LAPPEENRANTA UNIVERSITY OF TECHNOLOGY
School of Business
Finance / Master’s Degree Program in Strategic Finance (MSF)

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Do retail investors use technical analysis? Evidence from Stuttgart Stock Exchange.

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ABSTRACT

Author:	Nuotio, Lauri
Title:	Do retail investors use technical analysis? Evidence from Stuttgart stock exchange.
Faculty:	School of Business
Major / Master's Programme:	Finance / Master's Degree Programme in Strategic Finance (MSF)
Year:	2014
Master's Thesis:	Lappeenranta University of Technology 73 pages, 14 figures, 8 tables and 1 appendix
Examiner:	Professor Eero Pätäri, Associate Professor Kashif Saleem
Keywords:	Behavioral Finance, Technical Analysis, Pattern Recognition, Retail Investors

This thesis uses automatic technical analysis price pattern recognition algorithm and selection of dual-moving-average-crossover trading rules for explaining buy-sell-imbalance of retail investors' trades in Stuttgart Stock Exchange in order to answer the question "Do retail traders rely on technical analysis as a basis of their trading decisions?" Expectation, based on literature review on investor behavior and profitability of technical analysis, was that proof of use of technical analysis methods would be found. Evidence from daily DAX30 data over time period 2009 - 2013 does not provide enough clear results to support answer for the question. Slight evidence from DMAC rules, head-and-shoulders -pattern, broadening patterns and triangle patterns suggest that retail investors react in rational trend-following manner to trading signs from these indicators.

TIIVISTELMÄ

Tekijä:	Lauri Nuotio
Tutkielman nimi:	Käyttävätkö yksityissijoittajat teknisen analyysin menetelmiä? Todisteita Stuttgartin pörssistä
Tiedekunta:	Kauppatieteellinen tiedekunta

Pääaine / Maisteriohjelma: Rahoitus / Master's Degree programme in Strategic Finance (MSF)

Vuosi: 2014

Pro gradu –tutkielma: Lappeenrannan teknillinen yliopisto
73 sivua, 14 kuvaa, 8 taulukkoa ja 1 liite

Tarkastaja: Professori Eero Pätäri, Apulaisprofessori Kashif Saleem

Hakusanat: Tekninen analyysi, Kuviontunnistus, sijoittajien käyttäytyminen, yksityissijoittajat

Tutkielma käyttää automaattista kuviontunnistusalgoritmia ja yleisiä kahden liukuvan keskiarvon leikkauspiste –sääntöjä selittääkseen Stuttgartin pörssissä toimivien yksityissijoittajien myynti-osto –epätasapainoa ja siten vastatakseen kysymykseen "käyttävätkö yksityissijoittajat teknisen analyysin menetelmiä kaupankäyntipäätöstensä perustana?" Perusolettama sijoittajien käyttäytymisestä ja teknisen analyysin tuottavuudesta tehtyjen tutkimusten perusteella oli, että yksityissijoittajat käyttäisivät teknisen analyysin metodeja. Empiirinen tutkimus, jonka aineistona on DAX30 yhtiöiden data vuosilta 2009 – 2013, ei tuottanut riittävän selkeää vastausta tutkimuskysymykseen. Heikko todistusaineisto näyttää kuitenkin osoittavan, että yksityissijoittajat muuttavat kaupankäyntikäyttäytymistänsä eräiden kuvioiden ja leikkauspistesääntöjen ohjastamaan suuntaan.

ACKNOWLEDGEMENTS

First I’m thankful for Information and Market Engineering –department of Karlsruhe Institute of Technology, Professor Dr. Weinhardt, and Business department of Lappeenranta University of Technology for giving green light for this extraordinary master’s thesis project. Second, I thank my supervisor Dipl.-Math.oec. Felix Fritz for idea of this project, for data, for rigorous guidance and practical advice, trust, support and challenge. Third, I’m grateful for great help provided by Rick Wicklin at SAS, who provided me with some fundamental answers in programming, which I still didn’t know how to formulate the questions for. Finally I thank my professor and second supervisor Eero Pätäri for his comments and support, my friends and family for inspiration and providing support for and counterweight against this sometimes very intensive project.

in Nurmijärvi, November 2014

Lauri Nuotio

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1 Introduction

This master's thesis takes new approach into technical analysis by studying whether or not retail investors use technical analysis methods. Previous studies on technical analysis focus on profitability of such methods and behavioral studies take more interested in what kind of behavioral biases are common for investors. There appears to be an important research gap: "what tools, if any, retail investors use to form their trading decisions?"

There are plenty of reasons to increase our knowledge about retail investor behavior. Seeking of new profit opportunities has been and always will be a major goal of finance. If investors' behavior shows enough strong predictable patterns, taking an according position into following or opposing direction might be profitable. On the other hand, in many countries saving for retirement is in investors' own hands at least partially. Studying behavior helps in discovering typical pitfalls and increasing awareness into investors' own detrimental actions. Ethical wealth manager would take these into account when offering investing services to the less educated individual for the benefit of both parties. Prospering and satisfied individual brings better business for the wealth manager as well. Furthermore, individual investors' behavior reportedly matters. Kumar and Lee (2006) note that it can affect asset prices, Foucault et al. (2011) point to its effects on return volatility and Kornioitis and Kumar (2011) link it to macroeconomy.

It is not only one or two times the author has heard advice from laymen that "stock x cannot fall below price level y, or will rise back to price level z, because it historically has done so". Therefore empirically at least support and resistance levels, channel rules and some reoccurring of mean reversals seem to have strong support in beliefs of amateur traders, whether or not the practitioners realize what kind of patterns their thoughts are taking. Technical analysis has earned a lot of attention among practitioners with many dedicated websites like "MetaStock", brokers providing TA information, journals like “The Journal of Technical Analysis”, “Stocks and Commodities Magazine” and “Futures Magazine”. Many technical trading tools are readily available for everybody free of charge in Google Finance or Yahoo Finance.

Over 90 % of currency traders in London and Honkong, Singapore and Japan has been shown to utilize technical analysis (Allen and Taylor (1990), Lui and Mole (1998)). Findings are similar in US, Germany, Switzerland, Italy and Thailand (Menkhoff (2010)). Menkhoff (2010) argues that technical analysis might very well be the second best source of information. The logic is that if you have not resources to obtain latest information yourself, technical analysis might be able to capture moves of those who do so. Using of technical analysis might be self-fulfilling. Froot et al. (1992) argue that the use of technical analysis might be reason for others to use technical analysis as well, because such action has power to move markets.

Plenty of casual empiricism lets us expect that retail investors as well are at least receiving a lot of technical analysis information, and also feel many indicators intuitively appealing. Thus it is very reasonable to expect that these easy to use and readily available tools are indeed a part of individual investors’ tool kit. If retail investors rely on technical analysis, it is logical to expect that their trading activity, i.e. volume, is unusually high whenever a technical indicator gives, or is about to give, trading signal.

In this thesis, pattern recognition algorithm introduced by Lo et al. (2000), with some modifications presented by Savin et al. (2007) is used to produce a dummy data of 10 patterns. In addition to pattern selection of Lo et al., 16 dual-moving-average-crossover (DMAC) strategies are considered. The patterns and DMAC rules then used in regression analysis to discover changes in buy-sell-imbalance. This methodology is used on data from Stuttgart stock exchange, consisting of trading volumes of retail investors for 29 of DAX 30 stocks from April 2009 till the end of year 2013.

This thesis is limited by adopted methodology. As Gaginalp and Laurent (1998) point out, the pattern definitions are usually not undisputable and some patterns take long to fulfil, increasing the possibility for noise caused by other events. The utilized patterns could be altered with numerous different parameters. The methodological discussion is very interesting, but not a primary goal of this thesis. Hence, some discussion and information is provided to act as a basis for research interested in that particular topic. Head-and-shoulders patterns, observation window length and multiplier parameters follow definition of Savin et al. (2007), and the remaining 8 patterns follow definitions of Lo et al. (2000). Another strict limitation is the rather small sample size. 29 out of 30 Germany’s biggest companies are selected on basis of availability of data.

Finally the scope of this study is to inspect whether or not individual investors use technical analysis, leaving for example the interesting question of profitability of such behavior as a subject for future research.

Research questions are:

1) Do retail traders in Stuttgart stock exchange rely on technical analysis as a basis of their trading decisions?
2) If they do, when do the effects appear and what is the direction of impact?

Structure of the thesis is as follows: Section 2 introduces reader to technical analysis, inspects behavioral flaws of retail investors and reported profitability of such methods. Section 3 introduces data and methodology. Section 4 contains empirical results. Section 5 discusses these results in relation to previous literature. It also elaborates on implications of the results and discusses further research possibilities. Section 6 concludes.

2 Literature review and theoretical background

To the author's best knowledge, there are no previous stock market studies that approach this subject in similar fashion i.e. pursue an answer to question about whether retail investors follow technical analysis signals in their trading decisions (either consciously or sub-consciously due to very intuitive appeal of some rules) or not. There are plenty of articles about retail investor behavior and profitability of technical analysis based trading strategies and the scope of this master's thesis is in between these with some overlapping. Therefore, this section shortly covers (retail) investor behavior in section 2.2 and profitability of technical analysis based trading strategies in section 2.3 to find out what are the expectations about the use of technical analysis, summed up in section 2.4.

2.1 What is technical analysis

Savin et al. (2007) define technical analysis as use of "information about historical movements in price and trading volume, summarized in the form of charts, to forecast future price trends in a wide variety of financial markets". Pring (1991) further asserts that "the art of technical analysis – is to identify trend changes at an early stage and to maintain an investment posture until the weight of the evidence indicates that the trend is reversed". There are two kinds of indicators: qualitative and quantitative.

Familiar visual, i.e. qualitative, trading patterns according to Pring (2002) include gaps, spikes, flags, pennants, wedges, saucers, triangles, head-and-shoulders and various tops and bottoms. Bajgrowicz and Scallet (2012) recognize 5 classes of (quantitative) technical indicators: 1) filter rules which give buy or sell signal if sufficiently large change happens in direction of price movement, 2) moving averages, 3) support and resistance rules, e.g. when price seems to have a ceiling that it doesn't penetrate, 4) channel break outs which are pairs of parallel trend-lines and finally 5) on-balance volume averages: if price rises (falls) in a given day from yesterday's closing price, it's assigned with positive (negative) total trading volume.

Basic notion on the market is that all the information (at least publicly) available should be very fast embedded in price levels (Fama, 1970). If it was not so, some trader could make arbitrage profits by taking a trading position according to the information not yet incorporated into current asset price. However, if markets truly were efficient and all the information would be incorporated already into the prices, there would be no incentive to acquire information which is always time consuming and costly process (Grossman and Stiglitz, 1980). Evidence about efficiency of markets is time-variant and mixed and Odean and Barber (2011) conclude that evidence from behavior finance fails to support the efficient market models based on rational behavior.

70's was the golden era of comprehensive market models (see e.g. Merton (1973)). These models were based on the idea that stock prices were equal to present value of future dividends discounted with marginal rates of substitution of consumption assuming maximizing of the utility of consumption (Shiller (2003)). Grossman and Shiller (1981) argued that the relationship between stock price and the discounted dividends was very slight and not enough volatile to justify the actual price movements. West (1988) showed that variance of innovations in stock prices exceeded 20 times the theoretical limit implied by efficient market theory. Shiller (2003) concluded that markets contain so substantial noise that it dominates the market movement as a whole, meanwhile some individual stocks obey efficient market theory very well, in contrast with conclusions of Lo and MacKinley (1988) who showed that US stock return indexes show positive serial correlation, rejecting random walk hypothesis, meanwhile some individual stocks seemed to have random returns.

Technical analysis relies on assumption that price discovery is not instantaneous and markets experience imperfections big enough to justify use of trading strategies based on early recognition of those inefficiencies. Good trading strategy is such, which identifies a change in trend that matters and remains as little affected by noise as possible. There is, however, not likely such a thing as a constant optimal trend length. Sometimes day trading is better and sometimes really long interval buy and hold strategy is supreme. Interestingly, Schulmeister (2009) assert that profitable positions are always fewer and earn lower absolute returns than negative positions leading to conclusion that optimal technical analysis strategy is one that cuts the losses short and allows for profits to run. He also points to the importance of recognizing the big trend by showing that the "profitability of technical stock futures trading is exclusively due to the exploitation of persistent price trends around which stock prices fluctuate".

There are generally many frictions to trading, including trading cost, lack of interface, and access to reliable, timely data. Other frictions include noise in current equilibrium prices, sentiment, herding behavior and central bank interventions (Park and Irwin (2007)). Furthermore, collective judgment of investors is prone to make mistakes from time to time and therefore markets may behave predictably persistently over a short time period (Malkiel (2003)). Following sections elaborate more on market imperfections rising from human behavior and on evidence of profits to technical analysis trading strategies.

2.2 Investor behavior

Herbert (1957) introduced idea of *bounded rationality*, according to which human decision making is limited by cognitive abilities as well as availability of information, that is, a human does not always (or maybe even often) make optimal decisions based on available information. The author stated that people are only partially rational and induce emotions into their decision making.

People are most likely genetically hardcoded to exhibit some behavioral elements that were perhaps useful in history but bias our judgment in today's investing environment (Lo and Repin (2002); Taleb (2007)).

Given this early recognition of limited human capabilities and influence of emotions, behavioral finance, and retail investor behavior in particular, has raised increased academic interest rather late and peculiarly economic models, like Capital Asset Pricing Model, assume strong rationality. Some notable retail investor behavior articles (see e.g. Lease et al. (1974) and Cohn et al. (1975)), date back to the end of 70's but great body of this research formed during 90's and 2000's and plenty of questions remain still open.

Many divergences from rational behavior are documented among retail investors. These include discovering patterns where there are none, sharing popular models of value which disagree with academically proven ones, lacking in risk diversification and trading in harmful ways. (DeBondt, 1998)

One major behavioral bias is the reluctance of investors to realize losses and to sell winners instead, even though this kind of action is very detrimental if taxes on financial gains are in place (Sheffin and Statman (1985)). This disposition effect is shown to decrease with accumulation of investing experience (Feng and Seasholes (2005); Seru et al. (2010)). Furthermore, Summers and Duxbury (2007) noted that disposition effect does not exist when portfolios are not formed by the individual traders themselves and concluded that regret and pride play a significant role with the phenomenon.

Also the purchases are contrarian. Kaniel et al. (2008) and Hirshleifer et al. (2008) note that investors sell (buy) stocks that announce positive (negative) news. E.g. Griffin et al. (2003); Grinblatt and Keloharju (2000); Kaniel et al. (2008); Choe et al. (1999); Jackson (2003) show that investors, in broad selection of different markets, also buy stocks that show bad past performance. Goetzmann and Massa (2002) document that contrarian individual investors outnumber those who practice momentum trading two to one.

Kumar and Lee (2006) studied transactions by over 60 000 clients of a U.S. discount broker over 1991 – 1996. Specifically, they inspected buy-sell –imbalance (BSI) and found out that it explains significantly return co-movements after controlling for macroeconomic variables. BSI is a proxy for retail sentiment but has much more explanatory power. Small firms, lower priced firms and firms with lower institutional ownership were found to be more sensitive to BSI variable and thereby experience disproportionately high retail trading activity. This means that there is a common driver for retail investor trading decisions, the transactions do not happen independently individually. In addition, the authors conclude that retail investors spend far less time on investment analysis, engage in more attention-based trading and use different information sources than professional investors. Average investor in the sample holds 4 stocks and less than 5% of investors hold 10 or more stocks. On average, monthly portfolio turnover rate is 6.59% and small 2-7% portion of investors trade heavily, 5 or more transactions per month. These findings show lack of diversification and existence of portfolio churning.

In addition to the tendency to have only a handful of stocks, Goetzmann and Kumar (2008) show that the stocks in portfolio are more highly correlated than random selecting would predict. Investors probably have some dominating and narrow preference for certain business sector or sectors.

Geographically closely situated investors' portfolios also correlate with each other, i.e. there is some common driver in the stock selection preference of those individuals (Feng ans Seasholes (2004), Jackson (2003), Barber et al. (2003).

DeBondt (1998) conducted a case study in 1994-1995. The 45 participants in total were individual investors recruited in investment conference in Wisconsin. The participants were requested to forecast performance of a stock of choice as well as that of Dow Jones Industrial Average (DJIA). They also had to answer a set of Likert –scale -questions about investing. The forecasts for DJIA were statistically valid for the 2 week period but for the stock of choice, return forecasts were almost double of the actual return and perceived 2 week beta was 0.54 versus actual beta of 0.87. Summing up, these senior investors with long investing history and relatively big amount of money to invest carefully, were found to highly underestimate return co-movements, hold only a few stocks (and to believe that holding a few stocks they knew well is better risk management tool than diversification), deny role of luck, and even to deny trade-off between risk and return. The authors conclude that people tend to be overly optimistic about pretty much everything in their personal life, conclusion that is clearly supported by the overestimation of favorite stock returns. Obviously the investors also lack ability to infer basic economic rules from years of investing experience as well as do not trust in those rules, discussed widely in both popular and professional financial literature, like modern portfolio theory, which points to advantages of simple diversification and to role of luck in portfolio performance. Instead, most investors “perceive value through popular models, mental frames that are shared socially or tips from financial advisors or friends” and can’t make difference between good stock and good company. Hardships of investors to learn from their experiences has been documented also by Gervais and Odean (2001) and Seru et al. (2010).

At least on short-term, individual investors do not seem to adhere to the education provided by changed market conditions either. Hoffman et al. (2013) combined monthly survey data with transaction records among 1376 individual investor clients of Dutch discount broker during period 2008-2009 and found that during the most severe phase of financial crisis, the investors lowered their return expectations and increased risk perception, but return expectations recovered towards the end of crisis and investors perceived market risk to be even lower than before the beginning of crisis indicating that investors overweight really recent past in market evaluation. Despite devastating impact on asset values (fell to one half during the sample time) these participants were not found to decrease their portfolio risk by shifting to more secure asset classes (cash) or by diversifying more, but instead put more money after bad money, especially during the deepest bottom in September-October 2008. Investor with less experience, more money, higher risk tolerance and lesser use of derivatives was more likely to be a net-buyer during downfall. The authors point out that it is consistent with the idea that retail investors provide liquidity during bad times whereas institutions withdraw that liquidity. Risk awareness correlated positively with portfolio risk, suggesting that these findings are not due to investor's lack of understanding of the risk, but authors point out that results could be twisted because great fraction of investors were not trading during the time.

Ex post, increasing buying during the deepest state of crisis can be seen as the right thing to do, but as shown by perceiving market environment less risky even though the crisis had actually just began, investors as aggregate are clearly optimistic. Furthermore, Odean and Barber (2011) point that individual investors engage in naïve learning reinforcement. This means for example that they are fast to generate narratives to explain previous events even though the sample in reality is far too narrow to justify drawing of any conclusions (confirmation bias), and these narratives tend to be rosy, attributing positive events to skills and negative events to bad luck (self-attribution bias) (Taleb (2007)).

Investors also tend to overreact or underreact to news, especially strongly during economic or political crises (Daniel et al. (1998); Hong and Stein (1999)). Dorn and Sengmüller (2009) provide some insight into sensation seeking behavior by showing that investors who enjoy gambling tend to trade two times as actively as those who don't like gambling and that such sensation seeking trading activity is inversely related to availability to other gambling opportunities, like lottery.

Quite in contrary to behavior noticed by Hoffman et al. (2013), Massa and Simonov (2005) find that retail investors become defensive after being hurt by financial and real estate losses, conclusion also supported by Barberis (2013a). Difference in findings might be better quality of the data used by Massa and Simonov: they have information about all the income and investment gains, list of assets and a set of demographic variables of the Swedish retail investors included in their sample. The approach itself is very interesting as it differs from typical way of assessing financial wealth performance in isolation. The authors indeed find that performance in asset classes influence behavior over the asset borders. They claim that letting other asset classes, especially real estate performance, unconsidered brings biases about. Other explanation why Hoffman et al. (2013) find support for loss aversion, theory asserting that suffering prior losses increase risk taking, in contrary to findings from Swedish data, might indeed be the lack of trading during the sample time. It remains unclear were those investors increasing their holdings during the bottom those who had suffered losses previously. The Swedish evidence rather points to direction of house-money effect i.e. that gains are money that is easier to invest and losing them doesn’t hurt so much as losing the original capital. The effect is stronger for investors with high wealth and more liquid assets.

House money effect goes hand in hand with human tendency to anchor to previous price development when evaluating future upper and lower bounds (see eg. (De Bondt (1993)). The phenomenon is seen also with demand for return on risk. De Bondt (1998) argues that investors use usually market index or purchase price as a reference point and are content as long as they manage to be on the positive side.

Shefrin and Statman (1997) show that reputation of a company is inversely correlated with book-to-price –ratio, thus proving that investors pay more for well-known stocks.

Linnainmaa (2010) provides feasible explanation for some self-harming trading actions by individual investors which have been attributed to irrational behavior. By studying Finnish stock markets, he shows that limit orders explain great deal of trading activity which falsely pointed to misinterpretation of new information, poor stock-picking skills, disposition effect and contrarian trading behavior. 52% of orders are carried over from previous day and 22 % of orders are submitted prior to opening of markets. However, he also concludes that institutions' executed limit and market orders perform better than retail investors'. Linnainmaa (2010) argues that there is no mechanical way of profiting from this investors' picking of excess risk. However, he does not comment on findings of Kavajecz and Odders-White (2004) who show that technical analysis is able to point depth already in place in limit-order book. Combining these two articles, it indeed seems possible that there is a way to systematically profit from retail investors' tendency to use limit orders.

Dorn and Huberman (2005) conducted a survey on German discount broker clients. The 1345 attendants exhibited same objective traits as the invited population as whole, and can therefore be considered as representative sample. Difference to German household heads is vast. The clients are higher educated (college 70 % vs. 17 %), younger (38 vs. 51), earn more, have more wealth are more dominantly males (88 % vs. 69 %), and hold their assets in more diverse asset classes. The authors collected self-assessments and perceptions from the respondents and found these to be fairly accurate: portfolio volatility of most risk-averse investors was 28% between January 1995 and May 2000 whereas for least risk-averse group it was 45%. In addition, the risk-averse group also held double the amount of positions in their portfolio compared to risk-tolerant group. Previously emphasized age and gender effect lose considerably their explanatory power on portfolio turnover when self-reported risk-aversion variable is included in regression model. Furthermore, those with longer investment experience make better portfolio choices. Those who consider themselves as knowledgeable about financial securities diversify better, but those who think they know financial securities better than their fellow investors churn their portfolios more, and for their detriment. Finally, the authors state also that there is no evidence for bolder position taking for those who might be suspect to overconfidence stemming from illusion of control or self-enhancing attribution bias.

Evidence of individual investor performance in relation to market or professionals is mixed. Barber and Odean (2000) show evidence that individual investors' underperform in relation to market largely because of trading costs, instead of perverse stock picking skills. Grinblatt and Keloharju (2000) find out that individual investors tend to buy winning stocks only 44.8 % of days compared to 55 % of days by financial institutions. The performance evaluation period is 120 trading days following the purchase moment. This evidence indeed points to direction of individual investors' detrimental "skill" to pick the rotten apples. Barber et al. (2009) show that in Taiwanese stock markets (in which 90 % of trade was done by individuals) individuals' transfers to institutions, by losing in trades, accumulates to an amount equal to 2.2 % of the country's GDP. Odean (1999) concludes that stocks bought by individual investors underperform those that they sold by 3.3 % one year afterwards. On the other hand, Kaniel et al. (2008) and Kelley and Tetlock (2011) show that retail investor trading positively predicts short term returns. Kaniel et al. (2008) note that the magnitude of excess returns is greater with less liquid stocks. Furthermore, they show that during the week of intense selling the returns are positive and vice versa, i.e. returns for retail investor actions are negative on very short term up to one week. The authors also conclude that return reversal phenomenon has decreased greatly from the end of 80's to the end of their full sample in early 2000's, remaining present only in small stocks.

Profitable retail investing has been shown to be the game of a few. Barber et al. (2011) show that very small proportion of the 300 000 retail investors in Taiwan participating in day trading earn consistent supreme gross returns of over 50 bps per day. Coval et al. (2005) provide evidence of performance persistence among retail investors. Kornioitis and Kumar (2009) and Grinblatt et al. (2012) show that smart investors, according to IQ tests, perform better than their peers. Finally, Massa and Simonov (2005) argue that wealthy investors have higher gains than their less rich peers and in addition, investors with more liquid assets perform better.

Under expected utility theory, decision makers maximize their expected utility rather than mathematical outcome. If decision maker is risk averse enough, she may choose certain less profitable outcome in a game which offers higher expected return for a risky choice than for a risk-free choice for example receiving certain 8$ instead of 10% chance to get 100$ for which the expected payoff would be 10$. In this case, the utility premium paid for getting certain 8$ instead of risky 10$, would be 2$.

On the other hand, cumulative prospect theory, introduced by Kahneman and Tversky (1979), states that decision makers overweight small probabilities and underweight medium to large probabilities. This theory sets ground for popularity of lottery in which the expected net-outcome is negative and probability to win is extremely low. Furthermore, covering for negative outcomes by taking insurance isn’t rational behavior when considering expected value. Ebert and Hilpert (2013) show that trading based on simple moving average (SMA) rules biases outcome of investing in a way that is attractive according to CPT. When trading with these rules, long (short) position is closed after sufficiently large sudden negative (positive) change in asset price cutting and thickening the left tail of probability distribution and skewing it heavily to the right. Skewness to right implies large probabilities of small negative gains and small probabilities of large positive gains. Increase of skewness when trading according to SMA rules is robust towards different underlying stock price dynamics, different time horizons and validated on STOXX Europe 600 stocks.

Ebert and Hilpert (2013) argue that due to nature of CPT utility function, investors are loss-averse and less sensitive to small negative and positive outcomes, i.e. underweighting small outcomes and overweighting big gains with small probabilities. Barberis (2013b) notes that during recent years, empirical evidence of incorporation of skewness in returns into prices, has accumulated. He argues that decades long high equity premium in U.S. stock markets is due to overestimation of probabilities of wide crashes and pricing of that overestimated risk.

2.3 Profitability of technical analysis based trading

It's a general agreement that if there exists some publicly known trading scheme that is profitable, it will be exploited really fast and markets would reach new higher level of efficiency. On the other hand, Gaginalp and Laurent (1998) argue that academics overestimate the amount of available capital to take advantage of these apparent anomalies since most of mutual funds, for example, have to follow specific allocation and risk taking rules in their trading and operate therefore somewhat sluggishly. Furthermore, they point out that agreement about true price of any asset is under constant debate and spread between professional analysts' opinions of fair price of almost any asset is wide at any time. Even if there is a rather strong certainty of difference of fair price and current market price, the difference is not guaranteed to narrow soon, if at all, and is also dependent on strategies of other market participants. Kindleberger (1987) argues that irrationality can dominate over the power of arbitrage capital for as long as several years.

In order of technical analysis to be profitable, markets should be predictable. Ang and Bekaert (2007) show that dividend yield and short interest rates predict short run excess returns and that earnings yields predict future cash flows, but only weakly excess returns. Kim et al. (2011) study predictability of returns of Dow Jones Industrial Average Index over 1900-2009 time period. They find that market predictability is highly time-variant and depends on market conditions. During stock crashes no predictability is observed and uncertainty is extremely high. During bubbles predictability is lower than during normal times, but higher in presence of economic or political crises. The authors show that the DJIA index used to be more predictable before 1980 than thereafter and argue that this is a consequence of innovations in U.S. stock exchange during 1960's and 1970's as well as lower volatility of U.S. macro variables, of which interest rates, inflation and volatility affect predictability. However, the autohrs argue that it would not be possible to economically benefit from trading based on these findings because it is not possible to time downturns or upturns. Timmermann (2008) argues based on empirical evidence that stock returns are predictable only during short time periods and generally unpredictable.

Lo (2007, 2004) describes this constantly evolving market efficiency as an evolutionary framework “in which markets, instruments, institutions and investors interact and evolve dynamically according to the “law of economic selection”, a picture borrowed from Darwin’s theory of natural selection. Markets are not in constant state but rather an evolving organism and hence efficient market hypothesis -paradigm should be replaced with a paradigm of adaptive market hypothesis. Lo (2007) argues, that when market environment changes, old heuristics may not anymore work and in such situations behavioral biases are observed. Also aggregate risk preferences and market participants change because different types of behavior are profitable during different times. Malmendier and Nagel (2011) argue that dramatic experiences, taking the Great Depression as an example, can have permanent affection on investors’ perceptions and risk-taking behavior. The former argues that people change and the latter that behavior of people change.

One notable early study in favor of technical analysis was written by Sweeney (1988). He re-examined the data in Fama and Blume (1966). In the original study from 60’s, Fama and Blume showed that filter rules applied to 15 of 30 selected Dow Jones stocks earned excess returns over buy-and-hold strategies. Sweeney’s contribution was to show that 14 of those 15 stocks still produced excess returns for several years after the original sample, partially net of costs, indicating persistent existence of profitable technical analysis –based trading rules.

Arguably the greatest inspirer for technical analysis profitability research during 90’s and early 2000’s has been paper of Brock et al. (1992). They studied returns for 26 simple moving average and channel break-out rules on Dow Jones Industrial Average index from 1897 to 1986 and presented evidence questioning the market efficiency. Afterwards, their study has been criticized by Sullivan et al. (1999) among others. Using White's Reality Check bootstrap methodology (White (2000)), the authors show that findings of Brock et al. (1992) are a result of data-snooping, which occurs when a data-set is used "more than once for the purposes of inference or model selection" (Sullivan et al. (1999)).

Sullivan et al. (1999) construct the whole universe of trading rules, from which Brock et al. (1992) picked their selection of 26 rules, and perform data-snooping adjusted re-examination on the same data and in addition, on the following 13 years that had elapsed after the first research. The full universe amounts to 7846 trading rules on condition that they had to be in use for a substantial part of the sample time. They found out that some rules indeed outperformed benchmark during the sample, adjusted for data-snooping and proven by mean return as well as by the Sharpe ratio (a measure taking risk into account). The best-performing rules from the full universe were very different than those of Brock et al. (1992). During the whole new sample period spanning from 1897 to 1996, best performing rule from limited universe was 50-day variable MA rule with 0.01 band filter whereas the best performer from whole universe was standard 5-day MA rule with annualized returns of 9.4% and 17.2% respectively. These compare to benchmark buy-and-hold –strategy which earned 4.3% annually. Based on the Sharpe ratios, the best rule from limited universe lost substantially to the best performer of the whole universe, and further, was not significant in several sub-periods. Controlling for non-synchronous trading, the findings are hampered even more. Mean return during the whole sample for the best rule is only 7.8% with statistical significance, but based on the Sharpe ratio the best rule is statistically insignificant.

The authors formed also a trading strategy which utilized best rule based on historical information up to date and updated that daily. That strategy generated 14.9% annualized return, losing to the 17.2% of the best rule. Sullivan et al. thereby argued that investors could not know best performing rule ex-ante. Finally, out-of-sample results show that best performers during the sample of Brock et al. (1992)

cannot generate significant profits over the last 9 years. This is claimed to be an effect of increased market efficiency.

Friesen et al. (2009) introduce a model, which attempts to explain why some technical analysis based trading rules are profitable. They show that returns for stocks are autocorrelated and furthermore, that sequential jumps experience economically significant positive autocorrelation. Return autocorrelations are negative on very short term up to one week, positive after few weeks and up to 12 months and thereafter experience mean reversal, consistent with findings of Gutierrez and Kelley (2008). Friesen et al. (2009) attribute their findings to confirmation bias, that is, the tendency of investors to be biased towards last big piece of information when interpreting less influencing news.

Pätäri and Vilska (2014) study performance of dual moving average crossover (DMAC) strategies on Finnish stock markets over the 1996-2012 period. Studying the performance of 3020 DMAC trading strategies, combinations of short moving averages from 1 to 20 days and long moving averages from 50 to 200 days, on OMX Helsinki 25 index and individual stocks exclusively included in that index, shows clear evidence for profitability of utilizing some DMAC strategies in comparison to passive buy-and-hold (B&H) strategies after controlling for transaction costs and taxes. Vast majority of the trading rules beat the benchmark B&H strategy during both halves of the sample period and best performers on the 1st half also show some degree of superior performance during the 2nd half for individual stocks, but not for index. By splitting the sample into bullish and bearish era, the authors show that the superior performance of DMAC strategies over B&H strategies is mainly attributable to avoidance of losses during bearish times. The findings of superior performance of DMAC strategies during bearish periods are consistent with findings of Fong and Young (2005) and Felix and Rodriguez (2008) but inconsistent with Fong and Ho (2001) and Chang et al. (2004) who find superior performance in bull markets.

Gaginalp and Laurent (1998) studied predictive power of a set of three-day candlestick patterns with daily data on all S&P 500 stocks between 1992 and 1996. They tested hypothesis that existence of a three-day candlestick reversal pattern increases the likelihood of prices moving in favorable direction and found statistically and economically significant out-of-sample evidence. On average, profits were almost 1% for two-day holding period before transaction costs.

Bajgrowicz and Scallet (2012) examine number of previous articles, which have studied profitability of technical analysis on Dow Jones Industrial Average Index between 1897 and 2011, and found positive evidence. They argue that the studies suffer from methodological insufficiencies and lack of consideration for costs, especially lending costs or availability of stocks when going short. Even the most valiant proof in favor of profitability of technical analysis is rendered zero after introducing a 55 basis point one way transaction costs. The authors conclude that even knowing the business cycle ex-ante, would not help selecting the future outperforming rules.

Park and Irwin (2007) reviewed an exhaustive collection of technical analysis profitability studies and divided them into classes by methodologies and robustness tests used. They summarize that from all 95 modern studies, studies which use somewhat robust methodologies and control for biases, 56 found positive, 20 negative and 19 mixed evidence for profitability. For stock markets the numbers are 25, 12 and 10 respectively. Generally, technical trading strategies are profitable in developing markets and negligibly or diminishingly profitable by time in developed markets.

Very little research has been produced about intraday profitability of technical analysis in context of stock trading. Schulmeister (2009) conducted comparative study of 2580 technical trading rules with daily data on S&P 500 spot index during 1960 – 2007 and 30-minutes-data on index futures from 1983 to 2007. Spesifically, he tested performance of 1) moving average rules with short MA of 1-12 observations in length and long MA of 6-40 observations in length with restriction that long MA would have to be at least 5 observations longer than short MA and 2) momentum oscillators of similar fashion.

Schulmeister (2009) shows that profits using daily data have steadily fallen from 1960’s, being zero or negative for these models as an aggregate from in 80’s, 90’s and 2000’s. Annual gross rate of return (GRR) for period 1960 – 2000 was 1.9%. 8.6% of the models achieved t-statistic over 3 indicating high significance and produced annual GRR of 8.3%, much more than the whole set of models. For intraday data the findings are very different. GRR during the whole sample has been 7.2% and more interestingly, net rate after accounting for transaction costs, 2.6%. Furthermore, 97.3% of the models produced positive GRR and almost 60% of the models had t-statistic over 2.0, the whole set averaging 2.37 showing strong evidence of technical trading performance, less dependent on selection of right rules in stock index futures markets during the sample period. Twenty-five best performing rules beat also the stock market ex-ante during 1986 – 2007 by GRR of 14.5% vs. 7.5%, respectively. The timeliness of data was indeed the winning factor, shown by superior performance of the fastest trading rules, i.e. those utilizing relatively short MAs and momentum lengths. Also contrarian rules, i.e. those based on early recognition of coming turn in trend, performed better than follower rules, i.e. those trying to recognize already-in-place change of trend early on. The high performance season seem to be over though as the rules on average would have yielded negative GRR during 2004 – 2007. The author concludes that markets may have become more efficient lately and in addition, that the profitability has shifted to higher frequencies of data due to increased availability and use of such timely information.

Gatev et al. (2006) studied and reported success of some proprietary trading desks and hedge funds in the 80’s and 90’s based on statistical arbitrage strategies. The evidence shows that there at least has been persistent statistically identifiable and economically exploitable market inefficiency. Menkhoff and Taylor (2007) summarize that studies have in general found technical trading strategies profitable in currency trading context, net of costs.

2.4 Forming of null-hypotheses

Given that profits for technical analysis trading strategies are recently shown to be positive mostly in emerging or border economies (see e.g. Bajgrowicz and Scallet (2012); Park and Irwin (2007); Pätäri and Leivo (2014)) and shown to be negligibly small and shifting to higher observation frequencies in developed countries (see eg. Schulmeister (2009)), it's unlikely that following such strategies is profitable and thus smart in German stock markets.

Broad set of divergences of retail investors from rational behavior does not justify giving much weight on the profitability as a guide what comes to expectations of use of technical analysis tools. Contrarian behavior has been reported by many authors (see e.g. Kaniel et al. (2008); Hirshleifer et al. (2008); Griffin et al. (2003); Grinblatt and Keloharju (2000); Chloe et al. (1999)) suggesting that retail investors buy stocks in downfall and sell the raising stocks.

The prospect theory (see Kahneman and Tversky (1979)) is also evident in many areas of life positing that small additional costs are accepted to avoid very unlikely loss, even when the expected value of the situation is clearly negative. Ebert and Hilbert (2013) point that using of simple moving average strategies morphs return distributions into favorable direction for an investor with desires according to prospect theory. Most other technical analysis indicators aim also at recognizing of turn in price trend and would therefore be desirable tools. Evidence of return performance rather points to direction of investors following momentum with their trades on very short term, up to one week (see eg. Kaniel et al. (2008); Kelley and Tetlock (2011)).

Even while retail investors are generally far more educated and economically successful in life than population as a whole, (Dorn and Huberman (2005)) they hold naïve beliefs (De Bondt (1998)), follow popular models and tips from laymen (De Bondt (1998)), do not learn from experience (Gervais and Odean (2001), Seru et al. (2010)) and are sensitive to risk (Massa and Simonov (2005)).

Based on availability and popularity of free technical analysis information, suitability of such methods in altering risk in favorable direction according to prospect theory, historical success of simple trading rules, and built-in need of human mind for patterns and narratives leads to following expectation:

Null-hypothesis:

Retail investors use technical analysis methods.

3 Data and Methodology

This section starts by introducing data and sample period (3.1), is followed by presentation of smoothing algorithm (3.2), emphasizes one important methodological character, namely bandwidth parameter (3.2.1), introduces pattern recognition algorithm (3.3), patterns and dual-moving-average-crossover rules (3.4), construction of dependent variable (3.5) and ends with regression model of dependent variable on independent variables, including control variables (3.6).

3.1 Data

The firms chosen initially are the DAX 30 companies, 30 biggest listed companies in Germany, as was the composition of the group at the end of 2012. Full list of companies is included as appendix 1. Daily highest-, lowest- and closing quotes are obtained from Yahoo Finance and Google Finance. Trading volume data (for buy and sell side separately) is from Stuttgart stock exchange directly and exclusively.

Time frame of the sample is limited by availability of the Stuttgart data and spans from April 2009 till the end of December 2013. The Stuttgart data causes also some further constraints. Commerzbank was omitted due to severe lack of trading quotes in the Xetra –data (from Reuters). Final sample of 29 companies includes 5 healthcare companies and 4 car or tire manufacturers. Industry-level clustering might be driving the results to some extent, but small sample size does not allow for running separate regressions and holding statistical significance. Inclusion of firm dummies controls the effects partly.

First half of the sample illustrated in Figure 1 is characterized by 28-month-long constantly bullish period. During one month following the uptrend, index sunk from 7349 to 5470 points, marking the steepest drop during observation period. From 5072 points closing level on 12th of September 2011, the index experienced constant uptrend to the end of sample, reaching its sample top on 27th of December 2013 at 9589 points.

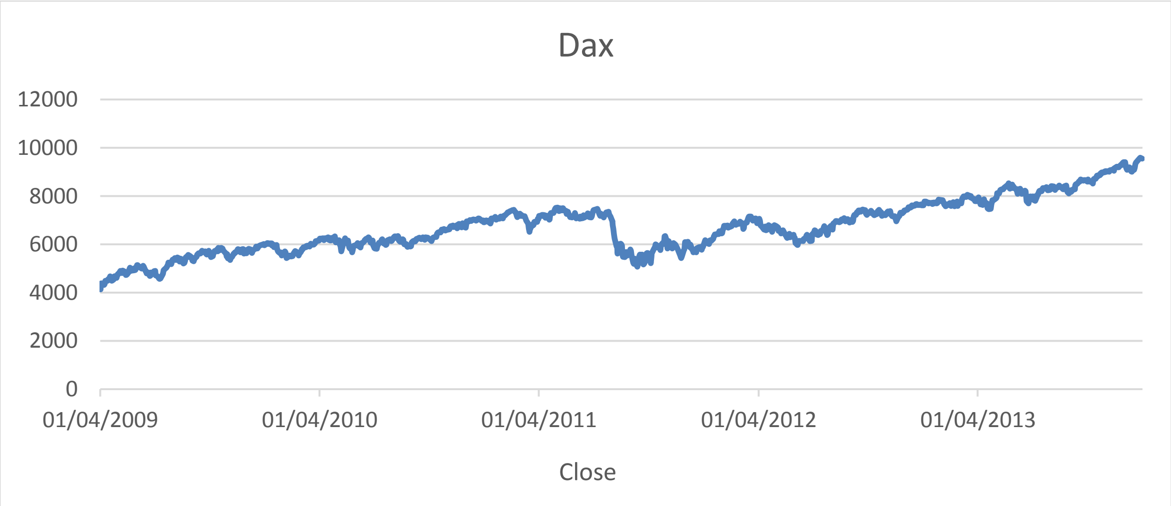

Figure 1: DAX index from the beginning of April 2009 till the end of December 2013.

3.2 Smoothing estimator

Smoothing algorithm is implemented as it's presented in Lo et al. (2000). This chapter starts with description of smoothing estimators, specifies the particular estimator used in this paper, kernel regression, and formulates the smoothing algorithm.

Smoothing estimators are a class of statistical estimators which extract nonlinear relations in price data by averaging out the noise, hence smoothing. Smoothing estimator works much like a human eye in this recognition of trends from noisy data and is therefore suited to be the basis of automated pattern recognition program. (Lo et al. (2000); Savin et al. (2007); Beymer and Poggio (1996))

Basis for technical analysis is a notion that price develops nonlinearly and contains some regularities, i.e. patterns. Lo and MacKinlay (1999) conclude that markets do not follow random walk or stationary mean reverting models presented by many researchers previously.

Under this assumption of nonlinear unknown price function, price P_t can be formulated as:

$$P_t = m(X_t) + \varepsilon_t, \quad t = 1, \ldots, T, \tag{1}$$

where $m(X_t)$ is unknown fixed function, X_t is a state variable, and ε_t white noise.

Smoothing estimator $\widehat{m}$ of any x can be expressed as

$$\widehat{m}(x) = \frac{1}{T} \sum_{t=1}^{T} \omega_t\,(x) P_t, \tag{2}$$

,where ω_t is weight that is lower for those values further away from x and higher for those close to x and P_t is the respective value of price data coupled with the weight at distance t-x from x. So smoothing estimator $\widehat{m}$ is essentially average of price observations P at point x and close to x. Weight function defines how much weight is given to values at certain distance.

Lo et al. (2000) use Kernel Regression as a method of smoothing and it is implemented in this master's thesis as such. In this method, the weight function is constructed from a probability density function K(x), a kernel:

$$K(x) \geq 0, \qquad \int K(u)du = 1 \tag{3}$$

,which is rescaled with respect to bandwidth parameter h > 0 to change Kernel's spread:

$$K_h(u) \equiv \frac{1}{h} K\left(\frac{u}{h}\right), \quad \int K_h(u)du = 1 \tag{4}$$

Parameter h determines how big is the neighborhood around X_t to be used to determine the X_t. With large h, the neighborhood is large and therefore the function is averaging a lot. With small h, smoothed estimator is close to the unsmoothed counterpart. There is a trade-off between averaging too much and losing relevant information and averaging too little inducing noise to the model.

Weight function to be used in weighted average equation (2) is defined as:

$$\omega_{t,h}(x) \equiv K_h(x - X_t)/g_h(x) \qquad (5),$$

$$g_h(x) \equiv \frac{1}{T} \sum_{t=1}^{T} K_h\,(x - K_t) \tag{6}$$

And substituting (6) into (2) results in Nadaraya-Watson kernel estimator $\widehat{m}_h(x)$ of m(x):

$$\widehat{m}_h(x) = \frac{1}{T} \sum_{t=1}^{T} \omega_{t,h}(x) Y_t = \frac{\sum_{t=1}^{T} K_h(x-X_t)P_t}{\sum_{t=1}^{T} K_h(x-X_t)} \tag{7}$$

Of wide array of suitable kernels, Gaussian kernel is used:

$$K_h(x) = \frac{1}{h\sqrt{2\pi}} e^{-x^2/2h^2} \tag{8}$$

There are also different methods to select the bandwidth parameter *h* by automation. Lo et al. (2000) use the most common of these, cross-validation method. Such value of h is selected which minimizes function:

$$CV(h) = \frac{1}{T}\sum_{t=1}^{T}(P_t - \widehat{m}_{h,t})^2 \tag{9}$$

where

$$\widehat{m}_{h,t} \equiv \frac{1}{T}\sum_{\tau \neq t}^{T} \omega_{\tau,h} P_\tau \tag{10}$$

The estimator $\widehat{m}_{h,t}$ is the same as Nadaraya-Watson kernel estimator in (7) except that the *t*th observation is omitted when estimate for X_t is constructed. Cross-validation function (9) works so that *h* minimizes the sum of squared distances between kernel estimator (with omitted *t*th observation) and the actual price observation.

In practice, minimizing this cross validation function does not go without issues. Due to losing of accuracy when dividing by a value close to zero, the function starts to suffer from false rounding if h<0.14 and below 0.13 the lower part of equation 7 becomes 0 and thus the equation is not defined. Also in a very few cases *h* would receive negative value which makes a little sense practically. Lo et al. (2000) or Savin et al. (2007) do not mention experiencing these issues so it’s unclear how they dealt with them.

Through experimenting, it was discovered that change in *K* is negligible between values of *h* from 0.14 to 0.40, implying very little smoothing. This is an interesting point when choosing multiplier for *h* as is done in both reference studies. In this master’s thesis, lower boundary of 0.14 is set for value of *h*. The findings are confirmed with other individually built algorithm and thus are not likely to be a result of false coding.

3.2.1 Bandwidth parameter h

Parameter *h* is the result from minimizing cross-validation function (9). It is calculated separately for every rolling window and *h* determines the degree of smoothing. None of the papers testing Lo et al.'s algorithm discuss the behavior of *h* in any detail except that Lo et al. (2000) use multiplier 0.3 whereas Savin et al. (2007) implicitly consider values of *h* too low and use multipliers from 1 to 2.5 instead. Dawson and Steeley (2003) are happy to replicate Lo et al. (2000) in everything, also in what comes to *h*, without further ado. This section however takes deeper look into behavior of this parameter crucial to the behavior and overall functionality of the smoothing algorithm. Mathematics involved are complicated and demand some insight into both human behavior in pattern recognition and mathematical optimization dynamics. This section is added purely to provide a ground for further evaluation of the smoothing method in this context.

The numbers presented in Figure 2 and Table 1 are for *Deutsche Bank*, but the results are relatively similar across different firms in the sample. Over one half of the sample for parameter *h* is in region which results practically in no smoothing at all whereas 25 % of observations take values over 0.693, and are thereby greatly affected by introduction of multiplier to *h*. Smoothing-algorithm loses information in price series and eventually flattens completely with increasing parameter *h* value. The logic is such that when a clear trend is present in the data, lots of smoothing is introduced and too local variance is cleaned out giving more precision for the underlying trend. When such a trend is not present, data is left unsmoothed to avoid losing of important information.

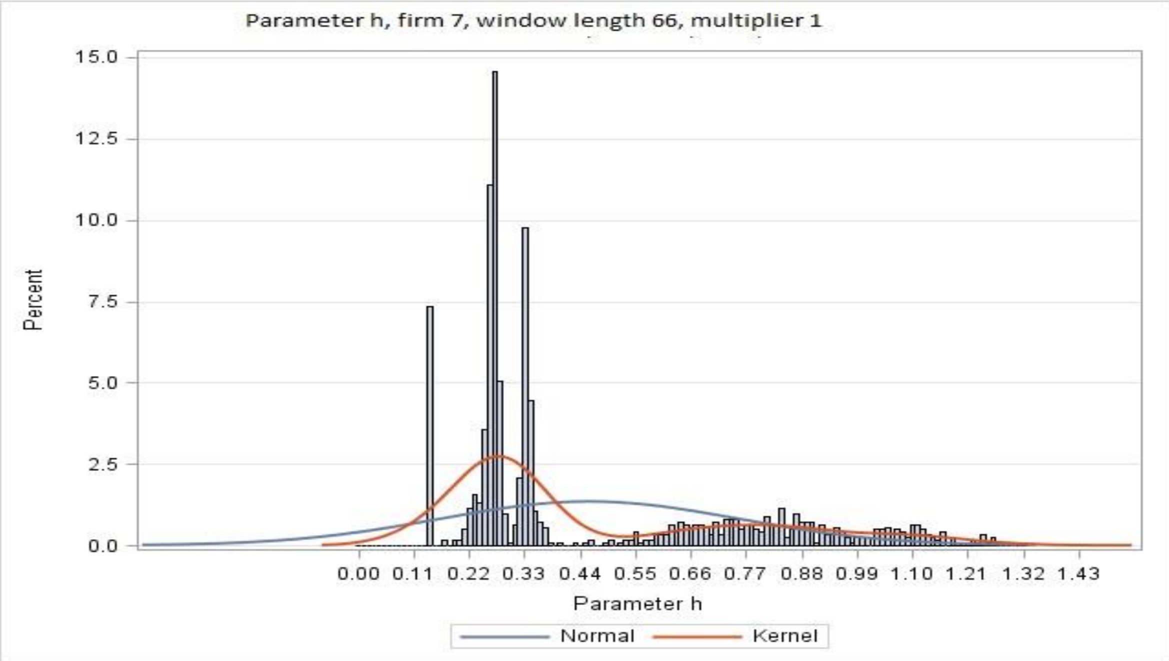

Figure 2: Distribution of parameter h for a randomly selected company from the sample.

Table 1: Summary statistics for parameter h of the randomly selected company.

Obs.	Mean	Std. d.	Min	Q1	Median	Q3	Max
1208	0.459	0.296	0.140	0.263	0.323	0.693	1.324

3.3 Pattern recognition algorithm

Pattern recognition also follows the example of Lo et al. (2000), that is, kernel regression is fitted for subsamples, windows of shorter length. In their study, authors use 38 day window of which 35 days for the pattern to fulfil and 3 days to recognize the pattern. Their reasoning of focusing into such less than two-month window on basis that it would be more relevant for “active equity traders” is questioned by Savin et al. (2007). The latter study uses 63 trading days as the length of rolling window, a length that is reported to be the average completion time for head-and-shoulder pattern in Bulkowski (2000).

In this thesis, window length of 66 trading days is used. This comes from keeping the time available for pattern fulfilment the same as in Savin et al. (2007) but increasing the time span to recognize the pattern from 3 days to 6 days. This means, that the rolling window length is 66 days and pattern is recognized on 60th day of a window in question. Adjustment is done because with increased smoothing, done by utilizing bigger bandwidth multipliers than in study by Lo et al. (2000), border bias comes more of a problem.

Kernel regression in a window using prices in that particular window as modified from Lo et al. (2000):

$$\widehat{m}_h(\tau) = \frac{\sum_{s=t}^{t+l-1} K_h(\tau - s) P_s}{\sum_{s=t}^{t+l-1} K_h(\tau - s)} \qquad t = 1, \dots, T - l + 1, \tag{11}$$

where *l* is window length.

Bandwidth parameter *h* is calculated for every window separately and a window full of smoothed parameter estimates formed on that basis. From these smoothed estimators, maxima and minima are defined. “Relevant extrema” are original price values on ext(P(x-1)…P(x+1) where *P(x)* is price on date *x* which is identified to be date of extreme value of smoothed price series and “ext” is either maximum or minimum. These relevant extrema are used in pattern recognition.

3.4 Patterns and moving average trading rules

This master’s thesis utilizes set of price patterns and set of dual-moving-average-crossover (DMAC) rules to track retail investors’ use of technical analysis as a base of their trading decisions. Ten common and easy to implement price patterns presented by Lo et al. (2000) are utilized with small modifications. In addition to these patterns, 32 different combination of moving average rules are formed from short moving averages of 1, 5, 10, 20 days and long moving averages (MA) of 50, 100, 150 and 200 days in following way: 1-50 up-down rule would be when 1 day MA crosses 50 day MA from above. 5-150 down-up rule would be when 5 day MA crosses 150 day MA from below. In their very comprehensive DMAC profitability and robustness research, Pätäri and Vilska (2014) state that these rules are commonly used. In following section the price patterns are presented one by one and in section 3.4.6 quality of the definitions are discussed.

3.4.1 Head-and-Shoulders and Inverse-Head-and-Shoulders

All patterns are defined as series of 5 consecutive local extrema ($E_1,\ldots,E_5$) in Lo et al. (2000).
Head-and-Shoulders (HS) pattern has following characteristics:

1) E_1 is a maximum
2) $E_3 > E_1$, $E_3 > E_5$
3) E_1 and E_5 are within 4.0 percent of their average
4) E_2 and E_4 are within 4.0 percent of their average

And inverse (IHS) pattern has the opposite logic in characteristics 1 and 2:

1) E_1 is a minimum
2) $E_3 < E_1$, $E_3 < E_5$

Savin et al. (2007) suggest, inspired by book of Bulkowski (2000), some modifications to these HS and IHS patterns in their paper focusing solely on these patterns in question. First, they allow for greater vertical distance between the shoulders: 4.0 % instead of 1.5 %. Second, they restrict average height of a shoulder as a proportion of the height of the head from the neckline, that is, a line that connects E_2 and E_4 to be between 0.25 and 0.70. Third, height of the head from a neckline has to be equal to or greater than 0.03. Fourth and final restriction rules out extreme horizontal asymmetries. The authors also emphasize the importance of neckline crossing condition, that is, price has to cross neckline on its way from E_5 to E_6. However, with empirical testing they find no evidence of increased predictive power due to these additional restrictions even though the restrictions drop HS pattern observations by 30%. Lo et al. (2000) validated their algorithms at some technical analysis professionals what comes to bandwidth parameter, so it can be read between lines that the algorithms as such were doing good enough job to convince the professionals of their usability.

In this thesis, the neckline condition is adopted. Price has to cross neckline on its way from E5 to next extreme. Following Savin et al. (2007), this is recognized by using E6 instead of E5 as the fulfilment point and conditioning that the neckline projected price is higher (lower) than actual price on day when E6 takes place for head-and-shoulders (inverse). The authors argue that the bias introduced by using E6 instead of actual neckline crossing is generally small. That is clearly an arguable issue, but in this thesis buy-sell-imbalances after the t-day are also studied conditioned on presence of a pattern. If the bias is somewhat constant, head-and-shoulder patterns could have higher impact on buy-sell-imbalance lagged by some steps. The vertical distance parameter of 4 % is used, following Savin et al. (2007).

The company used for the illustrations of patterns in this section is Münchener Rück, a re-insurance company randomly chosen from the sample. The patterns were also picked randomly, not to present the performance of algorithm in especially good or bad light. However, they are all acquired conditioning bandwidth multiplier to equal 1, introducing least smoothing. *Newp*, the blue line, is series of actual end of day values whereas *Smooth*, the red line, is smoothed price series. Circles mark the extrema of which the patterns consist of. *Time_Newp* is number of elapsed trading days, 1 being the 2nd of January 2009.

Figures 3 and 4 present head-and-shoulder and inverse head-and-shoulders respectively. In this particular case, smoothing is practically non-existent. Also there appears to be some 5 days between the actual neckline cross and the implied confirmation date. The pattern itself is very well formed.

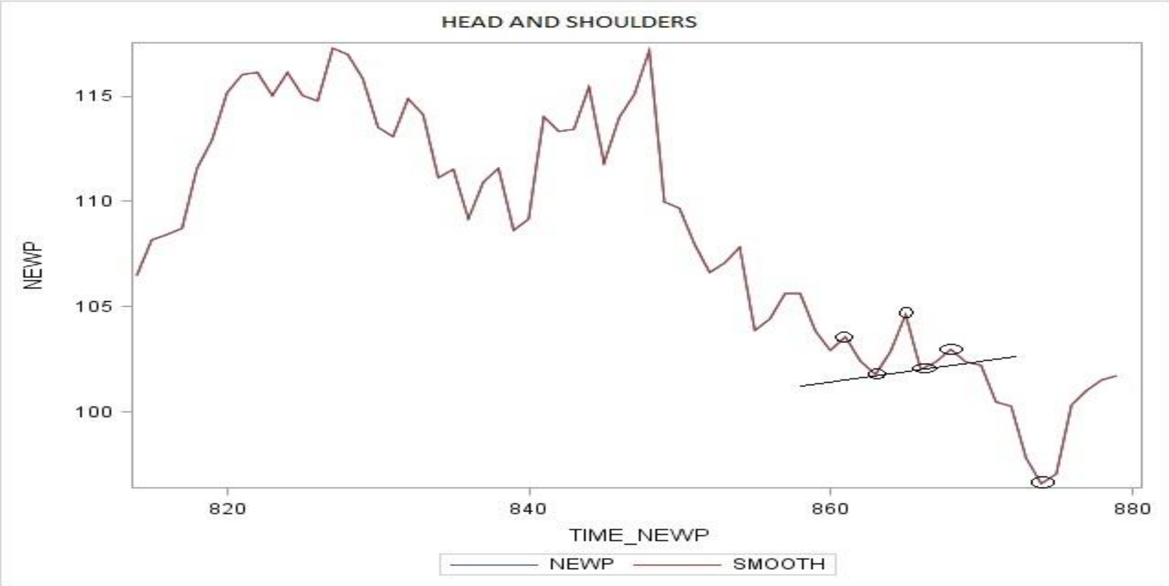

Figure 3: Head-and-shoulders fulfilling on day 874. h=0.25

This particular inverse head-and-shoulder pattern in Figure 4 is subject to more smoothing and the neckline-confirmation –bias appears smaller, amounting to 2 or 3 days.

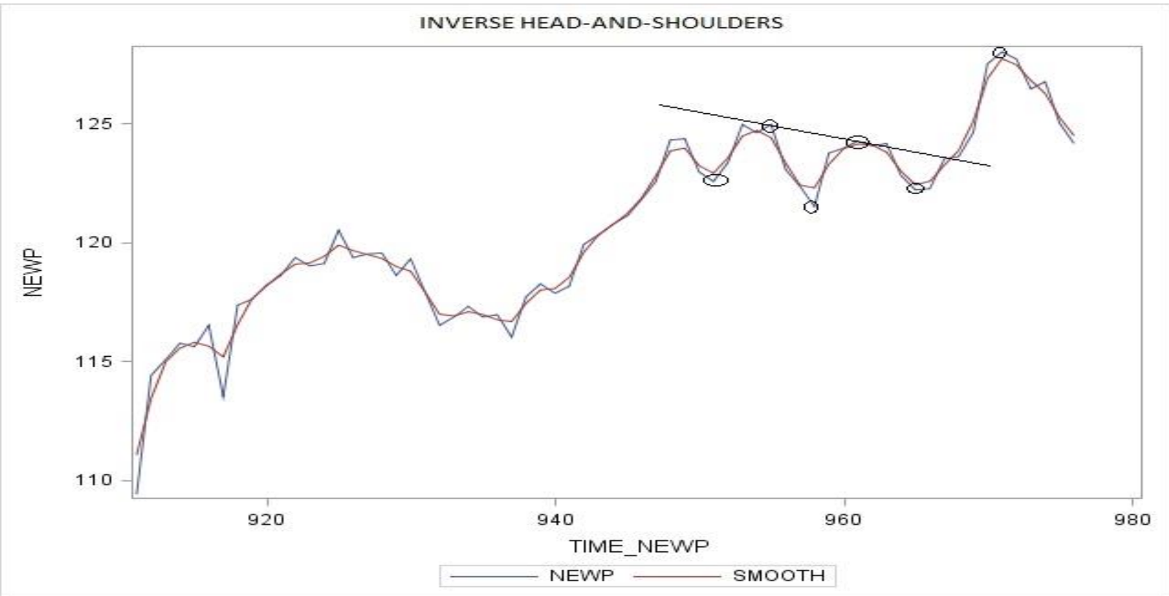

Figure 4: Inverse head-and-shoulders fulfilling on day 971. h=0.78

3.4.2 Broadening tops and bottoms

As defined in Lo et al. (2000) in broadening bottom pattern, the second and the third tops are higher than their preceding tops, and the second bottom is lower than the first bottom:

1) E_1 is a maximum
2) $E_1 < E_3 < E_5$
3) $E_2 > E_4$

Figure 5 illustrates broadening top pattern. The tops and bottoms are spreading wider. Here can be clearly seen the methodological fact that the price at point E is max(NEWP) (min(NEWP)) in region from 1 observation before to one observation after the date the maximum (minimum), E, takes place.

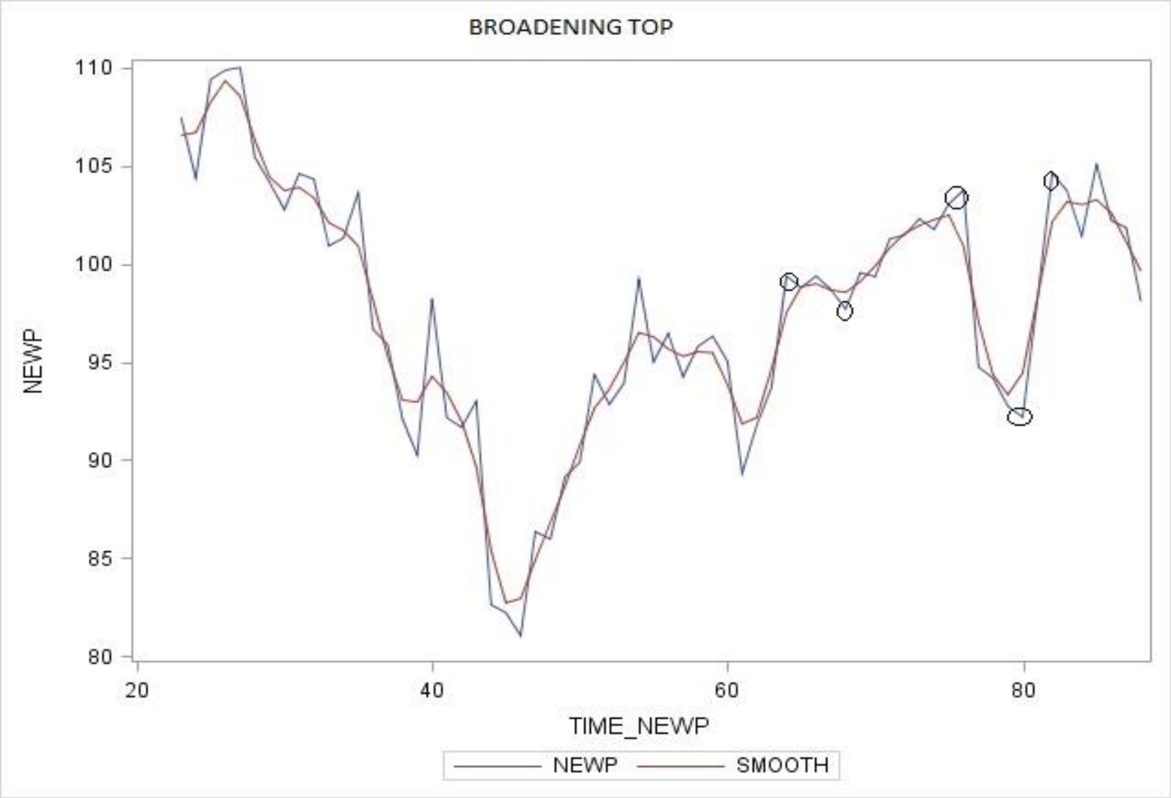

Figure 5: Broadening bottom fulfilling on day 83. h=0.94

Broadening bottom is the same, but with minimum starting the 5 extrema sequence:

1) E_1 is minimum
2) $E_1 > E_3 > E_5$
3) $E_2 < E_4$

Figure 6 illustrates broadening bottom. This is one of the many cases where optimal solution to the cross-validation function falls to region which leads to miss specification and set bottom value of 0.14 is used instead.

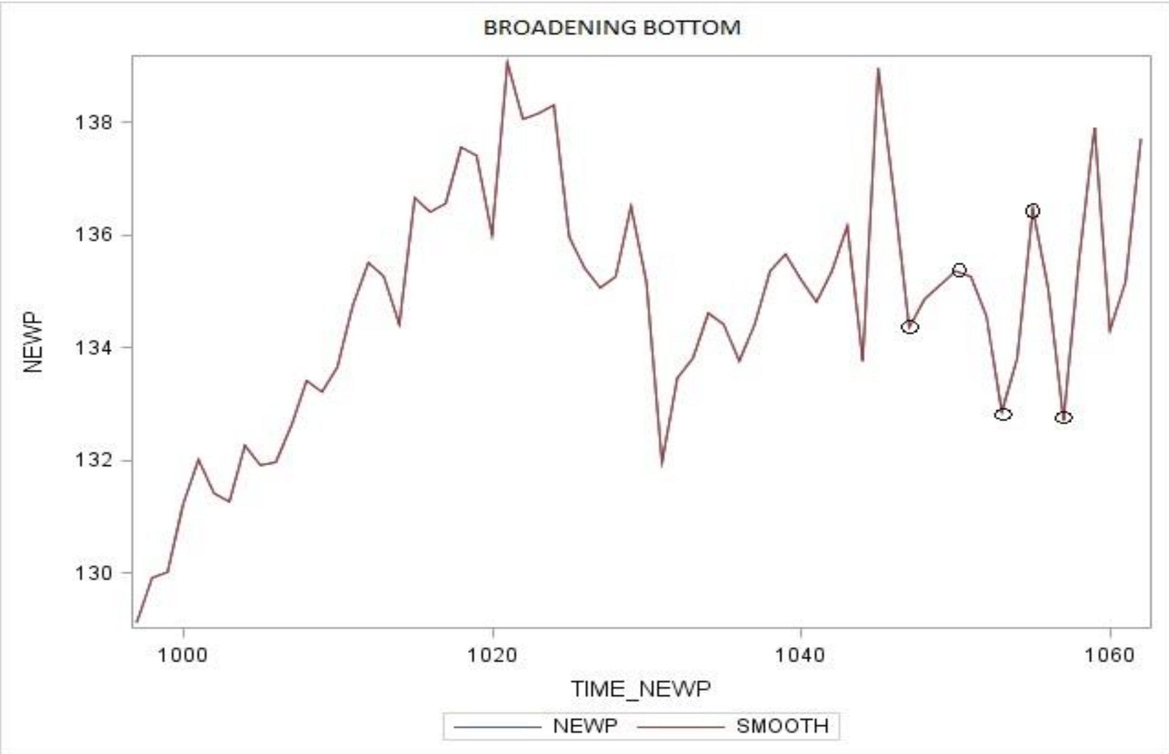

Figure 6: Broadening bottom fulfilling on day 1057. h=0.14

3.4.3 Triangle tops and bottoms

Triangle top and triangle bottom are mirror images of broadening top and bottoms, i.e. whereas the former are cones opening to future, the latter are like a cone with its tip pointing to future. Specifically, triangle top is defined as in Lo et al. (2000):

1) E_1 is maximum
2) $E_1 > E_3 > E_5$
3) $E_2 < E_4$

Figure 7 illustrates representative triangle top with contracting spread of extrema.

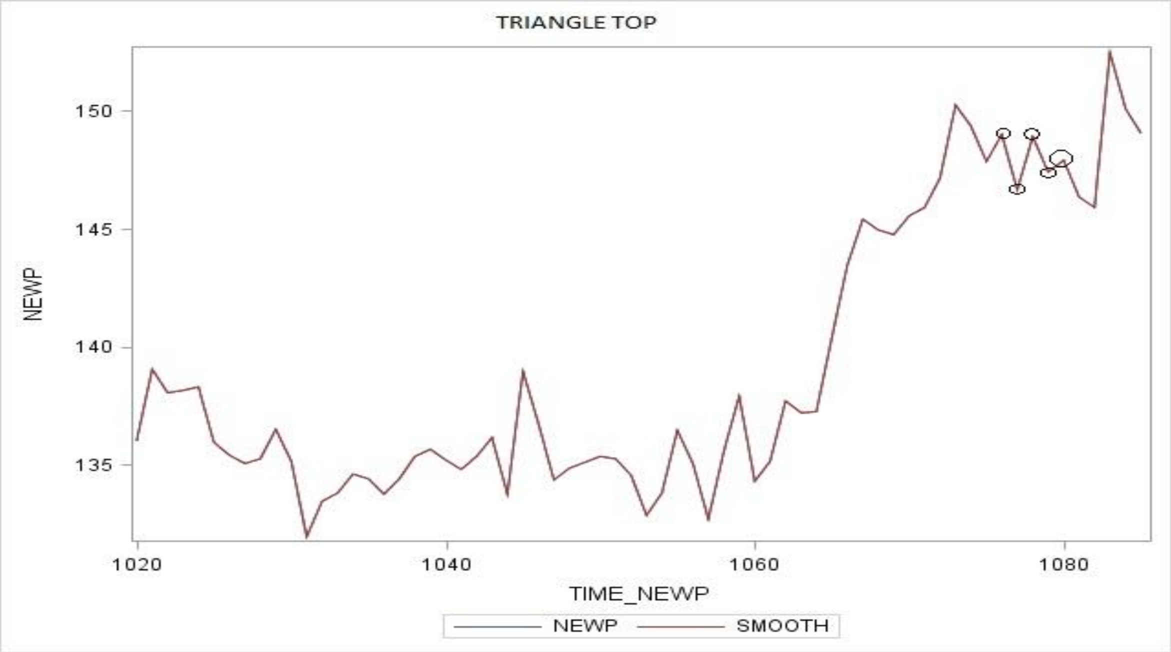

Figure 7: Triangle top fulfilling on date 1080. h=0.14

And triangle bottom:

1) E_1 is a maximum
2) $E_1 < E_3 < E_5$
3) $E_2 > E_4$

Figure 8 shows a wider and distinct triangle bottom pattern which does not satisfy other pattern conditions.

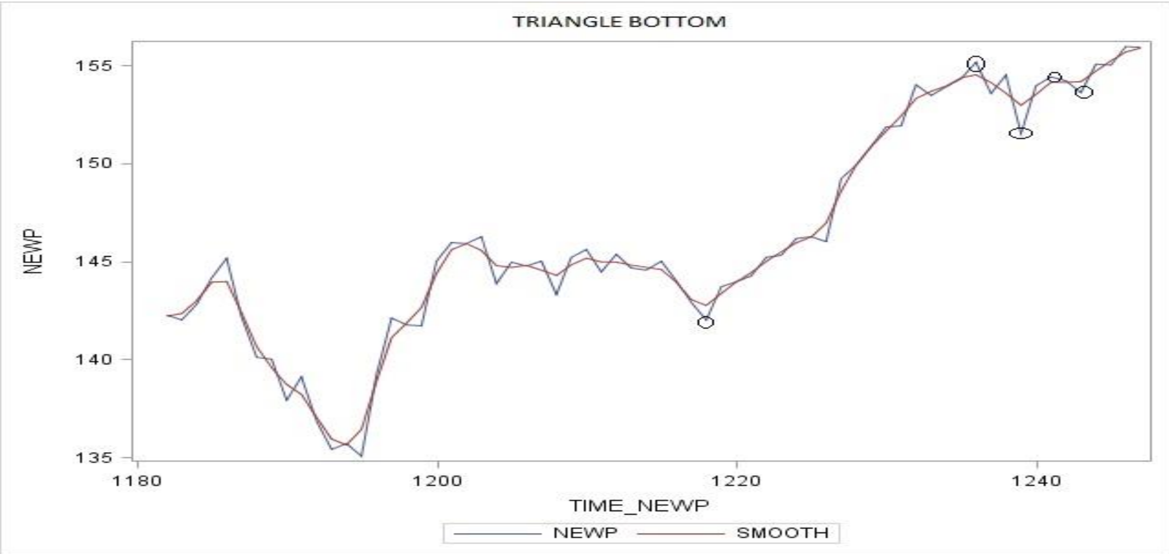

Figure 8: Triangle bottom fulfilling on day 1242. h=0.86

3.4.4 Rectangle tops and bottoms

Rectangle tops (bottoms) are defined as in Lo et al. (2000):

1) E_1 is a maximum (minimum)
2) tops are within 0.75 % of their average
3) bottoms are within 0.75 % of their average
4) lowest top > highest bottom

Figures 9 and 10 illustrates rectangle top and bottom respectively. This particular rectangle bottom pattern is a case in point example of pattern that satisfies also head-and-shoulder condition.

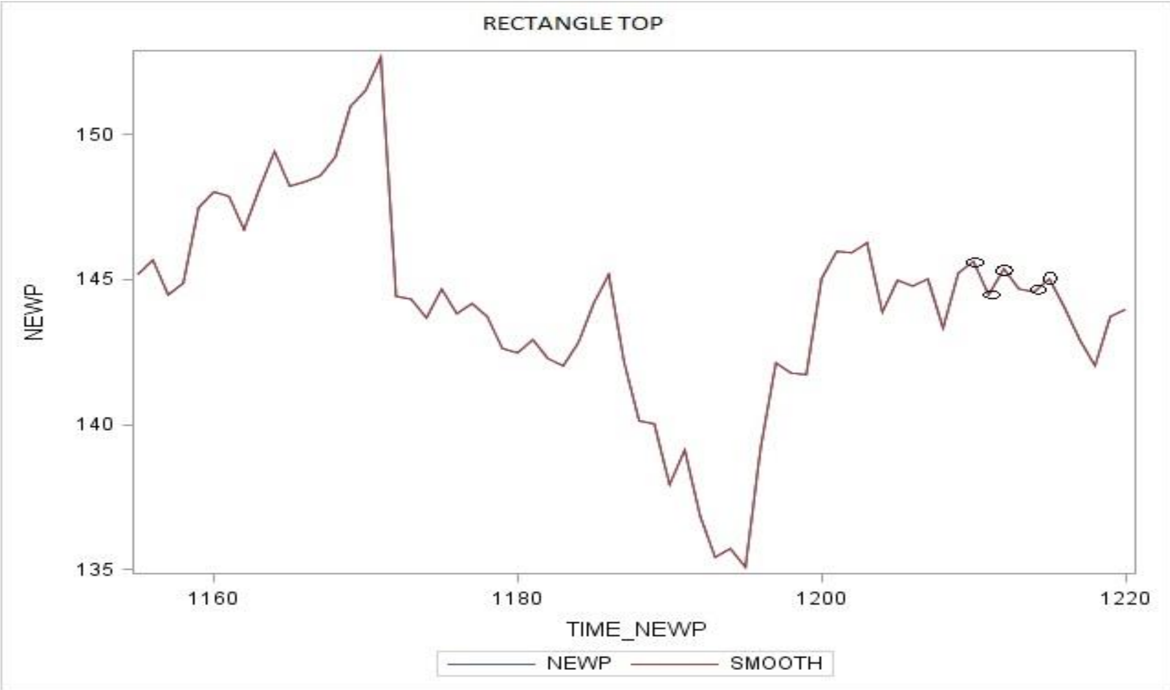

Figure 9: Rectangle top fulfilling on day 1215. h=0.14

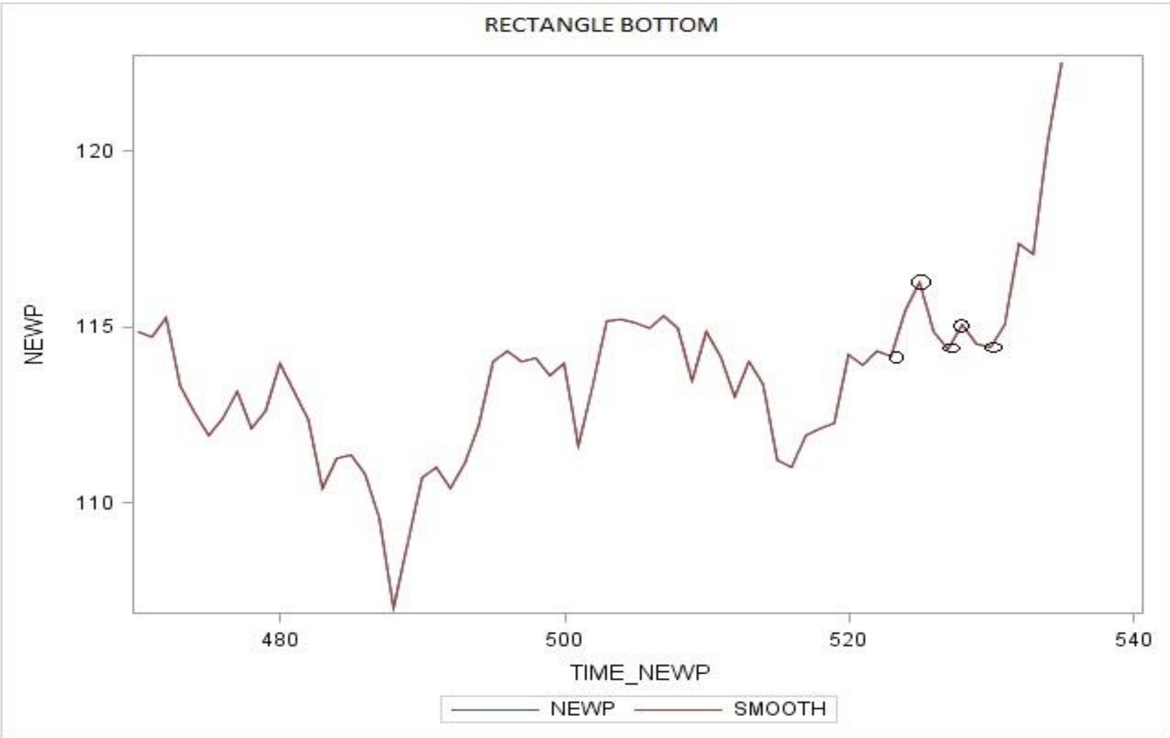

Figure 10: Rectangle bottom fulfilling on day 530. h=0.24

3.4.5 Double tops and bottoms

Double top (bottom) as defined by Lo et al. (2000):

1) E_1 is a maximum (minimum)
2) E_1 and E_a are within 1.5 % of their average
3) t_a-t_1 > 22

there is initial maximum E_1 which is followed by 22 trading days when price stays below level 0.985 times average of E_1 and E_a. After at least 22 trading days there is E_a, which satisfies rule 2). Figures 11 and 12 illustrate these patterns.

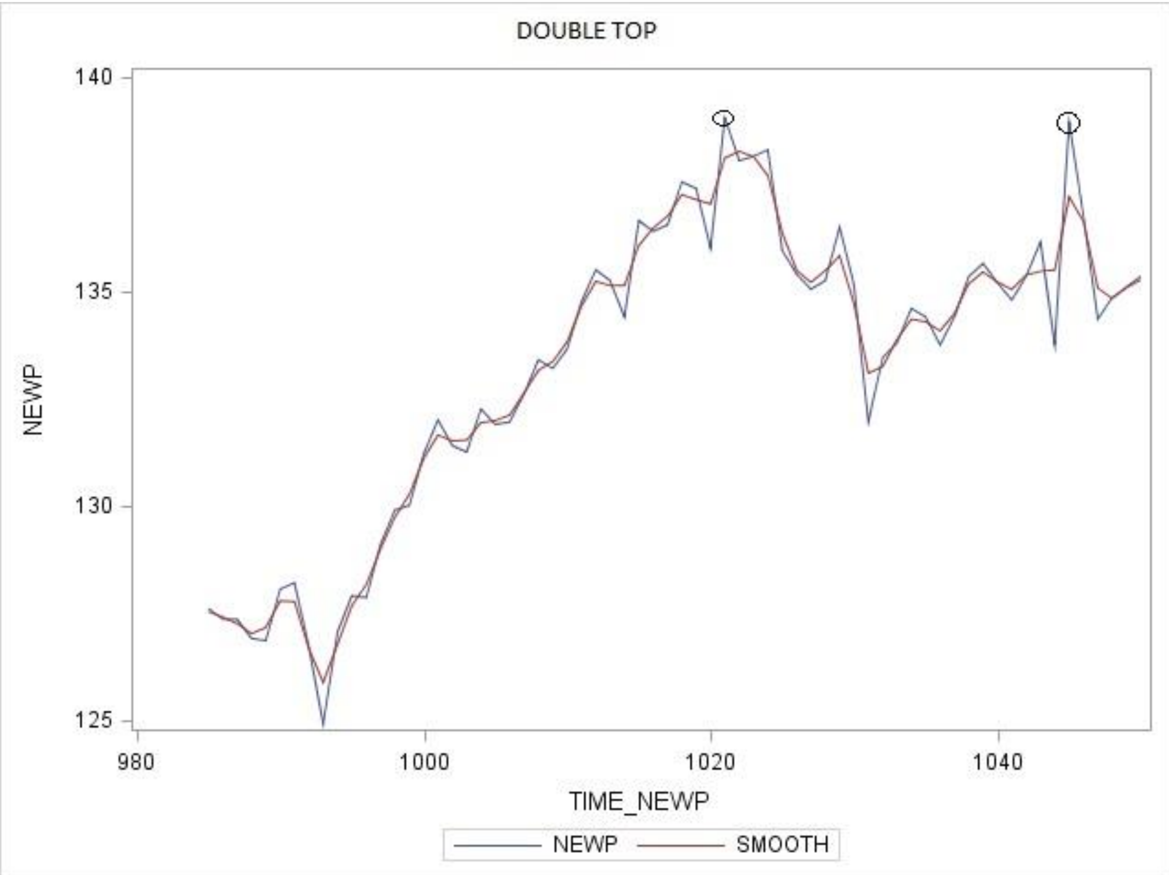

Figure 11: Double top fulfilled on day 1045. h=0.76

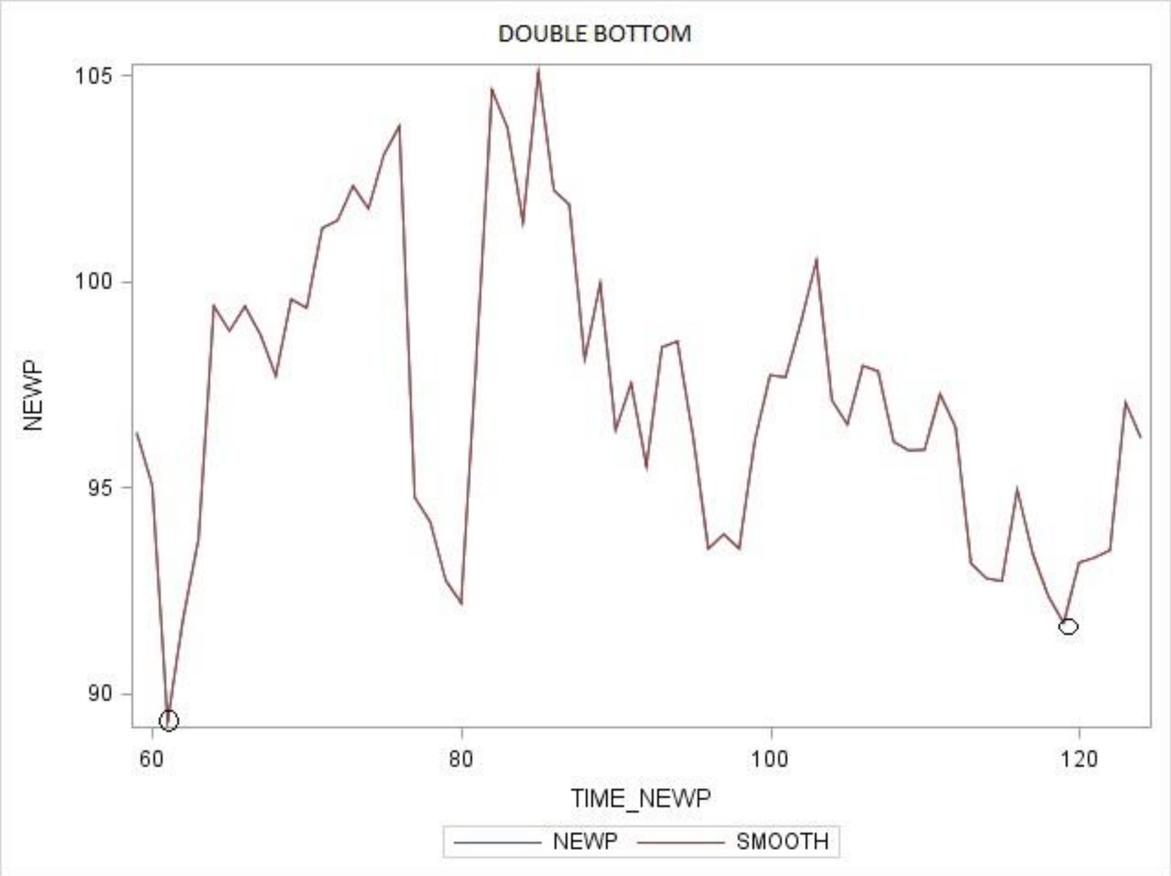

Figure 12: Double bottom fulfilled on day 119. h=0.14

3.4.6 Discussion on pattern definitions

Double tops and bottoms have rather strict constrains as for example the second top can occur only after a very steep rise in price because the extreme before that peak has to be below the 1,5 % band surrounding the average of peaks. This basically rules out patterns with clear but more gradually rising (sinking) peak (bottom).

The other patterns, in contrary, are very loosely defined. Rectangle formations are the “common factor” for the other 3 sets of patterns as they can all exist simultaneously with a rectangle formation. Also it is very common that broadening top follows broadening bottom or vice versa and the same applies for triangle formations.

All this overlapping is ought to hinder the explanation power of individual patterns when all considered together in the same model. They could be easily more distinguished with additional constraints to the shape, but there are three reasons not to do this. First, Savin et al. (2007) found that additional restrictions on head-and-shoulders pattern didn’t increase its explanatory power. Second, Lo et al. (2000) imply that they have validated their patterns on group of professionals. Third, model mining, i.e. fine tuning a model to get optimal results, steeply increases the changes of results being a product of luck and such action should not be taken (Levich and Thomas (1993)).

3.5 The models

The regression model utilized is standard pooled ordinary least squares linear regression with standard errors clustered simultaneously by time and firms, modification discussed for example in Thompson (2011). The natural logarithm of buy-sell-volume-imbalance in Stuttgart acts as a dependent variable. Figure 13 illustrates the distribution of normalized buy-sell-volume-imbalance without logarithmic transformation. The distribution exhibits extreme kurtosis and extremely long tails, range being from -19.59 to 24.70 standard deviations.

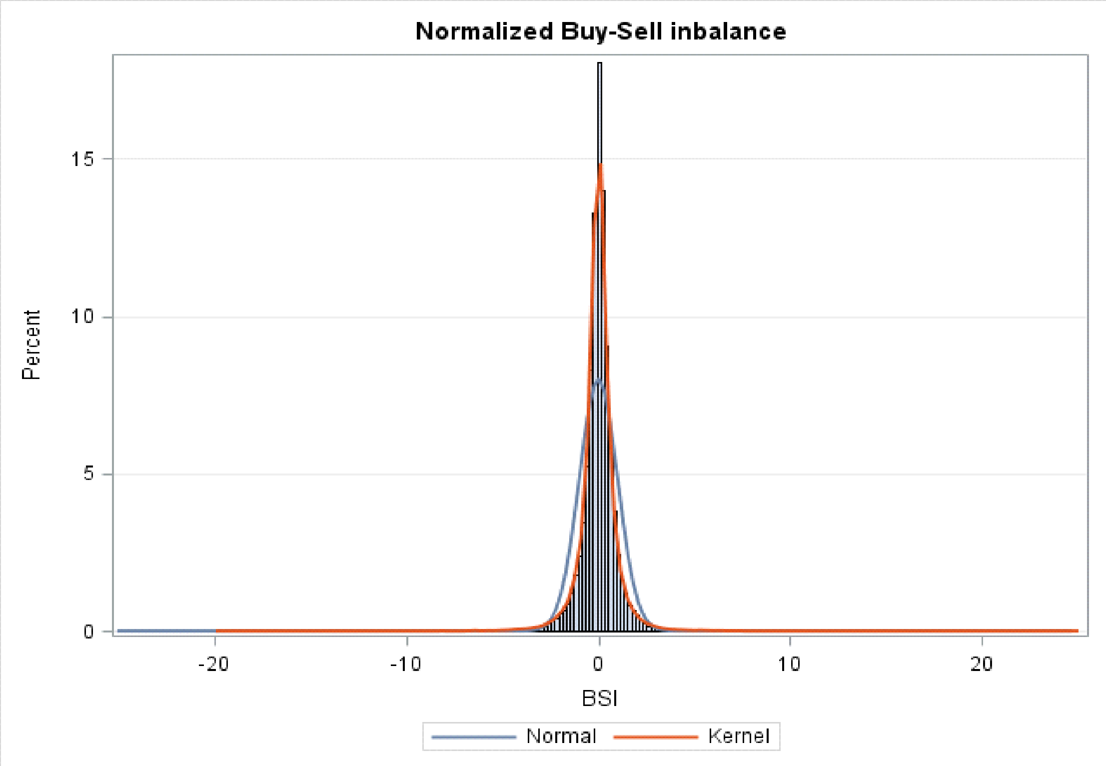

Figure 13: Normalized buy-sell-imbalance of 29 DAX30 stocks in Stuttgart

Figure 14 illustrates result of logarithmic transformation on the dependent variable. The transformation is performed by separating sign from normalized BSI values, by taking natural logarithm, and assigning signs back to the values. Such approach is dangerous because of the fact that logarithm operation has singularity at 0 (the logarithm of a value approaching zero approaches infinity). In this particular case, range remains considerably narrower with than without transformation, spanning from -9.51 to 10.34 with standard deviation of 1.806. Table 2 shows descriptive statistics of the transformed variable. The Kolmogorov-Smirnov statistic is very low but still clearly rejects zero hypothesis of normality. The distribution shows excess kurtosis implying high peak and fat tails. However, the distribution can be considered very close to normally distributed thus allowing for linear regression.

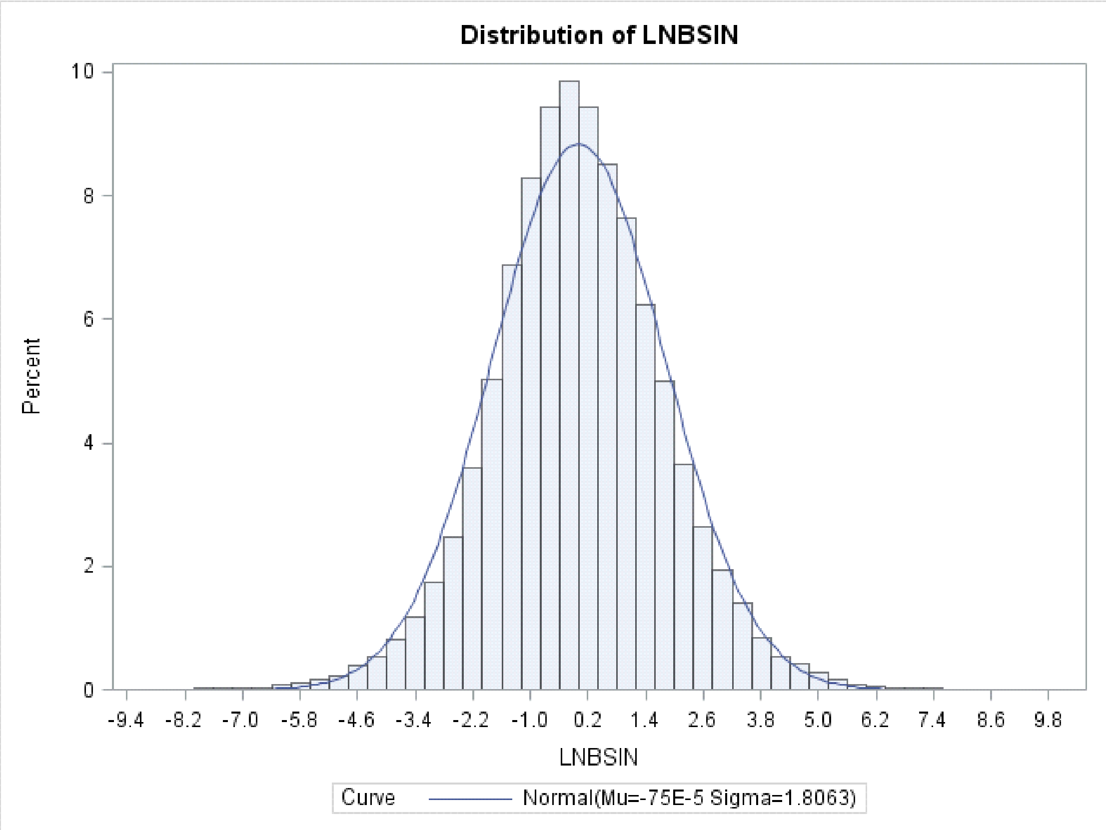

Figure 14: Distribution of ln(normalized buy-sell-imbalance)

N. Obs.	Mean	Std.	Excess kurtosis	Skewness	Kolmogorov-Smirnov	99%	1%
34645	-0.000	1.806	1.097	0.053	0.023**	4.588	-4.519

Table 2: Descriptive statistics of ln(normalized buy-sell-imbalance). Number of observations, mean, standard deviation, excess kurtosis, skewness, normality test(h0=normal), 99th percentile, 1st percentile.

Equation 12 presents the regression model of patterns on logarithm of buy-sell-imbalance, $\ln(TradVol_t)$:

$$\ln(TradVol_t) = \alpha + \sum_{i=1}^{20} \beta_i \ln(TradVol_{t-1}) + \sum_{i=1}^{10} \mathrm{X}_i \ln(High_{t-1}/Low_{t-1}) + \gamma_{1,t}C_1 \dots \gamma_{28,t}C_{28} + div_t + \beta_{1,s}hs_m + \beta_{2,s}ihs_m + \beta_{3,s}tt_m + \beta_{4,s}tb_m + \beta_{5,s}bt_m + \beta_{6,s}bb_m + \beta_{7,s}dt_m + \beta_{8,s}db_m + \beta_{9,s}rt_m + \beta_{10,s}rb_m + \varepsilon_t \tag{12}$$

Positive relationship between volume and volatility is controlled by inclusion of the volatility term *ln(High/Low)* and twenty lags of the dependent variable, *ln(TradVol)* are included to control for autocorrelation (Bender et al. (2012); Rogers and Satchell (1991)). Firm dummies C_1-C_{28} are included to control for firm specific effects. Dividend effects are controlled with dividend dummy, div_t. Underscore *s* of pattern betas runs from t-4 to t. Thus, the effect of pattern fulfilment is studied from day 0 to 4 days after. Subscript *m* marks multiplier of bandwidth parameter and takes values 1, 1.5, 2.0 and 2.5. Four-day range is completely arbitrary, but the longer the range, the more it is exposed to noise from other sources like micro news. On average these news effects are ought to cancel out, but might pose bigger impact on small sample size and be biased because of constant uptrend of overall economy. Including all of the more recent pattern lags than the one under inspection, for example, including lags 3, 2, 1 and 0 instead of modeling effect of lag 4 in isolation, ensures that effects of other patterns during the observation window are controlled for. Using “full” pattern lag model poses only negligible impact on parameter estimates and statistical significances when compared to testing pattern lag levels in isolation. Similar in design, the regression equation for dual-moving-average-crossover (DMAC) strategies is:

$$\ln(TradVol_t) = \alpha + \sum_{i=1}^{20}\beta_i \ln(TradVol_{t-1}) + \sum_{i=1}^{10}\mathrm{X}_i \ln(High_{t-1}/Low_{t-1}) + \gamma_{1,t}C_1 \ldots \gamma_{28,t}C_{28} + div_t + \beta_{1,s}du1_{50} + \ldots + \beta_{32,s}ud20_{200} + \varepsilon_t \qquad (13)$$

,where *du1_50* starts from down to up breaking strategies, i.e. those where short moving average crosses long moving average from below to above. There are 32 DMAC rules altogether. All 16 combinations of 4 short MA’s (1, 5, 10, 20) and long MA’s (50, 100, 150, 200) in both directions, from up to down and from down to up. Control variables are the same as in equation 12. Different lag levels are run separately because of technical limitations arising from incorporation of so many explanatory variables. Thereby effects of more recent explanatory events are not controlled for when examining lagged explanatory variables.

4 Empirical results

This section represents results from regression analysis introduced in section 3. First half of the section (4.1 and 4.2) deals with results for patterns, equation 12, and the second half (4.3) shows result for DMAC rules.

4.1 Patterns detected

Amount of patterns detected by recognition algorithms is listed in Table 3 by bandwidth multiplier. Rectangle formations are by far the most common patterns which is attributable to their rather loose definition. The distance allowed for a top (bottom) to diverge from average of tops (bottoms) is relatively large considering the variance of data. Most striking feat here is the small amount of head-and-shoulders (HS) and inverse head-and-shoulders (IHS) patterns and their relative proportion to each other. HS pattern is over two times as common as the inverse pattern. Double top and double bottom patterns are the only ones to increase in numbers coupled with increase in smoothing. With more smoothing, the last extreme in the 22-observation “valley” (“table”) section is more likely to satisfy the distance condition of double top (double bottom) definition.

Dawson and Sweeney (2003) use UK sample of 225 companies during 15 years, so their sample is roughly 23 times larger. They find about 1500 HS and IHS patterns, roughly consistent amount in relation to the 50 IHS patterns here with unity multiplier or 36 HS patterns with multiplier 2.5. Strikingly, they find only 370 and 274 broadening tops and bottoms respectively, roughly 1/20 of the patterns found here when considering sample size difference. With rectangle formations they find about 1/10 and with double formations 1/3 of the relative amount in this thesis. Overall conclusion is that the recognized amounts are completely inconsistent between this thesis and their study. Their findings on the other hand are consistent with those of Lo et al. (2000). This difference is easily explained by dramatic difference in multiplier value (both studies use multiplier of 0.3) and inclusion of neckline condition to head and shoulder pattern definitions.

Savin et al. (2007) have sample of S&P500 and Russel 2000 stocks over 10 years, 172 times bigger sample than utilized in this thesis. They find 14244, 9160, 5972 and 3550 head-and-shoulders patterns with multipliers 1, 1.5, 2.0 and 2.5 respectively. Proportional number of HS patterns found in this thesis are 24 to 157 % bigger. These amounts are on the same scale, but cannot really be considered equal. Small sample size, different economic era or different markets are a likely explanation for the difference.

Table 3: Amount of patterns recognized by algorithms by different bandwidth multiplier values. Head-and-shoulders (HS), inverse head-and-shoulders (IHS), broadening top (BT), broadening bottom (BB), triangle top (TT), triangle bottom (TB), rectangle top (RT), rectangle bottom (RB), double top (DT), double bottom (DB).

Pattern/ multiplier	**HS**	**IHS**	**BT**	**BB**	**TT**	**TB**	**RT**	**RB**	**DT**	**DB**
1.0	102	50	331	278	288	277	547	519	138	137
1.5	90	43	302	235	238	243	407	409	150	136
2.0	75	29	245	188	192	216	298	278	156	136
2.5	54	24	203	175	173	185	198	214	153	137

Table 4 presents amounts of DMAC events. The definitions are straight forward and thus no comparison to other studies is relevant. Events of both sides are very evenly distributed. Sample sizes are generally sufficient, over 200 observations, to come up with statistically strong results.

Table 4: Amounts of DMAC events. “Up” refers to the case when short moving average breaks long moving average from below to up and “down” refers to inverse case.

DMAC Rule, up	Count	DMAC Rule, down	Count
1-50	1241	**1-50**	1260
1-100	870	**1-100**	875
1-150	600	**1-150**	604
1-200	399	**1-200**	398
5-50	635	**5-50**	655
5-100	446	**5-100**	449
5-150	280	**5-150**	279
5-200	207	**5-200**	206
10-50	484	**10-50**	503
10-100	329	**10-100**	333
10-150	205	**10-150**	205
10-200	152	**10-200**	150
20-50	405	**20-50**	426
20-100	249	**20-100**	252
20-150	159	**20-150**	160
20-200	117	**20-200**	115

4.2 Regression results of ln(buy-sell-imbalance) conditional on patterns

Tables 5 and 6 present parameter estimates for patterns in equation 12. Interpretation of the results goes in following way: If a pattern is present, change size of beta takes place in logarithmic value of buy-sell-imbalance. In terms of non-logarithmic value, it depends what is the “base” level of the logarithmic value into which the change is added. For example e^1.5/e^1.0=~1.65 whereas e^3/e^2=~2.72. Thus the bigger the starting point, the bigger the impact. What, however can be intuitively interpreted, is the direction of change.

On third day after occurrence of HS pattern, buy-sell-imbalance declines, meaning that sell-side volume increases in relation to buy-side volume. HS pattern is ought to signal down-turn so the action is trend-following by that logic. IHS pattern does not show significant effect on any bandwidth values or lags.

Broadening top pattern shows effects in two direction. On fulfilment day, buy-side gains weight but on 3rd day after, reversal effect occurs. Broadening bottom does not show statistically significant impact.

Double top pattern is coupled with increase in relative share of buy-side volume on the 1st day after such a pattern has occurred. The findings are statistically highly significant with multiplier value 1.0, when least smoothing is in place, but in place and sign-wise consistent with other bandwidth values also. Similarly in logic, double bottom pattern increases relative share of sell-side volume on the fulfilment day and on 4th day after with bandwidth parameter 1.0. Double top signals presence of a roof for price, resisting penetration, and thereby down-turn can be expected. The effects found are thus contrarian.

Triangle tops are coupled with falling buy-sell-imbalance on 1st and 3rd day after the occurrence of pattern, mostly consistent with different bandwidth parameters. The effect is extremely significant with maximum smoothing. Fulfilment of triangle bottom is followed with increase in imbalance on 3rd day after.

Unlike with other patterns, rectangle top and bottom seem to cause effect in same direction. On occurrence day of either pattern, buy-sell-imbalance increases. For rectangle top the effect is consistent over different grades of smoothing, but found only with least smoothing for rectangle bottom pattern.

Table 5: Parameter estimates of patterns on ln(buy-sell-imbalance) with multiplier values h=1.0 and 1.5. “Lag0” indicates the day on which the pattern in question is fulfilled and “Lag4” measures the effect on 4th day after the pattern occurred. Patterns are head and shoulders (hs), inverse head and shoulders (ihs), triangle top (tt), triangle bottom (tb), double top (dt), double bottom (db), broadening top (bt), broadening bottom (bb), rectangle top (rt), rectangle bottom (rb). Significant parameter estimates are bolded. One two and three asterisks mean 95 %, 99 % and 99.9 % statistical significance respectively.

Pattern h=1.0	**Lag0**	**Lag1**	**Lag2**	**Lag3**	**Lag4**
HS	-0.03975	-0.32461	0.01162	**-0.50709***	-0.07481
IHS	-0.04947	-0.27936	-0.16292	-0.09506	0.02038
BT	**0.19101***	0.02824	0.00986	-0.21410	-0.03243
BB	0.03680	0.01760	-0.16136	-0.11720	0.05311
DT	0.05302	**0.44131****	0.08927	0.17255	-0.02725
DB	**-0.24127***	-0.19482	0.12199	-0.21566	**-0.31605***
TT	0.05636	**-0.27877***	-0.13485	**-0.30886***	-0.00414
TB	0.19481	0.17334	0.09603	**0.24255***	0.16916
RT	**0.17981***	0.10565	0.01624	0.00399	-0.06314
RB	**0.19101***	-0.03337	-0.00651	-0.08927	0.06945
Pattern h=1.5	**Lag0**	**Lag1**	**Lag2**	**Lag3**	**Lag4**
HS	-0.19968	-0.01469	-0.02144	0.01190	0.23089
IHS	0.22160	-0.38207	0.04070	-0.55188	-0.07007
BT	0.04929	0.23449	-0.01778	**-0.23785***	0.10903
BB	-0.17632	-0.19072	-0.12611	-0.13980	0.01708
DT	0.19748	**0.36853***	-0.14291	0.13329	-0.11535
DB	**-0.23427***	-0.26734	-0.06073	-0.27307	-0.11076
TT	0.02012	**-0.29171***	-0.14112	**-0.43113****	-0.16630
TB	0.09840	-0.06638	0.11704	0.09512	-0.12904
RT	**0.20176***	0.11391	0.00060	0.20016	-0.04776
RB	-0.05535	0.05260	0.08866	-0.03051	0.06704

Table 6: Parameter estimates of patterns on ln(buy-sell-imbalance) with multiplier values h=2.0 and 2.5. “Lag0” indicates the day on which the pattern in question is fulfilled and “Lag4” measures the effect on 4th day after the pattern occurred. Patterns are head and shoulders (hs), inverse head and shoulders (ihs), triangle top (tt), triangle bottom (tb), double top (dt), double bottom (db), broadening top (bt), broadening bottom (bb), rectangle top (rt), rectangle bottom (rb). Significant parameter estimates are bolded. One two and three asterisks mean 95 %, 99 % and 99.9 % statistical significance respectively.

Pattern h=2.0	**Lag0**	**Lag1**	**Lag2**	**Lag3**	**Lag4**
HS	-0.19968	-0.01469	-0.02144	0.01190	0.23089
IHS	0.22160	-0.38207	0.04070	-0.55188	-0.07004
BT	0.04929	0.23449	-0.01778	**-0.23785***	0.10903
BB	-0.17632	-0.19072	-0.12611	-0.13980	0.01708
DT	0.19748	**0.36853***	-0.14291	0.13329	-0.11535
DB	**-0.23427***	-0.26734	-0.06073	-0.27307	-0.11076
TT	0.02012	**-0.29171***	-0.14112	**-0.43113****	-0.16630
TB	0.09840	-0.06638	0.11704	0.09512	-0.12904
RT	**0.20176***	0.11391	0.00060	0.20016	-0.04776
RB	-0.05535	0.05260	0.08866	-0.03051	0.06704
Pattern h=2.5	**Lag0**	**Lag1**	**Lag2**	**Lag3**	**Lag4**
HS	-0.26623	-0.34604	-0.02901	0.12422	-0.18748
IHS	-0.15384	0.02988	0.13549	0.05588	0.07249
BT	-0.02606	0.18526	0.09808	-0.09526	**0.26658***
BB	-0.02167	-0.23340	-0.10981	0.05916	0.00820
DT	0.15084	**0.40463***	-0.23291	0.13355	-0.24677
DB	**-0.25616***	-0.06567	-0.06359	-0.18908	-0.22413
TT	0.01845	**-0.48643*****	0.00826	**-0.31863***	-0.10007
TB	0.10343	-0.05443	0.01858	0.19909	0.07187
RT	**0.26159***	0.17498	0.09285	0.21239	0.05513
RB	-0.02941	0.04994	-0.07049	-0.04485	0.16412

4.3 Regression results of excess volume conditional on DMAC rules

Tables 7 and 8 presents results for the DMAC rules in equation 13. Fast MA crossing slow MA from below to above (rules starting with “DU” in the table) signals that positive trend is in action. The shorter the short MA is, the faster it is in recognizing the trend change but also more volatile to “too local” variance, i.e. noise. Rational trend following investor should buy in such a situation and sell when the opposite happens: short MA crosses long MA from above to below.

All levels of lags are considered in isolation due to lack of memory cache for analyzing different levels of lags separately. All in all, there are 32 variables on each level and observation range is 5 days. When only the statistically significant rules from each level are hand-picked into a single regression, t-statistics and parameter values generally increase by 10 % which is quite a minor change.

Seven rules of each side show statistically significant effect on natural logarithm of buy-sell-imbalance. Only two of these rules are common for both sides, i.e. mirrors of each other. These rules are 1-50 and 1-100. If an investor was systematically and consciously following some rule, it would be logical to expect that the rule was used in both directions. On the other hand, DMAC strategies make their best use as stop-loss –tools, conclusion supported by findings of Pätäri and Leivo (2014). In such a case, a from-up-to-down breaking DMAC rule could be applied into a toolbox in which buy-signals are formed by some other tool. All the statistically significant rules except for DU1_100 on day 4 have sign that indicates trend following response. UD20_200 rule has strongest and most imminent impact, contracting buy-sell-imbalance on occurrence day and on the day after. UD1_100 on 1st day after, UD1_200 on occurrence day and DU5_50 on 3rd day after have statistically strongly significant effect, on 99 % confidence level. Eleven of sixteen effects appear on days 0 to 1, so the rules have short living impact at best.

Table 7: Regression results of downward breaking DMAC strategies. Significant parameter estimates are bolded. One two and three asterisks mean 95 %, 99 % and 99.9 % statistical significance respectively.

Variable	**Lag 0**	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**
UD1_50	0.0421	**-0.1345***	0.0050	-0.0792	-0.0153
UD1_100	-0.0261	**-0.2000****	-0.0927	-0.1215	-0.0491
UD1_150	-0.1067	-0.0749	-0.0814	0.0229	-0.0371
UD1_200	**-0.2809****	-0.0132	**-0.1982***	-0.1478	-0.1152
UD5_50	-0.1123	-0.0457	-0.0539	0.0287	-0.0867
UD5_100	**-0.1800***	-0.0812	-0.1095	-0.0531	-0.0325
UD5_150	-0.0178	-0.1112	0.0186	**-0.2176***	-0.0793
UD5_200	-0.0423	-0.1924	-0.1993	0.0312	0.0668
UD10_50	-0.0603	0.0327	0.0417	0.0094	-0.1589
UD10_100	-0.0898	-0.1028	0.0044	-0.1209	**-0.2086***
UD10_150	-0.0276	-0.1878	-0.0233	-0.0267	0.0798
UD10_200	-0.1270	-0.1052	0.0180	-0.1277	0.0970
UD20_50	-0.1076	0.1469	-0.0550	-0.1243	-0.0377
UD20_100	0.0371	0.0164	-0.1143	-0.1010	-0.0183
UD20_150	0.0274	-0.1685	-0.0475	-0.2838	-0.1351
UD20_200	**-0.3445***	**-0.3901***	0.1212	-0.1277	0.0474

Table 8: Regression results of downward breaking DMAC strategies. Significant parameter estimates are bolded. One two and three asterisks mean 95 %, 99 % and 99.9 % statistical significance respectively.

Variable	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
DU1_50	**0.1176***	0.0364	0.0913	0.0928	-0.0396
DU1_100	-0.0378	0.0090	-0.0196	-0.0981	**-0.1479***
DU1_150	-0.0095	0.0725	0.0766	-0.0055	0.0949
DU1_200	0.0981	-0.1858	-0.0768	-0.1527	-0.1195
DU5_50	0.0234	**0.1840***	0.0251	**0.2131****	0.0415
DU5_100	0.0813	-0.0783	0.0424	0.0111	0.0798
DU5_150	0.0884	0.0629	-0.1490	0.2369	0.1506
DU5_200	-0.0790	-0.0501	0.0298	0.0712	0.2018
DU10_50	0.0688	**0.2021***	0.1611	-0.0216	-0.0300
DU10_100	-0.0682	0.0991	-0.0219	-0.0413	0.0204
DU10_150	0.1265	**0.3160***	-0.1350	0.0235	0.0428
DU10_200	0.1519	0.2100	-0.0656	0.1439	-0.1413
DU20_50	-0.0464	0.1023	0.0798	-0.1109	-0.0282
DU20_100	**0.2687***	-0.0357	0.0466	0.0297	-0.0180
DU20_150	0.2074	0.1141	0.0406	0.1812	-0.2141
DU20_200	0.0469	-0.0980	0.2586	0.1132	-0.0148

5 Discussion

The evidence shows only slight support for impact of selected technical analysis price-patterns and DMAC rules on buy-sell-imbalance. All the patterns (except for IHS and BB) and 12 of 32 DMAC rules are followed by impact on buy-sell-imbalance. Not a single effect is consistent over the whole observation period of 5 days and only one rule, UD20_200 has impact over 2 consecutive days, day 0 and day 1.

Eleven of significant twelve DMAC rules have right sign if trend following response is expected. HS pattern is also coupled with trend following action on the 3rd day after neckline condition is satisfied and broadening and triangle formations support trend following behavior: broadening and triangle formations are mirror patterns of each other and logically have opposite impacts. Following a broadening formation, buy-sell-imbalance increases, supporting the idea that bigger price volatility is associated with increase in returns. Only clear piece of support for contrarian behavior arises from double –patterns. Double top is followed by increase in buy-sell-imbalance whereas the opposite is true for double bottom –pattern. Basing on the weakness of definitive evidence, research question one about the use of technical analysis by retail investors remains unanswered. The weak evidence supports rational trend following behavior as an answer for second question.

Correct signs of DMAC rules lead to expect that some DMAC rules can be found to persistently predict direction of buy-sell-imbalance of retail investors. The same applies for triangle and broadening formations. The bigger the proportion of individual ownership in stock, the stronger the effects are ought to be. Barber et al. (2005) and Hvidkjaer (2005) show that stocks with high small-trade buy volume underperforms those with high sell volume. This venue should be studied more.

Size effect could be large driver of technical analysis trading profitability because Kaniel et al. (2008) note that significant relation between past and future stock returns is driven in entirety by smaller stocks. Bigger sample would be needed to test these effects on trading volumes. However, this sample consist only from the biggest firms, and is thus a special case in itself. On the basis of Kaniel et al.'s findings, it would be expected that technical trading strategies on this sample would not be profitable.

Dawson and Steeley (2003) find some evidence of return conditioning and sign predictability, but argue that economic profits are unlikely to materialize. The patterns with effect on return distribution were HS, IHS, RBOT and RTOP. Size was significantly related to increase in number of patterns observed in study of Dawson and Steeley (2003), but less significant with U.S. data studied by Lo et al. (2000). Their methodological design however is significantly different from the one used in this thesis. Using similar parameters as utilized in this thesis, Savin et al. (2008) find strong evidence for ability of head-and-shoulders pattern to predict future returns. They also conclude that some, but not all, of the predictive power of the pattern arises from its ability to signal short position in negative momentum stocks. The profits are not substantial enough to support standalone trading strategy based on the pattern but instead improve performance when used with passive indexing strategy. Findings of this thesis adds to the body of research utilizing this pattern recognition technique showing that at least with these parameters, no robust statistical relations are to be found.

Further research possibilities are numerous. Testing of this methodology with broader sample and on different markets as well as with different instruments, for example futures contracts, would be interesting because currently there are no studies with this approach. Different parameters could be used for patterns. One clear starting point for further research in drivers of retail investor trading would be to conduct a survey or analyze browsing/clickstream –data.

The methodology itself could be studied in many ways. The selection of different multipliers is not justified by any arguments, evident is just that there is some implicit reason to do so. In this thesis is shown that great majority of bandwidth parameter values are in region which causes practically no smoothing at all. Different parameters on patterns alter at least number of detected patterns vastly. With any bigger sample, comprehensive study with broader set of parameters would demand exponentially more computing time from typical PC, but should be conducted if a computing pool is available. Validating the findings with practitioners or a technical analysis event database would yield insight on performance of the pattern recognition algorithm.

The buy-sell-imbalance variable isn't exactly normal even after transformation and thus linear regression methodologies are questionable. Nonparametric regression methods could be utilized, but sample size has to be far more representative for meaningful inferences because distribution expectations are flexibly formed based on the data. Distributions of buy and sell side as well as their aggregate were found to be far from normal. One optional research design not yet explored would be to calculate change in buy-sell-imbalance and study its sign on condition of pattern or DMAC indicator.

6 Conclusions

Despite of vast body of academic research on technical analysis and investor behavior, very little is still known about the actual drivers of retail investors' trading decisions. A lot of information is available to use as guidance for investment decisions and casual empiricism suggest, that investors do not believe in random walk and thus blind-eyed random selection of assets, but instead into some rules.

In this thesis, smoothing algorithm and pattern detection methodologies pioneered by Lo et al. (2000) along with a set of dual-moving-average-crossover (DMAC) rules were utilized in attempt to answer question "Do retail traders in Stuttgart stock exchange rely on technical analysis as a basis of their trading decisions?" Change of natural logarithm of buy-sell-imbalance was studied over 5 day observation period conditional on presence of a TA trading rule. The data set consisted of daily observations of 29 DAX30 companies over the time period 2009 – 2013.

The 10 technical analysis price patterns recognized by algorithm and set of 16 common DMAC rules failed to provide clear evidence to support the zero hypothesis stating that retail investors do use TA methods either consciously or subconsciously. Slight evidence was found in support of rational trend-following action following signals given by head-and-shoulders –pattern, triangle and broadening patterns, and selection of DMAC rules.

This thesis concludes that pattern recognition methodology of Lo et al. (2000) cannot be used to predict retail investor buy-sell-imbalance in DAX30 context with daily data. Other measures should be taken in order to increase understanding about drivers of retail investors' trading decision making.

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Appendices

Appendix 1: DAX 30 firms for which the data was collected are presented with their respective business sectors. “Included” means whether the company was held for analysis or omitted from the sample.

Name	Included	Sector
Adidas	1	Clothing, Sports
Allianz	1	Insurance & asset management
BASF	1	Chemical
Bayer	1	Health care, materials
BMW	1	Car manufacturing
Beiersdorf	1	Health care
Continental	1	Tyre manufacturing
Daimler	1	Car manufacturing
Deutsche Boerse	1	Stock exchange
Deutsche Bank	1	Bank
Deutsche Post	1	Logistics
Deutsche Telekom	1	Telecommunications
E.ON	1	Energy
Fresenius Medica	1	Health care acessories
Fresenius SE	1	Health care acessories
Heidelberg Cement	1	Cement
Henkel	1	Chemical
Infineon	1	Electronical components
K+S	1	Mineral mining and processing
Lanxess	1	Chemical, materials
Linde	1	Gases & engineering conglomerate
Lufthansa	1	Air transport
Merck	1	Health care
Munchener ruck	1	Insurance
RWE	1	Energy and disposal
SAP	1	Software
Siemens	1	Engineering & Electronics
Thyssen Krupp	1	Steel
Volkswagen	1	Car manufacturing