**	0.496		

that the directional system indicator's return is now substantially below the market return (10 percent). Furthermore, the return of the moving average indicator is now only 2.3 percent above the market return. Concerning the guerrilla indicators, a majority of the indicators have a significantly lower return than the benchmark. However, the Key Reversal and Reversal Gap indicators clearly outperform the market. As a majority of the indicators have negative returns, the hypothesis is false. In addition, less than a third of the indicators beat the return of the benchmark. Thus, it seems important for an investor to be able to pick the right indicators in order to be successful. Furthermore, the statistic in the mentioned tables unsurprisingly shows that the results for the trend indicators are generally more significant than those of the guerrilla indicators. Furthermore, they are more correlated with the stock market return and have a higher "goodness of fit" than the other indicators. However, the values of the beta coefficients and the coefficients of determination are quite low, which could be due to less than perfect forecasting abilities and lagging indicators.

Table 6.5 **Daily returns for standalone indicators adjusted for risk.**

Indicators	α^a	t	β^a	t	R^2
DMAC (LS)	0.123***	2.673	0.286***	3.222	0.347
DS (LS)	0.025	1.594	0.250*	1.953	0.179
LR (LS)	0.323**	2.006	0.576***	3.443	0.308
MACD (LS)	-0.303***	-2.397	-0.230*	-1.714	0.068
KR (NF:LS)	0.180	1.043	0.177	1.205	0.100
RD (NF;LS)	-0.068	-0.280	-0.095	-0.386	0.077
TDR (NF;LS)	-0.073	-0.470	-0.189	-0.278	0.093
ODR (NF;LS)	-0.146	-0.312	-0.141	-0.314	0.109
PG (NF;LS)	-0.101	-0.474	-0.058	-0.558	0.078
RG (NF;LS)	0.370***	2.327	0.245***	3.167	0.186
1234 (NF;LS)	0.112	1.590	0.105	1.509	0.093

[a]Significance levels: * at 10 percent level, ** at 5 percent level and *** at 2.5 percent level

Type of test: two-tailed test

α denotes the intercept coefficient, β denotes the slope coefficient

6.5. Results and analysis from hypothesis 5 and 6

- *Trading systems improve returns*
- *Combination systems outperform trend systems*

When comparing[15] the performance of the trading systems below with that of the first added indicator in the systems (the moving average indicator), it is clear that the hypothesis five is correct for the mathematical indicators. The trend and combination systems increase returns after transaction costs by about one and three percentage units respectively after adding one more indicator. Adding two further indicators, the returns increase by about another five to seven percentage units. This difference in returns remains after accounting for risk. The MACD indicator does not add value to the trend system. Hence, it might be better to remove it. Furthermore, one notes that much of the trend system's increase in return can be attributed to the Linear Regression indicator. As the trend system underperforms the linear regression indicator, one should consider using only the linear regression indicator instead. In the combination system on the other hand, all indicators add value. It hence seems to be a more well composed trading system. For the guerrilla indicators, the differences are even larger when adding another trading system component (the trend filter). All indicators are now decisively positive after adjusting for transaction costs and risk. Thus hypothesis five holds for the guerrilla indicators as well.

Comparing the trading systems' returns one sees that there is surprisingly little difference between the two. The return of the trend system after accounting for risk is less than four percentage units lower than that of the combination system, although this can partly be explained by the strong performance of the linear regression indicator. However, it can also due to the fact that, even though the trend indicators measure the same phenomenon (trend), they are also quite different as they all measure the trend by using different methods. Hence, the correlation might not be as high as for other systems using indicators that measure the same phenomenon. Since the combination system performs better than the trend system, and much of the trend system's increase in return can be attributed to the Linear Regression indicator, hypothesis 6 holds.

[15] Tables of interest for the trading systems: 6.6 and A2 in the appendix; for the standalone indicators: 6.3-6.5 A1 in the appendix

Table 6.6 **Daily trading system returns.**

Indicator	NT[a]	T[a]	α	Indicator	NT[a]	T[a]	α	Indicator	NT[a]	T[a]	α
Trend 1 (L)	0.217	0.187	0.121	**Comb. 2 (S)**	0.122	0.085	0.044	**TDR (F;LS)**	0.148	0.139	0.059
Trend 1 (S)	0.062	0.037	-0.011	**Comb. 2 (LS)**	0.309	0.238	0.186	**ODR (F;L)**	0.153	0.144	0.095
Trend 1 (LS)	0.258	0.203	0.152	**Comb. 3 (L)**	0.269	0.223	0.159	**ODR (F;S)**	0.069	0.060	-0.037
Trend 2 (L)	0.255	0.221	0.168	**Comb. 3 (S)**	0.117	0.079	0.048	**ODR (F;LS)**	0.114	0.105	0.034
Trend 2 (S)	0.132	0.101	0.037	**Comb. 3 (LS)**	0.347	0.265	0.201	**PG (F;L)**	0.356	0.347	0.279
Trend 2 (LS)	0.317	0.254	0.192	**KR (F;L)**	0.546	0.537	0.461	**PG (F;S)**	0.320	0.311	0.244
Trend 3 (L)	0.247	0.208	0.140	**KR (F;S)**	0.521	0.512	0.415	**PG (F;LS)**	0.338	0.329	0.207
Trend 3 (S)	0.096	0.061	0.026	**KR (F;LS)**	0.535	0.526	0.441	**RG (F;L)**	0.717	0.708	0.561
Trend 3 (LS)	0.313	0.242	0.163	**RD (F;L)**	0.477	0.468	0.405	**RG (F;S)**	0.676	0.667	0.580
Comb. 1 (L)	0.237	0.205	0.136	**RD (F;S)**	0.409	0.399	0.357	**RG (F;LS)**	0.697	0.688	0.573
Comb. 1 (S)	0.091	0.062	0.018	**RD (F;LS)**	0.445	0.436	0.379	**1234 (F;L)**	0.389	0.380	0.321
Comb. 1 (LS)	0.284	0.220	0.178	**TDR (F;L)**	0.144	0.135	0.070	**1234 (F;S)**	0.392	0.382	0.249
Comb. 2 (L)	0.251	0.214	0.143	**TDR (F;S)**	0.152	0.143	0.033	**1234 (F;LS)**	0.391	0.382	0.297

[a]NT stands for No Transaction costs, i.e. returns before transaction costs

T denotes Transaction costs, i.e. returns after transaction costs

6.6. Results and analysis from hypothesis 7

Returns increase when using weekly data.

For most indicators, weekly data generates better returns than daily data[16]. On average, returns are 5.8 percent higher when using weekly data adjusted for risk. This suggests that weekly data provides more accurate price predictions, possible due to greater informational content in weekly price changes. However, while standalone indicators based on weekly data perform on average 7 percentage units better, this difference is only about 4 percentage units for trading systems. The increased informational value of trading systems compared with standalone indicators therefore diminishes the difference between daily and weekly data.

Table 6.7 **Weekly returns.**

Indicator	NT	T	α	Indicator	NT	T	α
DMAC (LS)	0.298	0.287	0.214	**RD (NF;LS)**	0.081	0.072	0.017
DS (LS)	0.283	0.257	0.166	**RD (F;LS)**	0.492	0.483	0.413
LR (LS)	0.412	0.386	0.271	**TDR (NF;LS)**	0.061	0.052	-0.013
MACD (LS)	-0.059	-0.082	-0.157	**TDR (F;LS)**	0.158	0.149	0.080
Trend 1 (LS)	0.318	0.299	0.249	**ODR (NF;LS)**	0.171	0.162	0.091
Trend 2 (LS)	0.353	0.328	0.253	**ODR (F;LS)**	0.290	0.281	0.204
Trend 3 (LS)	0.333	0.303	0.229	**PG (NF;LS)**	0.212	0.203	0.126
Comb. 1 (LS)	0.341	0.320	0.264	**PG (F;LS)**	0.337	0.328	0.264
Comb. 2 (LS)	0.352	0.324	0.252	**RG (NF;LS)**	0.334	0.325	0.248
Comb. 3 (LS)	0.368	0.330	0.259	**RG (F;LS)**	0.541	0.532	0.499
KR (NF:LS)	0.245	0.236	0.171	**1234 (NF;LS)**	0.290	0.281	0.210
KR (F:LS)	0.451	0.442	0.357	**1234 (F;LS)**	0.424	0.415	0.341

[16] Tables of interest for daily data: 6.3-6.6 and A1-2 in the appendix; for weekly data: 6.7 and A3-A4 in the appendix

6.7. Results and analysis from hypothesis 8

Dividing the sample into three different periods, one notes[17], that overall the first period has the best performance, while the last period has the lowest returns. This is in line with Bessembinder and Chan (1998) and Olson (2004). The difference in return between the first and last period of the sample is however not large (about 2.4 percentage units on average after adjusting for risk). The return decrease is fairly constant for mathematical indicators, while the bulk of it is in the first two periods for guerrilla indicators. This relationship is also true when comparing daily and weekly data. The overall decrease is larger for guerrilla indicators, giving some support to the claim in Olson (2004), who argue that more sophisticated strategies are needed as markets become increasingly efficient.

Table 6.8 **Daily returns in sub-periods**

	1987-1994			**1995-2001**			**2001-2008**		
Indicator	**NT**	**T**	**α**	**NT**	**T**	**α**	**NT**	**T**	**α**
DMAC(LS)	0.286	0.242	0.178	0.240	0.195	0.131	0.211	0.166	0.102
DS(LS)	0.243	0.142	0.043	0.205	0.109	0.010	0.231	0.126	0.027
LR(LS)	0.479	0.383	0.314	0.509	0.419	0.350	0.440	0.353	0.284
MACD(LS)	-0.132	-0.244	-0.315	-0.119	-0.231	-0.302	-0.102	-0.219	-0.290
Trend 1 LS)	0.268	0.211	0.142	0.252	0.199	0.170	0.241	0.188	0.139
Trend 2 (LS)	0.340	0.284	0.217	0.320	0.261	0.194	0.292	0.232	0.175
Trend 3 (LS)	0.334	0.257	0.189	0.316	0.239	0.171	0.286	0.206	0.138
Comb. 1 (LS)	0.311	0.242	0.225	0.295	0.226	0.159	0.259	0.189	0.132
Comb. 2 (LS)	0.332	0.265	0.195	0.303	0.242	0.172	0.284	0.224	0.154
Comb. 3 (LS)	0.362	0.278	0.235	0.341	0.251	0.188	0.338	0.243	0.180
KR (NF; LS)	0.282	0.273	0.208	0.289	0.280	0.215	0.263	0.254	0.139
KR (F; LS)	0.498	0.489	0.423	0.574	0.565	0.499	0.531	0.523	0.457
RD (NF; LS)	0.078	0.069	0.001	0.031	0.022	-0.046	-0.028	-0.037	-0.125
RD (F; LS)	0.499	0.490	0.428	0.469	0.460	0.398	0.366	0.357	0.295
TDR (NF; LS)	-0.006	-0.015	-0.105	0.028	0.019	-0.051	0.036	0.027	-0.043

[17] Tables of interest for daily data: 6.8 and A5 in the appendix; for weekly data: 6.9 and A6 in the appendix

TDR (F; LS)	0.152	0.143	0.075	0.160	0.151	0.043	0.127	0.118	0.050
ODR (NF; LS)	-0.050	-0.060	-0.127	-0.092	-0.101	-0.168	-0.082	-0.092	-0.149
ODR (F; LS)	0.119	0.110	0.046	0.096	0.087	0.023	0.111	0.102	0.038
PG (NF; LS)	-0.018	-0.027	-0.092	-0.087	-0.096	-0.161	0.017	0.007	-0.058
PG (F; LS)	0.360	0.351	0.161	0.286	0.277	0.187	0.369	0.360	0.270
RG (NF; LS)	0.453	0.445	0.381	0.427	0.418	0.354	0.454	0.446	0.382
RG (F; LS)	0.681	0.672	0.526	0.785	0.776	0.710	0.619	0.610	0.514
1234 (NF; LS)	0.237	0.228	0.157	0.169	0.159	0.088	0.152	0.142	0.091
1234 (F; LS)	0.435	0.426	0.339	0.350	0.341	0.219	0.397	0.388	0.321

Table 6.9 **Weekly returns in sub-periods**

	1987-1994			**1995-2001**			**2001-2008**		
Indicator	**NT**	**T**	**α**	**NT**	**T**	**α**	**NT**	**T**	**α**
DMAC(LS)	0.340	0.329	0.261	0.292	0.282	0.209	0.264	0.253	0.185
DS(LS)	0.281	0.234	0.176	0.302	0.250	0.187	0.265	0.218	0.125
LR(LS)	0.412	0.385	0.316	0.294	0.269	0.185	0.407	0.382	0.313
MACD(LS)	-0.034	-0.079	-0.123	-0.071	-0.108	-0.172	-0.070	-0.109	-0.173
Trend 1 LS)	0.370	0.351	0.289	0.311	0.291	0.229	0.275	0.255	0.193
Trend 2 (LS)	0.400	0.373	0.305	0.353	0.325	0.257	0.309	0.283	0.215
Trend 3 (LS)	0.376	0.346	0.253	0.330	0.298	0.227	0.304	0.275	0.204
Comb. 1 (LS)	0.379	0.360	0.293	0.344	0.321	0.274	0.301	0.278	0.211
Comb. 2 (LS)	0.386	0.360	0.295	0.343	0.318	0.253	0.327	0.304	0.229
Comb. 3 (LS)	0.419	0.382	0.318	0.352	0.316	0.232	0.334	0.295	0.231
KR (NF; LS)	0.300	0.291	0.228	0.207	0.198	0.135	0.221	0.211	0.158
KR (F; LS)	0.527	0.518	0.453	0.356	0.347	0.282	0.414	0.405	0.340
RD (NF; LS)	0.061	0.052	-0.011	0.101	0.092	0.039	0.065	0.055	-0.008
RD (F; LS)	0.559	0.550	0.448	0.526	0.518	0.456	0.406	0.397	0.335
TDR (NF; LS)	0.056	0.047	-0.018	0.077	0.068	0.007	0.048	0.039	-0.026
TDR (F; LS)	0.174	0.165	0.102	0.111	0.102	0.039	0.176	0.167	0.104
ODR (NF; LS)	0.144	0.135	0.067	0.141	0.132	0.064	0.231	0.222	0.154
ODR (F; LS)	0.223	0.215	0.146	0.268	0.259	0.190	0.324	0.315	0.246

PG (NF; LS)	0.167	0.158	0.089	0.214	0.204	0.135	0.239	0.230	0.161
PG (F; LS)	0.384	0.375	0.306	0.308	0.299	0.230	0.318	0.308	0.239
RG (NF; LS)	0.413	0.405	0.335	0.281	0.272	0.202	0.271	0.262	0.192
RG (F; LS)	0.617	0.608	0.546	0.557	0.549	0.472	0.470	0.461	0.399
1234 (NF; LS)	0.320	0.312	0.250	0.297	0.288	0.204	0.253	0.244	0.182
1234 (F; LS)	0.465	0.456	0.369	0.393	0.384	0.317	0.419	0.410	0.343

6.8. Summary of hypotheses conclusions

Table 6.12 **Hypotheses conclusions**

H1:	*Technical analysis has informational value.*	**True**
H2:	*The indicators outperform the market before transaction costs.*	**True**
H3:	*The indicators outperform the market after transaction costs.*	**True**
H4:	*The indicators outperform the market after risk.*	**False**
H5:	*Trading systems improve returns.*	**True**
H6:	*Combination systems outperform trend systems.*	**True**
H7:	*Returns increase when using weekly data instead of daily data.*	**True**
H8:	*Technical returns have decreased over time.*	**True**

7. Conclusions

This thesis examines the prevalence of market efficiency by studying the informational value and profitability of a set of technical indicators and trading systems in the Swedish market. It further investigates whether there is a discrepancy between technical returns based on daily and weekly data and whether the profitability of technical analysis has changed over time. The results document that the distribution of returns from the technical trading rules are markedly different from those of the unconditional returns and the normal distribution. Technical analysis hence has informational value. The analysis of the profitability of the trading rules before transaction costs and risk show a clear discrepancy between the standalone indicators of the two types of trading rules studied (mathematical and guerrilla indicators), where many guerrilla indicators have poor returns even before adjusting for these factors. After accounting for both transaction costs and risk, the performance of the mathematical indicators is less convincing as well. However, the returns are greatly improved when combining the indicators into trading systems. The risk-adjusted returns of the trend and combination systems are about four and eight percentage units larger than that of the base indicator (Moving Average) in the trading systems respectively. Furthermore, the combination system outperforms the trend system by four percentage units. This suggests that combining different types of indicators increases returns more than when combining trading rules of the same kind. I also find that trades based on weekly data on average yield a six percent larger return than trades using daily data. A possible explanation is greater informational content in stock price moves during longer time periods. Finally, the results show that the Swedish market has become increasingly efficient, as returns diminish over the sample period. This suggests that technical traders have to use increasingly sophisticated trading techniques in order to earn profits in the future.

7.1. Suggestions for further studies

The indicators and systems investigated in this thesis have previously not received much attention by research. Therefore, there are plenty of opportunities for further research in this field. As there is evidence of markets becoming more efficient, research must focus on exploring the profitability of advanced trading systems. I suggest firstly that these studies should explore a wider array of indicators and systems similar to the ones examined in this paper in order get a more complete picture of the performance of these types of indicators and systems. Secondly, future research should study combinations of different time perspectives. For example, trade signals based on daily data which are activated once confirmed by weekly data could increase profitability. Thirdly, future studies should go one step further and try to incorporate both different indicator types and different time perspectives. Mathematical and guerrilla indicators are not only different types of indicators. Since guerrilla indicators are more short-sighted in nature, they have a different time perspective as well. Thus, this could increase profitability further. Finally, as previous research has shown a large difference in the predictive powers of technical rules globally, future studies should investigate the performance of these types of indicators and systems in emerging markets as well.

8. References

Books

Torssell, Johnny and Nilsson, Peter, 2000a. *Boken om teknisk analys*, Stockholm: Börsinsikt Utbildning.

Torssell, Johnny and Nilsson, Peter, 2000b. *Boken om trading*, Stockholm: Börsinsikt Utbildning.

Torssell, Johnny and Nilsson, Peter, 2003. *Tradinghandboken*, Stockholm: Börsinsikt Utbildning.

Databases

Reuters Datalink, *Thomson Reuters Corporation*, available [subscription]: http://www.equis.com/products/endofday/reutersdatalink/?overview

Interest and Exchange Rates, Treasury Bills, *The Riksbank*, available at: http://www.riksbank.com/templates/stat.aspx?id=17187

Statistical Publications

Statistics Sweden, 2006, "Consumer Price Index 1830-2005", available at: http://www.scb.se/statistik/PR/PR0101/1830I05/PR0101_1830I05_SM_PR15SM0601.pdf

Software

Metastock, *Equis International, Thomson Reuters Corporation*, available at [subscription]: http://www.equis.com/

Papers

Alexander, S. S. "Price Movements in Speculative Markets: Trends or Random Walks." *Industrial Management Review*, 2(1961):7-26.

Alexander, S. S. "Price Movements in Speculative Markets: Trends or Random Walks No. 2." *Industrial Management Review*, 5(1964):25-46.

Badrinath, S., and S. Wahal. "Momentum Trading by Institutions." *Journal of Finance*, 57 (2002):2449-2478.

Bennett, James A., Richard W. Sias, and Laura T. Starks. "Greener pastures and the impact of dynamic institutional preferences." *Review of Financial Studies* 16(2003):1203-1238.

Bessembinder H., and K. Chan. "The Profitability of Technical Trading Rules in the Asian Security Markets." *Pacific-Basin Finance Journal*, 3(1995):257-284.

Bessembinder H., and K. Chan. "Market Efficiency and the Returns to Technical Analysis." *Financial Management*, 27(1998):5-17.

Burch, Timothy, and Bhaskaran Swaminathan, 2003, "Earnings News and Institutional Trading", Working paper, Cornell University.

Brock, W., J. Lakonishock, and B. LeBaron. "Simple Technical Trading Rules and the Stochastic Properties of Security Returns." *Journal of Finance*, 47(1992):1731-1764.

Brunnermeier, Markus, and Stefan Nagel, "Hedge Funds and the Technology Bubble", *Journal of Finance* 59(2004):2013–2040

Caginalp, G., and H. Laurent, "The Predictive Power of Price Patterns." *Applied Mathematical Finance*, 5(1998):181-205.

Cai, Fang, and Lu Zheng, "Institutional Trading and Security Returns", *Finance Research Letters* 1(2004):178-189.

Chakravarty, Sugato, “Stealth-trading: Which traders' trades move security prices?”, *Journal of Financial Economics* 61(2001):289-307.

Chang, P. H. K., and C. L. Osler. “Methodical Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecasts.” *Economic Journal*, 109(1999):636-661.

Choe, H., Kho, B, and Stulz, R., “Do foreign investors destabilize security markets? The Korean experience in 1997”. *Journal of Financial Economics* 54(1999):227-264.

Choi, Nicole, and Richard W. Sias, 2008. “Institutional industry herding”. Working paper, Washington State University.

Cohen, Randolph, Paul Gompers, and Tuomo Vuolteenaho, “Who underreacts to cash-flow news? Evidence from trading between individuals and institutions”, *Journal of Financial Economics* 66(2002):409-462.

Cornell, W. B., and J. K. Dietrich. “The Efficiency of the Market for Foreign Exchange under Floating Exchange Rates.” *Review of Economics and Statistics*, 60(1978):111-120.

Dawson, E. R., and J. Steeley. “On the Existence of Visual Technical Patterns in the UK Security Market.” *Journal of Business Finance and Accounting*, 30(2003):263-293.

Day, T. E., and P. Wang. “Dividends, Nonsynchronous Prices, and the Returns from Trading the Dow Jones Industrial Average.” *Journal of Empirical Finance*, 9(2002):431-454.

Dennis, Patrick, and Deon Strickland, “Who Blinks in Volatile Markets, Individuals or Institutions?”, *The Journal of Finance* 57.5(2002):1923-1949.

Dennis, Patrick, and James Weston. 2001. “Who’s informed? An analysis of security ownership and informed trading”. Working paper, University of Virginia and Rice University.

Fama, E. F., and M. E. Blume. “Filter Rules and Security Market Trading.” *Journal of Business*, 39(1966):226-241.

Fang, Y., and D. Xu. “The Predictability of Security Returns: An Approach Combining Technical Analysis and Time Series Forecasts.” *International Journal of Forecasting*, 19(2003):369-385.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *American Economic Review* 85, 1088-1105.

Gompers, Paul, and Andrew Metrick, “Institutional Investors and Equity Prices”, *The Quarterly Journal of Economics, 116(2001):*229-259.

Goodacre, A., and T. Kohn-Speyer. “CRISMA Revisited.” *Applied Financial Economics*, 11 (2001):221-230.

Goodacre, A., J. Bosher, and A. Dove. “Testing the CRISMA Trading System: Evidence from the UK Market.” *Applied Financial Economics*, 9(1999):455-468.

Griffin, John, Jeffrey Harris, and Selim Topaloglu, “The dynamics of institutional and individual trading”, *Journal of Finance*, 58(2003): 2285-2320.

Grinblatt, M., Keloharju, M. “What makes investors trade?”, *Journal of Finance,* 56(2001):589-616.

Gunasekarage, A., and D. M. Power. “The Profitability of Moving Average Trading Rules in South Asian Security Markets.” *Emerging Markets Review*, 2(2001):17-33.

Hong, H., Lim, T., Stein, J. “Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies”. *Journal of Finance,* 55(2000):265–295.

Hudson, R., M. Dempsey, and K. Keasey. “A Note on the Weak Form Efficiency of Capital Markets: The Application of Simple Technical Trading Rules to UK Security Prices - 1935 to 1964.” *Journal of Banking and Finance*, 20(1996):1121-1132.

Jones, Charles, and Owen Lamont, 2002, “Short sales constraints and security returns”, *Journal of Financial Economics* 66(2002):207-239.

Kim, K., and J. Nofsinger. “Institutional Herding, Business Groups, and Economic Regimes: Evidence from Japan.” *Journal of Business*, 78 (2005), 213-242.

Lakonishok, Josef, Andrei Shleifer, and Robert Vishny, “The impact of institutional trading on security prices”, *Journal of Financial Economics* 32(1992), 23-43.

Leigh, W., N. Modani, R. Purvis, and T. Roberts. “Security Market Trading Rule Discovery Using Technical Charting Heuristics.” *Expert Systems with Applications*, 23(2002):155-159.

Leigh, W., N. Paz, and R. Purvis. “Market Timing: A Test of a Charting Heuristic.” *Economic Letters*, 77(2002):55-63.

Lipson, M. and A. Puckett, 2006, “Volatile markets and institutional trading”, Working paper, University of Virginia.

Lo, A., H. Mamaysky, and J. Wang. “Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation.” *Journal of Finance*, 55 (2000):1705-1765.

Lukac, L. P., B. W. Brorsen, and S. H. Irwin. “A Test of Futures Market Disequilibrium Using Twelve Different Technical Trading Systems.” *Applied Economics*, 20(1988):623-639.

Logue, D. E., and R. J. Sweeney. “‘White-Noise’ in Imperfect Markets: The Case of the Franc/Dollar Exchange Rate.” *Journal of Finance*, 32(1977):761-768.

Mandelbrot, B. “The Variation of Certain Speculative Prices.” *Journal of Business*, 36(1963): 394-419.

Mei, J., Scheinkman, J.A., Xiong, W., 2005. “Speculative trading and security prices: An analysis of Chinese A-B share premia”. Working Paper, New York University and Princeton University.

Nofsinger, John, and Richard Sias, "Herding and feedback trading by institutional and individual investors", *Journal of Finance* 54(1999):2263-2295.

Ofek, Eli, and Matthew Richardson, "Dotcom mania: The rise and fall of internet security Prices", *Journal of Finance* 58(2003):1113-1137.

Olson, D. "Have Trading Rule Profits in the Currency Markets Declined over Time?" *Journal of Banking and Finance*, 28(2004):85-105.

Parisi, F., and A.Vasquez. "Simple Technical Trading Rules of Security Returns: Evidence from 1987 to 1998 in Chile." *Emerging Markets Review*, 1(2000):152-164.

Pruitt, S. W., K. S. Maurice Tse, and R. E.White. "The CRISMA Trading System: The Next Five Years." *Journal of Portfolio Management*, (1992):22-25.

Raj, M. "Transactions Data Tests of Efficiency: An Investigation in the Singapore Futures Markets." *Journal of Futures Markets*, 20(2000):687-704.

Rouwenhorst, K. Geert, 1998, "International momentum strategies", *Journal of Finance* 53(1998):267-284.

Sias, Richard, Laura Starks, and Sheridan Titman, 2001, "The Price Impact of Institutional Trading", Working paper, University of Texas.

Shu, Tao, 2008, "Does Positive-Feedback Trading by Institutions Contribute to Security Return Momentum?", Working paper, University of Georgia.

Solt, M. E., and P. J. Swanson. "On the Efficiency of the Markets for Gold and Silver." *Journal of Business*, 54(1981):453-478.

Stevenson, R. A., and R. M. Bear. "Commodity Futures: Trends or Random Walks?" *Journal of Finance*, 25(1970):65-81.

Wermers, Russ, 1999, "Mutual fund herding and the impact on security prices", *Journal of Finance* 54(1999):581-622.

Wylie, Sam, 2005, "Fund Manager Herding: A Test of the Accuracy of Empirical Results using U.K. Data", *Journal of Business* 78(2005), 381-404.

9. Appendix

Table A1 **Daily returns for standalone indicators adjusted for risk.**

Indicators	α^a	t	β^a	t	R^2	Indicators	α^a	t	β^a	t	R^2
DMAC (L)	0.109***	2.331	0.226***	2.593	0.219	**RD (NF;LS)**	-0.068	-0.280	-0.095	-0.386	0.077
DMAC (S)	-0.027	-1.611	-0.073	-1.065	0.254	**TDR (NF;L)**	-0.041	-0.793	-0.142	-0.576	0.138
DMAC (LS)	0.123***	2.673	0.286***	3.222	0.347	**TDR (NF;S)**	-0.106	-0.377	-0.204	-0.315	0.070
DS (L)	0.061*	1.700	0.208	1.495	0.224	**TDR (NF;LS)**	-0.073	-0.470	-0.189	-0.278	0.093
DS (S)	-0.081	-1.103	-0.056	-0.751	0.113	**ODR (NF;L)**	-0.129	-1.146	-0.223	-1.205	0.164
DS (LS)	0.025	1.594	0.250*	1.953	0.179	**ODR (NF;S)**	-0.180	-0.835	-0.160	-1.176	0.091
LR (L)	0.240***	3.250	0.422***	3.625	0.280	**ODR (NF;LS)**	-0.146	-0.312	-0.141	-0.314	0.109
LR (S)	0.112*	1.732	0.253	1.641	0.224	**PG (NF;L)**	-0.128	-1.341	-0.130*	-1.956	0.069
LR (LS)	0.323**	2.006	0.576***	3.443	0.308	**PG (NF;S)**	-0.083	-0.845	-0.109	-0.977	0.082
MACD (L)	-0.147*	-1.708	-0.125	-1.534	0.080	**PG (NF;LS)**	-0.101	-0.474	-0.058	-0.558	0.078
MACD (S)	-0.179	-1.594	-0.349*	-1.833	0.106	**RG (NF;L)**	0.432***	2.574	0.341**	2.229	0.168
MACD (LS)	-0.303***	-2.397	-0.230*	-1.714	0.068	**RG (NF;S)**	0.300***	2.916	0.168***	2.746	0.201
KR (NF;L)	0.125*	1.933	0.121	1.164	0.206	**RG (NF;LS)**	0.370***	2.327	0.245***	3.167	0.186
KR (NF;S)	0.202	1.613	0.194**	2.051	0.160	**1234 (NF;L)**	0.186**	2.215	0.201*	1.926	0.129
KR (NF:LS)	0.180	1.043	0.177	1.205	0.100	**1234 (NF;S)**	0.026**	2.190	0.057*	1.949	0.177

RD (NF;L)	-0.062	-0.835	-0.041	-0.894	0.129	**1234 (NF;LS)**	0.112	1.590	0.105	1.509	0.093
RD (NF;S)	-0.074	-0.631	-0.093	-0.947	0.106						

Table A2 **Daily trading system returns adjusted for risk.**

Indicators	**α^a**	**t**	**β^a**	**t**	**R^2**	**Indicators**	**α^a**	**t**	**β^a**	**t**	**R^2**
Trend 1 (L)	0.121*	1.765	0.304***	2.409	0.435	**KR (F;LS)**	0.441***	2.503	0.217*	1.749	0.224
Trend 1 (S)	-0.011	-1.207	-0.207	-1.226	0.240	**RD (F;L)**	0.405***	3.056	0.265***	3.412	0.195
Trend 1 (LS)	0.152*	1.938	0.288**	2.081	0.303	**RD (F;S)**	0.357*	1.870	0.259*	1.850	0.211
Trend 2 (L)	0.168***	2.743	0.302***	2.561	0.306	**RD (F;LS)**	0.379*	1.953	0.339**	2.231	0.130
Trend 2 (S)	0.037***	2.419	0.269*	1.875	0.246	**TDR (F;L)**	0.070*	1.960	0.164*	1.868	0.263
Trend 2 (LS)	0.192***	3.944	0.346***	4.018	0.394	**TDR (F;S)**	0.033	1.372	0.106	1.433	0.212
Trend 3 (L)	0.140***	2.387	0.269**	1.994	0.334	**TDR (F;LS)**	0.059	1.356	0.219	0.879	0.234
Trend 3 (S)	0.026	1.630	0.200	1.247	0.229	**ODR (F;L)**	0.095*	1.936	0.230***	2.608	0.169
Trend 3 (LS)	0.163***	2.658	0.299***	2.334	0.353	**ODR (F;S)**	-0.037**	-2.049	-0.109*	-1.860	0.168
Comb. 1 (L)	0.136***	3.081	0.208***	2.438	0.398	**ODR (F;LS)**	0.034**	2.179	0.167**	2.030	0.107
Comb. 1 (S)	0.018*	1.879	0.217***	2.396	0.309	**PG (F;L)**	0.279	1.767	0.314***	2.629	0.251
Comb. 1 (LS)	0.178*	1.851	0.376***	2.323	0.353	**PG (F;S)**	0.244***	2.576	0.206***	2.528	0.206
Comb. 2 (L)	0.143***	3.219	0.246***	2.616	0.269	**PG (F;LS)**	0.207*	1.687	0.250*	1.925	0.157
Comb. 2 (S)	0.044*	1.792	0.180*	1.926	0.260	**RG (F;L)**	0.561***	2.495	0.325***	3.046	0.293
Comb. 2 (LS)	0.186***	3.260	0.341***	2.509	0.361	**RG (F;S)**	0.580***	4.425	0.296***	3.880	0.331
Comb. 3 (L)	0.159***	3.006	0.208***	2.800	0.336	**RG (F;LS)**	0.573***	2.523	0.311***	2.497	0.258

Comb. 3 (S)	0.048	1.641	0.209	1.524	0.346	**1234 (F;L)**	0.321***	3.177	0.309***	3.362	0.242
Comb. 3 (LS)	0.201***	3.648	0.313***	3.978	0.362	**1234 (F;S)**	0.249***	3.130	0.204***	4.555	0.223
KR (F;L)	0.461**	2.016	0.385***	2.718	0.270	**1234 (F;LS)**	0.297***	2.996	0.206***	3.204	0.172
KR (F;S)	0.415**	2.165	0.302***	2.350	0.166						

Table A3 **Weekly returns before and after transaction costs respectively.**

Indicators	NT	T	Indicators	NT	T	Indicators	NT	T	Indicators	NT	T
DMAC (L)	0.247	0.240	**Trend 3 (L)**	0.275	0.261	**RD (NF;L)**	0.033	0.024	**PG (NF;L)**	0.257	0.248
DMAC (S)	0.176	0.170	**Trend 3 (S)**	0.187	0.172	**RD (NF;S)**	0.121	0.112	**PG (NF;S)**	0.153	0.145
DMAC (LS)	0.298	0.287	**Trend 3 (LS)**	0.333	0.303	**RD (NF;LS)**	0.081	0.072	**PG (NF;LS)**	0.212	0.203
DS (L)	0.238	0.225	**Comb. 1 (L)**	0.277	0.265	**RD (F;L)**	0.476	0.467	**PG (F;L)**	0.349	0.339
DS (S)	0.141	0.124	**Comb. 1 (S)**	0.194	0.183	**RD (F;S)**	0.517	0.508	**PG (F;S)**	0.317	0.308
DS (LS)	0.283	0.257	**Comb. 1 (LS)**	0.341	0.320	**RD (F;LS)**	0.492	0.483	**PG (F;LS)**	0.337	0.328
LR (L)	0.297	0.287	**Comb. 2 (L)**	0.283	0.269	**TDR (NF;L)**	0.089	0.080	**RG (NF;L)**	0.353	0.344
LR (S)	0.191	0.180	**Comb. 2 (S)**	0.197	0.184	**TDR (NF;S)**	0.044	0.035	**RG (NF;S)**	0.316	0.307
LR (LS)	0.412	0.386	**Comb. 2 (LS)**	0.352	0.324	**TDR (NF;LS)**	0.061	0.052	**RG (NF;LS)**	0.334	0.325
MACD (L)	0.037	0.023	**Comb. 3 (L)**	0.295	0.278	**TDR (F;L)**	0.191	0.182	**RG (F;L)**	0.526	0.517
MACD (S)	0.028	0.012	**Comb. 3 (S)**	0.203	0.186	**TDR (F;S)**	0.133	0.124	**RG (F;S)**	0.557	0.548
MACD (LS)	-0.059	-0.082	**Comb. 3 (LS)**	0.368	0.330	**TDR (F;LS)**	0.158	0.149	**RG (F;LS)**	0.541	0.532
Trend 1 (L)	0.268	0.259	**KR (NF;L)**	0.252	0.243	**ODR (NF;L)**	0.257	0.248	**1234 (NF;L)**	0.326	0.317
Trend 1 (S)	0.172	0.163	**KR (NF;S)**	0.237	0.228	**ODR (NF;S)**	0.089	0.080	**1234 (NF;S)**	0.252	0.243

Trend 1 (LS)	0.318	0.299	**KR (NF:LS)**	0.245	0.236	**ODR (NF;LS)**	0.171	0.162	**1234 (NF;LS)**	0.290	0.281
Trend 2 (L)	0.290	0.279	**KR (F;L)**	0.495	0.486	**ODR (F;L)**	0.339	0.330	**1234 (F;L)**	0.435	0.426
Trend 2 (S)	0.198	0.186	**KR (F;S)**	0.413	0.404	**ODR (F;S)**	0.236	0.227	**1234 (F;S)**	0.416	0.407
Trend 2 (LS)	0.353	0.328	**KR (F;LS)**	0.451	0.442	**ODR (F;LS)**	0.290	0.281	**1234 (F;LS)**	0.424	0.415

Table A4 **Weekly returns adjusted for risk**

Indicators	**α^a**	**t**	**β^a**	**t**	**R^2**	**Indicators**	**α^a**	**t**	**β^a**	**t**	**R^2**
DMAC (L)	0.181***	2.416	0.290***	2.557	0.291	**RD (NF;L)**	-0.036	-0.787	-0.123	-0.812	0.115
DMAC (S)	0.102	1.371	0.180	0.977	0.222	**RD (NF;S)**	0.046	0.432	0.244	0.537	0.096
DMAC (LS)	0.214***	2.711	0.320***	2.700	0.300	**RD (NF;LS)**	0.017	0.314	0.105	0.346	0.095
DS (L)	0.156*	1.767	0.194	1.960	0.194	**RD (F;L)**	0.402***	2.694	0.340***	3.005	0.167
DS (S)	0.057	1.115	0.117	0.928	0.144	**RD (F;S)**	0.427***	2.460	0.247***	2.311	0.179
DS (LS)	0.166	1.344	0.307*	1.825	0.201	**RD (F;LS)**	0.413***	2.573	0.319***	2.260	0.135
LR (L)	0.227***	2.977	0.325***	3.060	0.291	**TDR (NF;L)**	0.014	0.345	0.113	0.288	0.126
LR (S)	0.112	1.451	0.223	1.498	0.218	**TDR (NF;S)**	-0.028	-0.340	-0.119	-0.388	0.090
LR (LS)	0.271***	2.616	0.364***	2.876	0.319	**TDR (NF;LS)**	-0.013	-0.184	-0.125	-0.187	0.112
MACD (L)	-0.041	-1.296	-0.104	-1.006	0.070	**TDR (F;L)**	0.129*	1.835	0.183*	1.661	0.255
MACD (S)	-0.054**	-2.029	-0.227*	-1.766	0.121	**TDR (F;S)**	0.069*	1.656	0.118	1.324	0.214
MACD (LS)	-0.157*	-1.953	-0.318*	-1.866	0.069	**TDR (F;LS)**	0.080	1.374	0.093	1.006	0.213
Trend 1 (L)	0.197**	2.094	0.275***	2.578	0.369	**ODR (NF;L)**	0.159	1.128	0.188	1.264	0.152
Trend 1 (S)	0.118	1.406	0.200	1.481	0.276	**ODR (NF;S)**	0.029	0.876	0.103	0.988	0.119

Trend 1 (LS)	0.249**	2.215	0.350*	1.891	0.348	**ODR (NF;LS)**	0.091	0.381	0.175	0.350	0.108
Trend 2 (L)	0.206***	2.683	0.328***	3.216	0.387	**ODR (F;L)**	0.216**	2.012	0.303***	2.730	0.202
Trend 2 (S)	0.139**	2.234	0.289*	1.871	0.286	**ODR (F;S)**	0.125*	1.901	0.123**	2.090	0.183
Trend 2 (LS)	0.253***	4.084	0.444***	4.275	0.365	**ODR (F;LS)**	0.204***	2.361	0.226**	2.156	0.142
Trend 3 (L)	0.191**	2.223	0.341**	2.105	0.308	**PG (NF;L)**	0.165	1.417	0.181**	1.971	0.090
Trend 3 (S)	0.098	1.421	0.230	1.048	0.226	**PG (NF;S)**	0.073	1.028	0.175	0.872	0.075
Trend 3 (LS)	0.229**	2.237	0.279***	2.330	0.344	**PG (NF;LS)**	0.126	0.560	0.185	0.601	0.071
Comb. 1 (L)	0.198***	3.235	0.225***	2.319	0.336	**PG (F;L)**	0.270***	2.325	0.274***	2.673	0.229
Comb. 1 (S)	0.120	1.638	0.204**	2.176	0.270	**PG (F;S)**	0.251***	2.630	0.247**	2.191	0.214
Comb. 1 (LS)	0.264***	2.446	0.382***	2.554	0.317	**PG (F;LS)**	0.264**	1.995	0.309**	2.133	0.167
Comb. 2 (L)	0.235***	2.732	0.238***	2.472	0.342	**RG (NF;L)**	0.267***	2.318	0.307***	2.738	0.206
Comb. 2 (S)	0.151**	2.018	0.228	1.616	0.276	**RG (NF;S)**	0.217***	2.627	0.363***	3.259	0.197
Comb. 2 (LS)	0.252***	2.822	0.315***	3.144	0.333	**RG (NF;LS)**	0.248***	2.278	0.233***	2.672	0.178
Comb. 3 (L)	0.222***	3.383	0.290***	3.068	0.383	**RG (F;L)**	0.417***	3.111	0.419***	4.013	0.353
Comb. 3 (S)	0.156*	1.854	0.211	1.513	0.300	**RG (F;S)**	0.491***	3.781	0.304***	3.894	0.309
Comb. 3 (LS)	0.259***	3.222	0.277***	3.442	0.404	**RG (F;LS)**	0.499***	2.892	0.334***	2.556	0.306
KR (NF;L)	0.179*	1.726	0.182	1.404	0.172	**1234 (NF;L)**	0.257***	2.335	0.230***	2.372	0.125
KR (NF;S)	0.155*	1.953	0.183**	2.025	0.174	**1234 (NF;S)**	0.180**	2.038	0.173**	2.252	0.163
KR (NF:LS)	0.171	1.188	0.184	1.418	0.133	**1234 (NF;LS)**	0.210	1.847	0.142	1.617	0.092
KR (F;L)	0.387***	2.644	0.347***	3.050	0.265	**1234 (F;L)**	0.331***	3.224	0.319***	3.214	0.230
KR (F;S)	0.328***	2.602	0.321***	2.466	0.211	**1234 (F;S)**	0.336***	3.064	0.242***	4.089	0.217

KR (F;LS)	0.357**	2.163	0.293	1.537	0.226	**1234 (F;LS)**	0.341***	3.435	0.298***	3.822	0.167

Table A5 **Daily returns in sub-periods**

	1987-1994			**1995-2001**			**2001-2008**		
Indicator	**NT**	**T**	**α**	**NT**	**T**	**α**	**NT**	**T**	**α**
DMAC(L)	0.240	0.214	0.150	0.202	0.178	0.114	0.176	0.150	0.086
DMAC(S)	0.051	0.027	-0.042	0.076	0.050	-0.019	0.070	0.043	-0.026
DMAC(LS)	0.286	0.242	0.178	0.240	0.195	0.131	0.211	0.166	0.102
DS(L)	0.204	0.150	0.079	0.164	0.108	0.037	0.190	0.138	0.067
DS(S)	0.023	-0.040	-0.111	0.067	-0.002	-0.073	0.062	-0.003	-0.074
DS(LS)	0.243	0.142	0.043	0.205	0.109	0.010	0.231	0.126	0.027
LR(L)	0.407	0.364	0.199	0.458	0.412	0.317	0.392	0.350	0.225
LR(S)	0.260	0.211	0.145	0.194	0.144	0.078	0.227	0.177	0.111
LR(LS)	0.479	0.383	0.314	0.509	0.419	0.350	0.440	0.353	0.284
MACD(L)	-0.066	-0.126	-0.195	0.026	-0.036	-0.105	0.000	-0.066	-0.135
MACD(S)	-0.017	-0.086	-0.151	-0.059	-0.130	-0.195	-0.052	-0.116	-0.181
MACD(LS)	-0.132	-0.244	-0.315	-0.119	-0.231	-0.302	-0.102	-0.219	-0.290
Trend 1 (L)	0.236	0.208	0.140	0.209	0.181	0.113	0.193	0.165	0.097
Trend 1 (S)	0.040	0.014	-0.050	0.070	0.044	0.020	0.076	0.053	-0.021
Trend 1 LS)	0.268	0.211	0.142	0.252	0.199	0.170	0.241	0.188	0.139

Trend 2 (L)	0.283	0.246	0.182	0.271	0.231	0.167	0.240	0.197	0.153
Trend 2 (S)	0.130	0.098	0.032	0.114	0.081	0.015	0.143	0.110	0.054
Trend 2 (LS)	0.340	0.284	0.217	0.320	0.261	0.194	0.292	0.232	0.175
Trend 3 (L)	0.274	0.231	0.166	0.258	0.219	0.154	0.225	0.189	0.124
Trend 3 (S)	0.092	0.058	0.018	0.072	0.041	-0.025	0.121	0.091	0.065
Trend 3 (LS)	0.334	0.257	0.189	0.316	0.239	0.171	0.286	0.206	0.138
Comb. 1 (L)	0.266	0.235	0.171	0.245	0.214	0.150	0.191	0.163	0.099
Comb. 1 (S)	0.076	0.050	-0.020	0.128	0.104	0.034	0.094	0.070	0.021
Comb. 1 (LS)	0.311	0.242	0.225	0.295	0.226	0.159	0.259	0.189	0.132
Comb. 2 (L)	0.280	0.239	0.168	0.255	0.214	0.143	0.226	0.182	0.111
Comb. 2 (S)	0.108	0.074	0.012	0.135	0.103	0.041	0.118	0.082	0.060
Comb. 2 (LS)	0.332	0.265	0.195	0.303	0.242	0.172	0.284	0.224	0.154
Comb. 3 (L)	0.295	0.247	0.183	0.288	0.235	0.171	0.231	0.182	0.118
Comb. 3 (S)	0.123	0.083	0.088	0.126	0.084	0.019	0.091	0.045	0.020
Comb. 3 (LS)	0.362	0.278	0.235	0.341	0.251	0.188	0.338	0.243	0.180
KR (NF; L)	0.257	0.248	0.177	0.236	0.227	0.086	0.235	0.226	0.135
KR (NF; S)	0.328	0.319	0.151	0.380	0.371	0.233	0.292	0.283	0.215
KR (NF; LS)	0.282	0.273	0.208	0.289	0.280	0.215	0.263	0.254	0.139
KR (F; L)	0.501	0.492	0.425	0.607	0.598	0.531	0.508	0.499	0.432
KR (F; S)	0.496	0.486	0.420	0.548	0.539	0.473	0.547	0.538	0.472
KR (F; LS)	0.498	0.489	0.423	0.574	0.565	0.499	0.531	0.523	0.457

RD (NF; L)	0.105	0.096	0.027	0.100	0.091	0.022	0.021	0.012	-0.057
RD (NF; S)	0.066	0.057	-0.009	-0.019	-0.028	-0.094	-0.057	-0.066	-0.132
RD (NF; LS)	0.078	0.069	0.001	0.031	0.022	-0.046	-0.028	-0.037	-0.125
RD (F; L)	0.583	0.574	0.507	0.482	0.473	0.406	0.387	0.378	0.311
RD (F; S)	0.422	0.413	0.327	0.447	0.438	0.372	0.357	0.348	0.282
RD (F; LS)	0.499	0.490	0.428	0.469	0.460	0.398	0.366	0.357	0.295
TDR (NF; L)	0.025	0.016	-0.052	0.026	0.017	-0.051	0.063	0.054	-0.014
TDR (NF; S)	-0.075	-0.084	-0.152	0.031	0.022	-0.046	0.008	0.000	-0.086
TDR (NF; LS)	-0.006	-0.015	-0.105	0.028	0.019	-0.051	0.036	0.027	-0.043
TDR (F; L)	0.158	0.149	0.084	0.133	0.124	0.059	0.142	0.133	0.068
TDR (F; S)	0.148	0.139	-0.021	0.193	0.184	0.094	0.117	0.108	0.038
TDR (F; LS)	0.152	0.143	0.075	0.160	0.151	0.043	0.127	0.118	0.050
ODR (NF; L)	0.006	-0.003	-0.071	-0.077	-0.086	-0.154	-0.082	-0.091	-0.159
ODR (NF; S)	-0.118	-0.127	-0.195	-0.109	-0.118	-0.186	-0.083	-0.092	-0.160
ODR (NF; LS)	-0.050	-0.060	-0.127	-0.092	-0.101	-0.168	-0.082	-0.092	-0.149
ODR (F; L)	0.142	0.133	0.064	0.146	0.137	0.068	0.171	0.162	0.153
ODR (F; S)	0.097	0.088	0.019	0.065	0.056	-0.063	0.035	0.026	-0.043
ODR (F; LS)	0.119	0.110	0.046	0.096	0.087	0.023	0.111	0.102	0.038
PG (NF; L)	-0.059	-0.069	-0.134	-0.119	-0.129	-0.194	0.025	0.016	-0.049
PG (NF; S)	0.007	-0.002	-0.067	-0.045	-0.054	-0.119	0.011	0.002	-0.063
PG (NF; LS)	-0.018	-0.027	-0.092	-0.087	-0.096	-0.161	0.017	0.007	-0.058

PG (F; L)	0.347	0.338	0.253	0.338	0.328	0.263	0.386	0.377	0.312
PG (F; S)	0.370	0.361	0.293	0.245	0.236	0.168	0.355	0.346	0.278
PG (F; LS)	0.360	0.351	0.161	0.286	0.277	0.187	0.369	0.360	0.270
RG (NF; L)	0.564	0.555	0.485	0.471	0.463	0.393	0.486	0.478	0.408
RG (NF; S)	0.329	0.319	0.252	0.378	0.369	0.312	0.407	0.398	0.331
RG (NF; LS)	0.453	0.445	0.381	0.427	0.418	0.354	0.454	0.446	0.382
RG (F; L)	0.704	0.695	0.624	0.812	0.803	0.532	0.613	0.604	0.533
RG (F; S)	0.663	0.654	0.487	0.750	0.741	0.674	0.624	0.615	0.558
RG (F; LS)	0.681	0.672	0.526	0.785	0.776	0.710	0.619	0.610	0.514
1234 (NF; L)	0.254	0.245	0.181	0.252	0.243	0.179	0.270	0.261	0.197
1234 (NF; S)	0.223	0.214	0.124	0.077	0.068	-0.002	0.014	0.005	-0.065
1234 (NF; LS)	0.237	0.228	0.157	0.169	0.159	0.088	0.152	0.142	0.091
1234 (F; L)	0.450	0.441	0.372	0.371	0.361	0.292	0.362	0.353	0.314
1234 (F; S)	0.422	0.412	0.189	0.313	0.304	0.241	0.448	0.439	0.286
1234 (F; LS)	0.435	0.426	0.339	0.350	0.341	0.219	0.397	0.388	0.321

Table A6 **Weekly returns in sub-periods**

	1987-1994			**1995-2001**			**2001-2008**		
Indicator	**NT**	**T**	**α**	**NT**	**T**	**α**	**NT**	**T**	**α**

DMAC(L)	0.289	0.283	0.220	0.246	0.238	0.175	0.222	0.215	0.152
DMAC(S)	0.196	0.190	0.125	0.149	0.144	0.079	0.182	0.176	0.111
DMAC(LS)	0.340	0.329	0.261	0.292	0.282	0.209	0.264	0.253	0.185
DS(L)	0.233	0.220	0.159	0.257	0.243	0.179	0.225	0.210	0.126
DS(S)	0.142	0.125	0.055	0.149	0.133	0.063	0.131	0.117	0.047
DS(LS)	0.281	0.234	0.176	0.302	0.250	0.187	0.265	0.218	0.125
LR(L)	0.327	0.317	0.219	0.238	0.229	0.162	0.325	0.317	0.270
LR(S)	0.186	0.174	0.095	0.204	0.192	0.123	0.184	0.174	0.105
LR(LS)	0.412	0.385	0.316	0.294	0.269	0.185	0.407	0.382	0.313
MACD(L)	0.054	0.040	-0.024	0.023	0.009	-0.055	0.035	0.021	-0.043
MACD(S)	0.012	-0.004	-0.071	0.039	0.023	-0.044	0.033	0.018	-0.049
MACD(LS)	-0.034	-0.079	-0.123	-0.071	-0.108	-0.172	-0.070	-0.109	-0.173
Trend 1 (L)	0.301	0.292	0.229	0.263	0.255	0.192	0.240	0.232	0.169
Trend 1 (S)	0.202	0.192	0.129	0.134	0.124	0.061	0.179	0.170	0.107
Trend 1 LS)	0.370	0.351	0.289	0.311	0.291	0.229	0.275	0.255	0.193
Trend 2 (L)	0.326	0.316	0.252	0.286	0.276	0.219	0.259	0.248	0.184
Trend 2 (S)	0.244	0.233	0.198	0.153	0.141	0.096	0.196	0.184	0.129
Trend 2 (LS)	0.400	0.373	0.305	0.353	0.325	0.257	0.309	0.283	0.215
Trend 3 (L)	0.318	0.304	0.241	0.264	0.248	0.185	0.244	0.226	0.163
Trend 3 (S)	0.193	0.177	0.108	0.137	0.122	0.053	0.173	0.158	0.089
Trend 3 (LS)	0.376	0.346	0.253	0.330	0.298	0.227	0.304	0.275	0.204

Comb. 1 (L)	0.304	0.293	0.228	0.281	0.270	0.205	0.248	0.237	0.172
Comb. 1 (S)	0.219	0.208	0.142	0.173	0.162	0.096	0.191	0.181	0.115
Comb. 1 (LS)	0.379	0.360	0.293	0.344	0.321	0.274	0.301	0.278	0.211
Comb. 2 (L)	0.307	0.294	0.228	0.275	0.260	0.294	0.267	0.251	0.185
Comb. 2 (S)	0.248	0.235	0.171	0.206	0.193	0.129	0.227	0.214	0.150
Comb. 2 (LS)	0.386	0.360	0.295	0.343	0.318	0.253	0.327	0.304	0.229
Comb. 3 (L)	0.336	0.319	0.275	0.281	0.265	0.207	0.268	0.253	0.189
Comb. 3 (S)	0.278	0.261	0.198	0.212	0.194	0.141	0.214	0.197	0.134
Comb. 3 (LS)	0.419	0.382	0.318	0.352	0.316	0.232	0.334	0.295	0.231
KR (NF; L)	0.325	0.316	0.263	0.166	0.157	0.094	0.259	0.250	0.187
KR (NF; S)	0.276	0.267	0.203	0.232	0.223	0.159	0.187	0.178	0.114
KR (NF; LS)	0.300	0.291	0.228	0.207	0.198	0.135	0.221	0.211	0.158
KR (F; L)	0.552	0.543	0.478	0.362	0.353	0.288	0.450	0.441	0.376
KR (F; S)	0.483	0.474	0.403	0.350	0.341	0.270	0.388	0.379	0.318
KR (F; LS)	0.527	0.518	0.453	0.356	0.347	0.282	0.414	0.405	0.340
RD (NF; L)	0.014	0.005	-0.047	0.085	0.076	0.014	0.002	-0.007	-0.069
RD (NF; S)	0.150	0.141	0.074	0.109	0.100	0.033	0.106	0.097	0.030
RD (NF; LS)	0.061	0.052	-0.011	0.101	0.092	0.039	0.065	0.055	-0.008
RD (F; L)	0.529	0.520	0.449	0.498	0.488	0.417	0.404	0.395	0.324
RD (F; S)	0.593	0.584	0.522	0.554	0.545	0.483	0.408	0.399	0.337
RD (F; LS)	0.559	0.550	0.448	0.526	0.518	0.456	0.406	0.397	0.335

TDR (NF; L)	0.085	0.075	0.028	0.153	0.144	0.077	0.033	0.024	-0.043
TDR (NF; S)	0.022	0.013	-0.049	0.036	0.027	-0.035	0.072	0.063	0.001
TDR (NF; LS)	0.056	0.047	-0.018	0.077	0.068	0.007	0.048	0.039	-0.026
TDR (F; L)	0.150	0.141	0.072	0.269	0.261	0.192	0.194	0.185	0.116
TDR (F; S)	0.185	0.175	0.113	0.093	0.084	0.022	0.152	0.143	0.081
TDR (F; LS)	0.174	0.165	0.102	0.111	0.102	0.039	0.176	0.167	0.104
ODR (NF; L)	0.104	0.094	0.032	0.274	0.265	0.203	0.319	0.310	0.248
ODR (NF; S)	0.166	0.157	0.090	0.032	0.023	-0.044	0.115	0.106	0.039
ODR (NF; LS)	0.144	0.135	0.067	0.141	0.132	0.064	0.231	0.222	0.154
ODR (F; L)	0.160	0.151	0.082	0.356	0.346	0.277	0.389	0.380	0.311
ODR (F; S)	0.271	0.262	0.197	0.150	0.140	0.075	0.185	0.176	0.111
ODR (F; LS)	0.223	0.215	0.146	0.268	0.259	0.190	0.324	0.315	0.246
PG (NF; L)	0.180	0.171	0.100	0.286	0.277	0.206	0.247	0.238	0.179
PG (NF; S)	0.127	0.117	0.048	0.106	0.097	0.028	0.232	0.223	0.154
PG (NF; LS)	0.167	0.158	0.089	0.214	0.204	0.135	0.239	0.230	0.161
PG (F; L)	0.376	0.367	0.299	0.323	0.314	0.246	0.360	0.351	0.283
PG (F; S)	0.390	0.381	0.317	0.298	0.289	0.235	0.276	0.267	0.203
PG (F; LS)	0.384	0.375	0.306	0.308	0.299	0.230	0.318	0.308	0.239
RG (NF; L)	0.432	0.423	0.357	0.324	0.315	0.249	0.304	0.295	0.229
RG (NF; S)	0.394	0.385	0.319	0.257	0.248	0.182	0.238	0.229	0.163
RG (NF; LS)	0.413	0.405	0.335	0.281	0.272	0.202	0.271	0.262	0.192

RG (F; L)	0.635	0.626	0.557	0.472	0.463	0.394	0.414	0.405	0.336
RG (F; S)	0.482	0.473	0.402	0.657	0.648	0.577	0.532	0.523	0.482
RG (F; LS)	0.617	0.608	0.546	0.557	0.549	0.472	0.470	0.461	0.399
1234 (NF; L)	0.378	0.368	0.303	0.323	0.313	0.248	0.278	0.269	0.204
1234 (NF; S)	0.263	0.254	0.190	0.258	0.249	0.185	0.236	0.227	0.163
1234 (NF; LS)	0.320	0.312	0.250	0.297	0.288	0.204	0.253	0.244	0.182
1234 (F; L)	0.545	0.535	0.453	0.355	0.346	0.275	0.380	0.371	0.300
1234 (F; S)	0.359	0.350	0.280	0.419	0.410	0.340	0.449	0.440	0.395
1234 (F; LS)	0.465	0.456	0.369	0.393	0.384	0.317	0.419	0.410	0.343