Intraday trading in the Helsinki Stock Exchange using moving average trading rules
Master's Thesis 2018

Author: Juuso Tyrväinen
Supervisor: Eero Pätäri
Second examiner: Timo Leivo
TIIVISTELMÄ

Tekijä: Juuso Tyrväinen
Tutkielman nimi: Liukuvien keskiarvojen käyttö päiväkaupassa Helsingin pörssissä
Pro Gradu -tutkielma: Lappeenranta University of Technology, 69 sivua, 21 kuvaajaa, 11 taulukkoa, 3 kuvaa
Vuosi: 2018
Tiedekunta: LUT School of Business and Management
Maisteriohjelma: Strategic Finance and Business Analytics
Tarkastajat: Eero Pätäri ja Timo Leivo
Hakusanat: Liukuva keskiarvo, päiväkauppa, tekninen analyysi, ylituotto, kaupankäyntikulut

This thesis investigates if moving average strategies can be implemented in day trading to produce excess returns compared to buy and hold strategy. Strategies were tested using one minute interval data of OMXH 25 index for period from 2006 to 2016. In total 1002 moving average strategies were tested. Moving average strategies used in this thesis were formed by using two different moving averages and crossing of these two moving averages was interpreted as buy or sell signal. Strategies were examined for two subsets and whole period excluding and including transaction costs. Evidence is found that moving average strategies can produce significant excess returns compared to buy and hold especially when transaction costs are not taken in consideration. When transaction costs are taken in to the consideration moving average strategies can only produce excess returns in falling market while losing to buy and hold in rising market. Total return for whole period even when transaction costs are included is found to be higher than simple buy and hold.
Acknowledgements

I would like to express my gratitude for everyone who helped me in writing of this thesis, it took a while to get here and it would have been impossible to get here without all the help and encouragement I received. Especially I would like to thank Eero Pätäri for providing support and encouragement to pursue this topic.

I would like to thank Thomson Reuters and Justyna who helped with acquisition of crucial data for the thesis, without you this thesis would have been just an idea with no way to proceed to this point.

Thank you all colleagues at work for encouragement and making it possible to finish this thesis while working full time. Thank you Niko for helping with technical side and pushing me on.

Special thanks to friends and family who kept encouraging and supporting me during this quite lengthy process, finally made it!

Juuso Tyrväinen

Espoo 28.11.2018
# Table of Contents

1. **Introduction** .................................................................................................................. 7 
   1.1 **Background** ............................................................................................................... 9 
   1.2 **Research problem, objectives and delimitation** ....................................................... 10 
      1.2.1 Research question and hypothesis ........................................................................ 10 
      1.2.2 Delimitation ........................................................................................................... 13 
   1.3 **Structure of the study** ............................................................................................... 13 

2. **Literature review** ......................................................................................................... 14 
   2.1 **Technical analysis** .................................................................................................. 14 
   2.2 **Moving averages** .................................................................................................... 16 
      2.2.1 Simple moving average (SMA) ............................................................................. 16 
      2.2.2 Exponential moving average (EMA) ..................................................................... 17 
      2.2.3 Dual moving average crossover (DMAC) .............................................................. 17 
      2.2.4 Ribbon moving average ....................................................................................... 19 
      2.2.5 Moving average convergence divergence .............................................................. 20 
   2.3 **Neural networks and machine learning** ..................................................................... 21 
   2.4 **Day trading/intraday trading** .................................................................................. 21 
      2.4.1 High frequency trading ....................................................................................... 22 
   2.5 **Investor/Human bias** .............................................................................................. 23 
      2.5.1 Herding .................................................................................................................. 23 
      2.5.2 Positive feedback .................................................................................................. 24 
      2.5.3 Disposition effect .................................................................................................. 25 
      2.5.4 Overconfidence ..................................................................................................... 25 
   2.6 **Market efficiency** ..................................................................................................... 26 
   2.7 **Random walk** ......................................................................................................... 27 

3. **Data** ............................................................................................................................. 28 
   3.1 **OMXH 25 index** ...................................................................................................... 28 
      3.1.1 Underlying data ..................................................................................................... 30 
   3.2 **Descriptive statistics** ............................................................................................... 30 
      3.2.1 Subset 1 ................................................................................................................ 33 
      3.2.2 Subset 2 ................................................................................................................ 34 

4. **Methodology** ................................................................................................................. 35 
   4.1 **Methodology** .......................................................................................................... 35 
      4.1.1 Dual moving average crossover .......................................................................... 35
List of symbols and abbreviations

ETF = Exchange traded fund, fund which is traded in stock market similar to stocks but is managed by a fund

SMA = Simple Moving average

DMAC = Dual moving average crossover

MA = Moving average, in framework of this thesis same as Simple Moving Average

EMA = Exponential moving average

OMXH 25 = OMX Helsinki 25 index

Bull market = upward trend in the market, prices rise

Bear market = downward trend in the market, prices fall

HFT = High frequency trading
1. Introduction

Intraday trading has been a hot topic in financial discussion for a while now and has gained questionable reputation as some sort of sophisticated gambling where day traders make fortunes in very short period of time. This image of "wall street trader" has gained even more visibility through the movies such as Wolf of Wall street and The Big Short. Intraday trading or day trading for short can be characterized as short term trading heavily based on various forms of technical analysis which attempts to predict the future based on history while discarding all the fundamentals typically used in investing and high volume of trading (Ryu 2012). Interestingly enough there seems to be strong disbelief for use of technical analysis in the academical world while in the financial world use of these tools is very common. This thesis attempts to shed some light on reasons and usage of these technical analysis tools in day trading and research is done in order to find out if some of these strategies can be used to create excessive returns.

Technical analysis can be defined as "financial analysis that uses patterns in market data to identify trends and make predictions." Several methods can be used in technical analysis such as moving averages, which are focus point of this thesis. Other techniques commonly used in technical trading are such as resistance-support levels, momentum and chart patterns. (Marshall et al. 2008)

Technical analysis has received quite mixed results in previous research. While some research has found various strategies successful general consensus among seems to be that there is no way pure technical analysis can work. Especially applying these trading strategies to real world can be challenging as research commonly ignores factors such as transaction costs, which usually turn profitable strategies into value destroying strategies.
Main focus of this thesis is technical analysis based on moving averages but technical analysis and their use can be seen as a part of the bigger megatrend of digitalization as increase in computation power makes it possible to perform even more complex analysis of data in real time. Graph 1 illustrates the rise in use of purely computer based trading in recent years. If strategies like this can be implemented successfully it would certainly raises questions whether asset management should be left to technical analysis done by computers thus eliminating emotion based choices and reducing management fees. Removal of human interaction would also reduce number of bad investment decisions caused by human bias. It is certainly possible asset management is done by computers in the future and there are already some companies which have employed these algorithm based asset managers (Bloomberg 2017). Technical analysis based strategies, if executed correctly, could take away some of those human elements. Moving average can be tested from data before using it and if deemed successful it could be fully automatized so that there is no possibility for human errors. Moving average based strategy derives information from past and uses this to predict the movement in the future. This is of course very risky assumption on its own as it ignores all other information available such as macroeconomic indicators and so on.

Graph 1. Percentage of HFT in daily US equity market. Financial Times 2017
This thesis implements moving strategies based on very short intervals. The data employed is one minute interval data and moving averages are calculated based on minutes instead of more often used daily moving averages. This opens up various new ways to look in to the topic of moving averages. One of the challenges emphasized due to use of this very short interval data is the hard task to find any kind of pattern from very noisy data as changes calculated on minute level are very small, fractions of percentage. Usage of such a short interval data has some specific points : number of trades increases dramatically driving up transaction costs, risk is reduced as time exposed to markets is reduced and closing losing position is done quickly given that technical analysis can correctly detect these losing positions.

1.1 Background
Personally I have had interest in investing and world surrounding investing for a long time and I find this topic very interesting as it is totally possible that trading strategies which can be processed by computers such as moving averages will be thing of the future with increase in computing power and access to various data. As a goal of investing is typically maximizing profit in defined time period it is often very important for investor to stick to personal investing strategy. However, humans are known to have several biases which can cause investor to deviate from strategies set beforehand such as overconfidence and positive feedback.
Gaining access to this kind of high interval data made me want to research further if such trading rules could be implemented in real world. Research on high interval data like has not been performed in the Finnish market before making this very interesting opportunity to see if using strategy like this could provide good returns. Pätäri & Vilska (2014) have done some research on Finnish stock exchange market and has found some effective strategies which could be used and this research is also expanding on knowledge gained there.
I picked interest in this subject as I see this as a growing trend with increase in purely computer based high frequency trading (HFT). Also this subject has not been widely studied before and could help further create evidence on usability of the technical analysis and trading strategies based purely on these. I also had a wonderful opportunity to access data used in this study thought my job in Thomson Reuters and this study would have never been possible without their help with the data.

1.2 Research problem, objectives and delimitation

Primary goal of this study is to find answer to the research question:

**Can moving average based strategies produce excess returns when used in intraday trading?**

In this case benchmark, to which these returns will be compared is returns of buy and hold strategy implemented over chosen period of time. Research gap to be filled here is that moving averages are typically used with daily interval data but this thesis implements moving average strategies in minute interval data to see if these rules can be used in shorter interval as well.

1.2.1 Research question and hypothesis

Hypothesis of this thesis is that moving strategy which can produce excess return compared to buy and hold strategy can be found in OMX Helsinki 25 index. This hypothesis is based on previous studies and assumption that because Helsinki Stock Exchange is rather small market, such exploitable market inefficiencies could exist. Testing process is further explained in section 4.

Research question of this thesis can be presented as:

**Can moving average based strategies produce excess returns when used in intraday trading?**

Sub research question:

**What is the effect of transaction costs to profitability of intraday trading?**
Methodology used follows similar research done before on moving averages, such as one first introduced by LeBaron (1992). As purpose of this paper is to find out whether or not moving average return can be used to create excess return compared to buy and hold strategy following hypotheses are created to test this:

**Hypothesis 1:** Mean of buy signal returns produced by moving average strategy is different from mean of market return.

**Hypothesis 2:** Mean of sell signal returns produced by moving average strategy is different from mean of market return.

**Hypothesis 3:** Mean of buy signal returns and mean of sell signals are different.

These hypothesis are tested using following formulas:

H1: \( \bar{r}_b - \bar{r}_h = 0 \)

H2: \( \bar{r}_s - \bar{r}_h = 0 \)

H3: \( \bar{r}_b - \bar{r}_s = 0 \)

where \( \bar{r}_b \) being mean return of buy signals produced by moving average strategy, \( \bar{r}_s \) being mean return of sell signals produced by moving average strategy and \( \bar{r}_h \) being mean of buy and hold returns (market returns). Following research of LeBaron et al (1992) and various other research done afterwards they are calculated as:

\[
\bar{r}_b = \frac{\sum_{n=1}^{N_b} r_b}{N_b}
\]

\[
\bar{r}_s = \frac{\sum_{n=1}^{N_s} r_s}{N_s}
\]

\[
\bar{r}_h = \frac{\sum_{n=1}^{N_h} r_h}{N_h}
\]
Statistical significance is tested using following hypothesis corresponding t-test formulas:

T test formula1

\[ t = \frac{\bar{r}_b - \bar{r}_h}{\sqrt{\frac{\text{Var}(b)}{N_b}} + \sqrt{\frac{\text{Var}(h)}{N_h}}} \]

T test formula 2

\[ t = \frac{\bar{r}_b - \bar{r}_h}{\sqrt{\frac{\text{Var}(b)}{N_b}} + \sqrt{\frac{\text{Var}(h)}{N_h}}} \]

T test formula 3

\[ t = \frac{\bar{r}_b - \bar{r}_s}{\sqrt{\frac{\text{Var}(b)}{N_b}} + \sqrt{\frac{\text{Var}(s)}{N_s}}} \]

Research in done by using one minute interval data from OMX Helsinki 25 index which includes 25 most traded companies in the Helsinki Stock Exchange. By using this data various different moving averages are generated and used to create trading strategies. As such this research is quantitative research and could provide results which can be generalized further. In depth description of the data and methodology are discussed in sections 3 and 4.
1.2.2 Delimitation
This thesis focuses on use of moving averages using one minute interval data of OMXH 25 index. Various other technical analysis tools are reviewed based on literature in section 2 but further testing on them is not performed. Used moving average strategies were also limited to around 1000 and due to this limitation it is possible that some strategies producing excess returns are left out. These limitations are used to keep this thesis focused on one subcategory of technical analysis and perform more in depth analysis on gained results. Strategies used are further examined in section 4.
While data used was received from Thomson Reuters it is still possible that underlying data contains some errors which are hard to detect due to large volume of the data. Therefore data has been skimmed through visually to detect any obvious errors but further actions are not performed.

1.3 Structure of the study
Section 2 will define used terms and literature framework regarding this topic. Section 3 focuses on used data. Section 4 goes through the testing methodology itself. In section 5 results of the study are introduced. Section 6 draws final conclusions, discusses financial implications of the results and possible research questions for future research.
2. Literature review

In this section commonly used terms in framework of day trading and technical analysis are defined. This chapter also takes a look into the previous research done regarding technical analysis and moving average based strategies. This chapter focuses on illustrating the most important terms used in this thesis. After reading this chapter, the reader should have a basic understanding of terms used and literature framework they are used in.

2.1 Technical analysis

Technical analysis attempts to forecast movements of the assets by using historical data in various ways. It should be noted that this goes against few very fundamental assumptions. Typically it is thought that price of an asset reflects various things such as expectation and performance of the past but technical analysis relies solely on historical data (Fama 1970). Technical analysis can be seen as an opposing strategy to fundamental analysis which relies heavily on the surrounding market and various other information in order to analyze if an asset is fairly priced based on historical information.

Technical analysis has been used for quite a while now. Taylor and Allen (1992) did a survey on London-based forex dealers and found out that some 90% of them are using technical analysis in their work. Their survey revealed use of technical analysis is especially focused on short term and gradually decreasing when time horizon gets longer. This would imply that while traders have faith in technical analysis they seem to acknowledge possible weakness of this method in longer time horizons where fundamentals have greater impact on asset prices. Menkhoff (2010) has also done research on use of technical analysis in more recent environment. In his research Menkhoff found out that 87% of the fund managers use information gained from technical analysis and 18% of the fund managers prefers technical analysis to other methods to process information. Similarly to Taylor’s and Allen’s findings use of technical analysis is more important in short time horizon where it is seen more important than fundamental analysis. After time horizon gets longer than few weeks fund managers prefer to use fundamental analysis. Based on these findings it can be concluded that use of technical
analysis is very common among fund managers and investing professionals even though it has received quite mixed results in academic research. It should be noted that technical analysis has been used for a long time now which would logically imply that there is some gain to be obtained from use of technical analysis.

Technical trading rules can be broken in to five major "families" , Filter, Moving average, Support and resistance, channel breakout and On-Balance volume. Filter rule can be seen as a momentum strategy as it implies rising prices will continue to rise and falling prices will keep falling. Filter rule is set to x% and when prices rise x% from previous low trader initiates a position and when prices fall x% from previous high traders sells the position. Alexander (1961) is considered the first to study these rules and he found out that these rules can be profitable. Moving average strategies use averages of the past prices to predict direction of the market. Moving averages are main focus of this study and are closely examined in the following chapter.

Support and resistance use previous low and highs of the n period as the "support" and "resistance levels indicating that when price "breaks resistance" and prices rise above previous high this indicates bull market. When prices fall below "support" level it is seen as a bear market signal (Osler 2000).

Channel breakouts can be seen as a modification of support and resistance, "channel" is formed when difference between previous high and low is x% and when prices rise out of the channel it indicates bull signal.

On-Balance volume rule uses volumes of trading as indicator for price movement. This rule focuses on idea that when volume of trading in the market increases or decreases it will also indicate changes in the price. Trend of the volume is followed and volume can be used in the set of moving average model but instead of prices it uses volume to indicate buy and sell signals. (Marshall et al., 2008)

Technical analysis can mean various different methods which are all based on use of historical pricing data to predict the future. This thesis focuses on the moving average strategies and other tools of the technical analysis are not further discussed or used in this thesis.
2.2 Moving averages

Moving averages can be seen as a subcategory of the technical analysis. It is one of the widely used tool of technical analysis. Moving averages can be used in various ways and this chapter focuses on different moving averages and their uses in technical analysis.

2.2.1 Simple moving average (SMA)

Simple moving average is calculated as calculating sum of observations divided by the number of observations as illustrated by formula 1.

\[
p_{SM} = \frac{p_M + p_{M-1} + \cdots + p_{M-(n-1)}}{n}
\]

\[
= \frac{1}{n} \sum_{i=0}^{n-1} p_{M-i}
\]

Formula 1: Simple Moving Average, where p is price of the underlying asset and n is number of observations included in calculation of the average.

Math is quite simple on this one as average is simply calculated for defined time period. As time progresses latest date drops out and new data enters into the formula. Simple moving average will be the main technical tool used in this thesis. Use of exponential moving averages was also considered. However, as this thesis tries to find optimal trading strategies from large array of possible strategies adding weights used in exponential moving averages would have complicated the process significantly. Exponential moving averages could be on way to expand the research after promising strategies are identified using simple moving averages first. In the context of this thesis when term moving average is used it refers to simple moving averages.
2.2.2 Exponential moving average (EMA)
Exponential moving average is similar to simple moving average but exponential moving average puts weight to observations by depending when observation was made. Most recent observations receive higher weight and older observations receive less weight with weight of each observation decreasing exponentially. Result of this is that exponential moving average reacts faster to the recent changes in the underlying data. Weight can be determined by individual resulting in weighting recent observations more heavily. (Roberts 1958)

2.2.3 Dual moving average crossover (DMAC)
Strategies which use two different length moving averages of form buy and sell signals are called Dual moving average crossover (DMAC). Usually two moving averages are used to find signals of the market movement. DMACs use two moving averages with different lengths, such as MA of 50 days and MA of 200. When these two moving averages cross it can be interpreted as a signal to buy or sell. When shorter moving average value becomes lower than longer term moving average this crossing is called "Death cross". Death cross is seen as a signal of the downturn in market and market entering bear market. This death cross is illustrated in Graph 2 as first red cycle. When shorter moving average goes above longer average it is called "Golden cross". Golden cross indicates bull market and as such investor should invest in the market. This is visualized in Graph 2 as second red circle.
Graph 2. Examples of "Death Cross (first red circle) and Golden Cross (second red circle) from Shanghai Stock Exchange composite index. Business Insider 2010

This method has been implemented in various studies in the past. LeBaron et al. (1992) conducted research on US equity market on moving average strategies and found out that these strategies were effective and they could produce excess returns. They did not include transaction costs in their work but their research launched further research on this topic. Metghalchi et al. 2008 found out that in Swedish stock market moving average strategies could produce excess returns even when transaction costs are considered. Similar results were also found by Dusan and Hollistein (1999) in Swiss stock market. Han et al. (2016) successfully employed moving average strategies on commodities, producing excess returns compared to buy and hold. DMACs are main focus of this thesis and they are typically referred as “MA strategies” as well in framework of this thesis.
2.2.4 Ribbon moving average

Ribbons is variation of moving average strategy which uses several moving averages, to determining buy or sell signals and has received its name ribbon like patterns it produces on graphs like in Graph 3. Ribbons requires more decision from investor as number of moving averages increases interpreting them and deciding lengths of moving averages adds investors’ input to trading. Investor needs to decide how many moving averages to use, what kind of intervals to use and how many crossings would flag buy or sell signal. In scope of this thesis studying ribbon based systems becomes increasingly hard as number of possible strategies rises significantly. (Zakamulin 2017)
2.2.5 Moving average convergence divergence

MACD moving average convergence divergence was first created in the 1970s by Gerald Appel and it has been used actively since that time.

MACD uses three constant exponential moving averages, typically formatted as MACD(a,b,c) where a, b and c are different length EMAs and they are used to interpret the changes in markets. MACD is calculated by subtracting two EMAs to form price indicator which is then compared to another EMA typically called signal line. Various interpretations can be made from these indicators but main use is to follow crossings of two calculated lines similar to other moving average strategies. Chong and Ng (2008) studied effectiveness of MACD in the London Stock Exchange and they found out that MACD could be used to produce excess returns compared to buy and hold strategy.

Figure 1. MACD example
2.3 Neural networks and machine learning

Neural networks and machine learning has really expanded in few last year as software and calculation power has increased. Typically machine learning relies heavily on data used to "train" the program as data is fed to system which then attempts to find best solution to problem it is given such as maximizing of profits in trading case (Rasmussen 2004). Problem with these is usually that they become "black boxes" where only input and output can be observed but actual process cannot be seen.

Neural networks have shown promising results in various fields and they are also under interest of financial sector. Problem of these systems is also that as they are based on historical their reaction to new situation is very hard to predict. It is said that "flash crashes" observed in the market in last few years have been caused by trading algorithm going haywire in new market situation (Li et al. 2018). But as amount of available data increases and computing capabilities increase it is probable that these systems will also be further implemented in the future in attempt to gain competitive advantage in the market. Humans have ability to quickly adapt to new information and patterns while neural networks rely on larger data set from the past. However Schimdhuber (2015) argues that neural networks will eventually be able to adapt in similar manner as a lot of lot of research and resources are used to improve the systems currently in place.

2.4 Day trading/intraday trading

SEC defines day trading as follows: "Day traders rapidly buy and sell stocks throughout the day in the hope that their stocks will continue climbing or falling in value for the seconds to minutes they own the stock, allowing them to lock in quick profits." (SEC 2011) As data used in this thesis is very high interval it results in activity which can be clearly recognized as intraday trading. Intraday trading can be seen as something typically done by institutional investors as they have the access to the very high frequency data and advanced analysis tools.
Various studies have shown that trading is in fact harmful for your returns from stock market. Barber and Odean (2000) found in their paper that individual investors who trade gains are around five percentage points compared to buy and hold market returns. Typically intraday trading is done on high volume stock as they have smaller bid-ask spreads. These stock are also typically attention grabbing and popular stocks. Research has found evidence that individual investors are net buyers stocks which appear on the news during big events and also with large daily price changes. This indicates that individuals provide liquidity to markets during large price changes. (Barber & Odean 2008)

While individuals seems to have poor returns there is evidence that institutional investors can overcome this. Puckett & Yan (2011) found that institutions gain major part of their profits from trading between quarters and they can outperform markets regularly. Institutional investors have great pool of skilled people to execute trading and come up with new strategies to outperform the market (Anand et al, 2011). It could be concluded that while individual investors are big portion of the market volume vise they seem to perform rather poorly compared to institutions which have advantage in skills and access to information.

2.4.1 High frequency trading
As moving average based strategies in this study are based on high interval data it is relevant to have a look at the possible outcomes of this research in framework of high frequency trading. Term High frequency trading (HFT) is used typically when trading is fully automatized and trades take place in few milliseconds when prices move even slightly in some direction. HFT is becoming more and more common as technical analysis based strategies such as moving averages are easy to execute in fully computer based system where system executes trades based on given parameters. Machine based systems can react fast to possible changes and execute trades in very short time periods. (Brogaard et al 2014)
Increase in HFT is also possible responsible for lack of research in technical analysis as big investment companies scramble to gather talented people from the field in order to keep up with the competition. Some big investment banks are already recruiting more engineer and IT background people than pure finance people showing that pressure is there to drive market more toward HFT/algorithm based (Business insider 2015).

While high frequency trading is very interesting topic there are very limited options to study these systems as they are highly protected by companies owning these trading algorithms and getting any kind of access to them is very difficult.

2.5 Investor/Human bias

One key reason for using technical analysis is to reduce the amount of human bias in the trading. If investor systematically follows the set trading rules he or she can remove typical various problems caused by biased actions of humans. As technical analysis could be performed solely by the set computer system it would be possible to remove all of the biases mentioned below. These human biases are believed to be main reasons why especially individual investors do so poorly on trading. They may lack the experience and knowledge of these biases which result in suboptimal trading as well. Naturally it is possible to fall for these biases when creating and testing various tools, humans typically see patterns where they don’t really exists and evaluating returns objectively can be challenging if investor has already decided to use some strategy while not supported by testing of it. Typical biases that investors face are introduced below.

2.5.1 Herding

"That famous mutual fund bought this equity I should do it too” Herding manifests itself in many forms. Few typical examples include buying stock because some famous and well recognized mutual fund buys in to new company (Kumar & Goyal 2015). One example of this could be fund managed by the Warren Buffet. If they invest in new companies it usually breaks in to the news on some level and investors are tempted to follow such a famous instances thinking "If they are investing to it they have to be right” even if there is no guarantee of results. Herding is also very important factor in creation of bubbles and
crashes. Typically bubbles are formed as positive feedback (also discussed below) creates herding effect as everyone starts to buy in to the market (Devenow and Welch 1996). In market crash this is reversed as everyone is trying to sell their stock. Wermers (1999) found out that mutual funds seem to be free of this bias as he found no significant evidence of herding in buy and sell decisions made by mutual funds and observed herding is more related to positive feedback bias where funds collectively buy stocks with good past performance and sell weakly performing ones. Nofsinger and Sias (1999) found similar results and concluded that while herding appears within institutional investors it seems that these decisions are not irrationally based as assets bought related to herding also produced excess returns but relation in this context is hard to pin point as institutional investors could also favor same kind of characteristic when looking for investments resulting in investing to same assets which further drive prices up.

However, professionals tend to still fall to another form of this bias as observed by Trueman (1994), who found out that analysts tend to release forecasts closer to the ones released by their peers and previous forecasts even when their private information would suggest larger difference.

2.5.2 Positive feedback

Buying during bull and selling during bear. Buying in to bull market gives feel of success in trading which reinforces the action. Positive feedback is another phenomena typically involved in the market. When in rising market investor buys in to the market and as prices rise investor receives positive feedback from the market creating good feeling for investor creating feeling that investor is making correct choices and ends up buying more stock to reinforce this feeling (Bradford & Long 1990). This leads typically to buying stocks which have performed well in the past and sell those that have performed poorly even if there is no other evidence to support this behavior (Nofsinger and Sias 1999).
2.5.3 Disposition effect

Reluctance to realise losses, eagerness to realise profit. Investors tend to realise losses more easily than profits leading to suboptimal returns as good investments get sold too early and losing investments keep capital locked to them. Term disposition effect was created by Shefrin and Statman’s (1985) research on this topic. This is most likely caused by reluctance to accept failed investments “hit to the ego” while positive trades create feeling of success even when it could be too early to make exit from investment. Odean (1998) studied disposition effect on trading records of 10 000 individual investor broker accounts and found significant disposition effect in sample causing lower returns for investors falling for this bias. He also concludes that portfolio rebalancing or reluctance to pay relatively higher transactions costs for lower priced stocks cannot explain the behavior observed. Taxation selling at the end of the year can be seen as one manifestation of this as December is the deadline to realise losses. Investors realise tax benefit of realizing losses but realise them at the end of year hoping for possible bounce back of loss-making asset during the next year (Shefrin and Statman 1985).

2.5.4 Overconfidence

"I can beat the market" while most don’t

Overconfidence is typical for most individuals and research has found out that this is typically bigger problem for male investors. Investors facing this bias believe that they can beat the average market returns, which is formed as average return from whole market. Investor like this tends to favor stock picking to index investing. However research has found out that in reality some 90% of the active investors/traders fail to beat the market. In light of these results average investor should stick to index investing rather than stock picking. Index investing lacks the excitement of stock picking and maybe so many investors still prefer to pick their stocks rather than simply invest to indexes. Overconfidence typically seems to result in excessive trading which in average is destroying value rather than adding it especially when transaction costs are considered. (Odean 1999)
Another appearance of this bias was found by Lakonishok et al (1994) when they fund out in their research that investors tend to overestimate returns provided by growth stock and underestimate value stocks. Growth stocks can be seen as typical targets for trading and stock picking as their returns are perceived as better than value stocks especially in short term making them perfect for overconfident investors as they try to outperform market.

2.6 Market efficiency

Use of technical analysis goes strongly against market efficiency theory introduced by Fama (1970). He argued that market are efficient and as such they reflect all the information available including historical prices such as historical data and expectations. However technical analysis uses only historical data to predict prices and as such existence of technical analysis strategies which can produce excess returns should not be possible. Technical analysis seems to be widely used by financial professionals which adds to argument that markets are in fact inefficient and strategies such as moving averages can be used to gain excess returns.

Market efficiency has not been widely studied on very short time frames which is intended scope of this thesis. Hypothetically it could be possible that market efficiency has gaps in very short time frames and various strategies could be used to identify these inefficiencies and exploit them before they are closed. Similar to this is forex trading and finding temporary arbitrage opportunities in currency exchange rates.

There has been evidence (Shiller 1981) that in short term market reactions are much stronger and usually even out in long term. These events especially include cases where new information enters the market, mergers or large deviations in earnings. Short term reaction can be very strong but evens out over longer term as information is further processed and absorbed by market. Shiller also concluded that level of short term volatility cannot be explained by long term fundamentals creating a gap which could be theoretically exploited.
2.7 Random walk

Stock market movement can be considered to be “white noise” or random walk especially on short term. In this case mean is zero and distribution is fairly normal, this is also case with OMXH 25 as seen in Figure 2. Long term returns of stock market is positive and as such distribution is slightly shifted as mean is above zero. Financial data is typically riddled with fat tail problem, while distribution close to zero is similar to normal distribution large changes happen way more frequently than normal distribution would indicate.

This process of random walk makes it hard to predict stock movements and active investing consistently runs in to problem of losing to buy and hold strategies. Active trading can be defined as looking for ways to find logic in this random walk. Biondo et al (2013) found out that returns gained from purely random strategy are not really different from technical analysis ones but random strategy is seen as less risky.
3. Data

Data used in this study was received from Thomson Reuter’s database. Data covers 10 years from October 2006 to October 2016 as such covering some major market events such as financial crisis of 2008 and downturn of economy caused by doubts over Greek and EU as whole around 2013 as well as Brexit voting results of 2016. As such this data has both up and downturns and should provide comprehensive data to test various strategies. Detailed information about data and formation of index is discussed further in this chapter.

3.1 OMXH 25 index

OMXH 25 consists of 25 most traded stock in Helsinki stock exchange. They are weighted based on their market caps but in a way that maximum weight of one stock/company is 10%. In Helsinki stock exchange Nokia is only company which has hit this limit during the time of the index in its peak valuation. Some large companies such as Nokia can have impact in the index in case of large events, for example when Nokia decided to sell its mobile phone business to Microsoft Nokia’s stock gained some 30% in short time also pushing the OMXH25 Index up several percentage points (Graph 4). This is unfortunate but cannot be avoided in the rather small Finnish market and due to the composition of the index only including 25 companies. Even so OMXH 25 is seen as great overall indicator of Finnish market and is regarded as one of the benchmark for the Finnish stock exchange and frequently used index for derivatives (Nasdaq 2018). Index is updated semiannually in the beginning of February and August and is adjusted for corporate actions such as stock splits. (Nasdaq 2016)
Data consists of OMXH 25 index and values of the index are used to form moving averages in this study. It should be noted that instrument perfectly replicating the index is not available in the market, instead various funds and exchange traded funds (ETF) exists which replicate this index. This leads to slightly varied results but the underlying strategies could be used regardless as investor could technically form their own fund with identical performance of the index. It should be noted that available ETFs also follow very closely to the index and could be used as proxy to implement these trading strategies.

3.1.1 Underlying data

Original data was in tick format of OMXH 25 Helsinki index meaning it included all the changes in the index on accuracy of one hundredth of the second and on four decimal places. This dataset was further refined to make dataset of one minute interval data which consist of minute close value for index over the covered period.

Data is formed by one minute interval closing price data of the OMXH 25 index. Typical trading hours for the Helsinki Stock Exchange are from 10:00 to 18:30. This results to 510 observations per trading day. As stock exchange is closed during some days of the year (e.g. Christmas) stock market is open approximately on 250 days during the year. (Nasdaq 2017). Data had some errors where index values were recorded as zero but these errors were patched in a way that zero values were replaced with previous closing value. Total number of these errors (8021) was insignificant when considering the size of the full sample. Following chapter provides descriptive statistics of the data in more detail.

3.2 Descriptive statistics

Data was split into two subsets in order find MA strategies in one subset and test them separately in order to reduce and avoid data snooping. Descriptive statistics of the both subsets are shown below. Descriptive statistics below are for ln minute returns obtained from both subsets. Ln return is defined as:

\[ r = \ln I_n - \ln I_{n-1} \]

Subset 1 descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>639000</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>-5,05301E-07</td>
</tr>
<tr>
<td>Mean</td>
<td>0,045766275</td>
</tr>
<tr>
<td>Max</td>
<td>-0,042929743</td>
</tr>
<tr>
<td>Min</td>
<td>2,92477E-07</td>
</tr>
<tr>
<td>Var</td>
<td>0,000540812</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0,012867443</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>328,396971</td>
</tr>
</tbody>
</table>
Subset 2 descriptive statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>638990</td>
</tr>
<tr>
<td>Mean</td>
<td>8,88091E-07</td>
</tr>
<tr>
<td>Max</td>
<td>0,043293713</td>
</tr>
<tr>
<td>Min</td>
<td>-0,0756625</td>
</tr>
<tr>
<td>Var</td>
<td>2,15255E-07</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0,000463956</td>
</tr>
<tr>
<td>Skewness</td>
<td>-4,1731995</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1807,965624</td>
</tr>
</tbody>
</table>

Results show very high kurtosis in the data. This is logical as majority of the changes are very small and close to zero causing values close to zero to be over presented compared to normal distribution. Further actions to adjust for this kurtosis are not done in this thesis. Both subsets include very large minimum and maximum values and these changes typically occur in as the market opens. Further examination of the data revealed that these are typically caused by major external events released outside out Helsinki stock exchange trading hours are Helsinki’s market catching up to these changes at the start of the trading day. Events like these include political events such as Brexit and escalation of worries over Greece’s debt problem.

Both subsets had average return close to zero but for subset 1, it is slightly negative whereas for subset 2 it is slightly positive. This is also reflected in data as subset 1 includes 2008 financial crisis with negative buy and hold return while subset 2 covers mainly rising markets with positive buy and hold return.

Finnish market closely follows general market directions and as such events which happen during the open hours in other markets such as US take effect in delay and are reflected at the opening prices of the market in Helsinki in the following day. This also proves the point of some traders who prefer to stay out of the trading during the first hour of the trading in order to avoid instances like these which are typically political in nature and very hard to foresee while their effect on market can be huge. OMXH 25 faced tough times during the period in scope of this study. Quite shortly after recovering from 2008
crash turbulence in euro area was caused by worries over Greek’s economic condition. This event caused setback in equity prices and it took fairly long for OMXH 25 to catch up with peak reached before the recession of 2008. While SP500 reached the peak levels of 2007 in 2013 OMXH 25 needed two more years to return to levels reached before financial crisis. As seen on Graph 5 OMXH 25 has continued quite steady raise in the last few years following the global trend of long positive outlook of the market causing some economists to worry over the future. Current bull market has lasted for a long time while monetary policies around the world have remained quite loose in order to keep the growth going. Data used in this thesis cover crash of 2008 and troubles caused in Eurozone but typically to financial crashes these events were relatively short-term before market started to recover from bottoms. As such data available for bear markets is relatively smaller portion of the data used. For sake of building good strategies detecting these downturns can be crucial as equities can lose large percentage of the value in short time while recovering typically spans over longer period with smaller daily changes.

3.2.1 Subset 1

Subset 1 covers timeframe from October 2006 to October 2011. While 2006 was still favorable year for markets they took sharp downturn in 2007 and 2008 as seen from graph below. Subset 1 captures major downfall of the market started in 2008 launched by the collapse of Lehman Brothers.

Graph 6. Subset1 OMXH25 index values
3.2.2 Subset 2

Subset 2 covers timeframe from October 2011 to October 2016. This time period had few smaller downturns but mainly it can be considered as a continuous bull market as seen in graph 7. This is also seen from positive mean of the returns captured in that time. Period covered by subset 2 had rising markets and quite a bit of stagnant prices as well.

Graph 7. Subset 2 return
4. Methodology

This study is based on dual moving average crossover strategies (DMAC). DMAC is created by using two averages of the different length and using values of these averages as indicators to signal certain trend occurring in the market and based on this investor can make investment decisions. As example we can take average of last five minutes’ closing prices and averages of the last 20 minutes’ closing prices to form averages. These will be referred as "short" and "long" averages where 5 minute average would be that "short" and 20 minute "long". These averages are updated constantly when new data is available at close of each minute. Newest data point is added to average calculation and oldest data point is removed from the calculation thus the name "moving average".

4.1 Methodology

This thesis follows similar methods used in previous research such as Pätäri&Vilska (2014). Buy and sell signals are evaluated as how well they can differentiate returns from the mean which is zero. Buy signals should have positive returns while sell signals should have negative returns to prove that these signals actually differ from randomly picked ones.

4.1.1 Dual moving average crossover

Typical strategy which uses moving averages tries to extract info regarding future movement of the market uses crossing points of the short and long moving averages as turning point in bear and bull market. Typically when shorter average passes the longer one this is seen as buy signal indicating that market has started more permanent rise while passing of short average below longer average can be seen as a sell signal.
Response to the buy and sell signals is constructed in a way that when strategy flags crossing of two moving averages it buys or sells the index on next minute’s closing price. This structure is in place to ensure these strategies could be realistically implemented in real world as well. This setting gives one minute time window to detect the crossing and execute the buy which should be enough if system is mostly or totally automated.

4.1.2 Data snooping
In order reduce and avoid data snooping best strategy is searched in subset 1 and then applied to subset 2 to see how it would have performed. This way we can avoid data snooping in which best strategy is picked after having a look at the data rather than choosing it before looking into the data. In framework of this study it means that subset 1 is used to find strategies and subset 2 would be where found strategies are executed. Best strategies for subset 2 alone are also tested and applied back to whole period and back to subset 1. In this way we can simulate case where subset 2 price changes would have happened before subset 1 (reversing subset 1 to subset 2 and subset 1 to subset 2).

Strategies are also inspected for whole period to simulate situations where investor would have picked strategy randomly and the start of subset 1 and executed it until end of subset 2.

4.1.3 Tested strategies
In total 1002 dual moving average crossover strategies were tested for both subsets. These strategies had some basic restrictions. Shortest "short" moving average used was 5 and longest 120 minutes. Shortest “long” MA used was 30 minutes and longest "long" moving average used was formed from last 720 minutes. Long interval limit was set to 720 minutes as quick overview of the results indicated that returns started to get lower when extending the timeframe much longer also 720 minutes already spans over one day of trading. As scope of this research is to mainly focus on short term trading indicators maximum limit used can be considered reasonable.

Pairs of short and long moving averages were set in a way that "long" MA was double the "short" MA used. Using this framework strategies and their respective returns were
calculated using computer. Long MA changes were calculated with 5 minute interval causing possibility of missing some effective strategies. Given the characteristics of strategies further examined at the next chapter it can be concluded that even if better strategies exists between intervals tested their performance should not be significantly better than ones tested. Tested strategies are further illustrated in following table 1.

Table 1. Strategies used.

<table>
<thead>
<tr>
<th>Short MA</th>
<th>Long MA</th>
<th>Number of tested strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>10-720</td>
<td>142</td>
</tr>
<tr>
<td>10</td>
<td>20-720</td>
<td>140</td>
</tr>
<tr>
<td>15</td>
<td>30-720</td>
<td>138</td>
</tr>
<tr>
<td>30</td>
<td>60-720</td>
<td>132</td>
</tr>
<tr>
<td>45</td>
<td>90-720</td>
<td>126</td>
</tr>
<tr>
<td>60</td>
<td>120-720</td>
<td>120</td>
</tr>
<tr>
<td>90</td>
<td>180-720</td>
<td>108</td>
</tr>
<tr>
<td>120</td>
<td>240-720</td>
<td>96</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1002</td>
</tr>
</tbody>
</table>

It should be noted that especially longer moving averages use data for two trading days and these trades are typically open longer compared to short MA strategies. This leaves open positions exposed to external factors such as political events. Brexit would be example of this as it had a great impact on markets and reaction was realised at start of trading the following day after somewhat surprising results of Brexit vote. Some traders may wish to avoid these events by restricting trading only to one day and excluding first hour of trading. This approach is not followed in this study as it would further increase number of trades and with large data set as one used here data should include both positive and negative events evening the results gained. This approach could be further studied in future research.
4.2 Characteristics of strategies

This chapter outlines some findings regarding the nature of strategies used and how change in both short and long moving average change the number of trades executed, profit profiles and average returns gained per trade. All cases are presented in no transaction scenario as main objective of following analysis is to find possible patterns and connections in the data and strategies used.

4.2.1 Change in Long MA

Change in long MA has exponentially reducing effect to number or trades, when long moving average gets longer number of trades reduce exponentially. This effect is outlined in following graph 8 where effect of change in long MA is examined in case where short MA is set 5 minutes.

Graph 8. Number of trades in subset 1
Increasing duration of long MA has positive effect on average absolute return per trade done. However relation seems to be more like linear compared to exponential one of the reduction in number of trades. From this it can be derived that while profit per trade is increasing only in linear fashion with longer MA the increase is offset to greater degree by the exponential decrease in number of trades resulting in superior results for short MA strategies especially in zero transaction case.
4.2.2 Change in short MA

While increase in long MA causes exponential decrease in number of trades as illustrated by graph 8, change in short moving average causes curve to shift while retaining its shape as seen in graph 10. Increase in short MA results in lower amount of trades.

Graph 10. Effect of making short moving average longer to number of trades
Graph 11. Effect of long MA to profit per trade

While number of trades reduces exponentially profit per trade increases only in somewhat linear fashion as seen on Graph 11 resulting in overall superior performance of strategies with short moving averages. However this only applies in zero transaction cost scenario, when we introduce transaction costs things change and general threshold levels can be derived from information provided from graph 11. If transaction cost per trade is higher than average profit per trade these strategies run in to trouble. It should be noted that this graph represents average returns and as such it could be possible that even if transaction costs exceed level of average profit strategy could produce good returns if few good trades can offset the made losses. Profit distributions of best strategies are further examined in next chapter.
4.2.3 Subsets

While characteristics of the subsets vary quite greatly it seems to have little to no effect on number of trades executed by same strategy in different subsets as seen in Graph 12. Subset 1 which has negative buy and hold results has only slightly more trades than subset 2 which captures rising market with minor shorter market corrections. As such it could be concluded that underlying data has only a minor impact to number of trades executed by strategy while changes in underlying strategy effects the number of trades significantly. This is interesting information as investor can estimate number of trades to be executed based on historical data.

Graph 12. Number of trades in both subsets using same strategy
Graph 13 shows that average trade profit per trade is systemically higher in subset 1 regardless of strategy used. This is interesting as subset 1 buy and hold return is negative providing further evidence found on earlier studies such as Pätäri&Vilska (2014) that moving average strategies tend to perform well in bear market.

When measuring best strategies by their absolute returns it can be also observed that essence of best strategies change as well. Low/no transaction strategies seem to be those with shortest time spans used in MA resulting in large number of executed trades. In cases like these analysis gives very fast alert when pricing takes a dip and exits from the market and closing the deal and cashing in the profits while protecting from the downturn. Exact opposite seems to be the case when transactions costs are applied, strategies with longer time spans are favored over the short ones, resulting in fewer trades with higher average per trade profits. However average profit per trade does not rise in exponential manner, while number of trades is reduced exponentially with longer MAs profits per trade only rise in somewhat linear way. Due to this strategies struggle to exceed transaction costs resulting in worse results than buy and hold strategies. Transaction costs are further examined in next chapter as well.
Insights gained from things discussed in this chapter are further viewed on next chapter. Based on information gained here it should be clear that strategies with shortest moving averages should be able to produce excellent returns especially in environment of no transaction costs due to exponential nature of long MA effect while profit per trade changes only linearly.
5. Analysis of results

This chapter focuses on results of most effective strategies and effect of transaction cost to profitability of these strategies. Based on results retrieved from the research it seems like there are strategies which can be used to beat the buy and hold strategy. However these returns are very heavily affected by the transaction costs of the trading. As our study is focusing on very short term trading resulting in high amount of trades transaction costs play a major role in total return figures achieved by these strategies. Results are provided in absolutes, percentage and annual returns. Absolute return is calculated as sum of all trades assuming that investor would get position valued same as OMXH 25 index. For Buy and hold investor this would mean buying at value at start of 2006 and selling that position at 2016 absolute profit being difference between buy and sell price. For MA absolute return is composed as sum of returns from all the trades again assuming position valued at OMXH25 index value. Percentage return is calculated as absolute profit divided by start value of the index. Annual return indicates annual compounding rate of return which investor would get.

5.1 Zero transaction cost

This chapter takes a look at the most profitable MA strategies in both subsets and how total returns would have been like if strategies formed during subset 1 would have been applied to whole period and provide a retro perspective look on whole period which strategy would have delivered the best returns and is the profit would have been better than one received as buy and hold investor. Results represented here are transaction free ones and results including transaction costs are further analyzed in chapter 5.2.
5.1.1 Subset 1
Subsets 1 illustrates results similar to those found in earlier research as well. While buy and hold return for period is negative MA strategies producing clear profits could be found and technical analysis seems to deliver excellent results on bear market. Moving average strategies clearly outperforming buy and hold strategy. For non-transaction cost strategies all tested strategies outperformed buy and hold returns.

The best strategy found was the strategy using 5minute MA of short moving average and 10minute MA as long one (5,10). As seen on table 2 results are excellent compared to negative returns of buy and hold.

Table 2. Returns of best MA strategy compared to buy and hold in subset 1.

<table>
<thead>
<tr>
<th></th>
<th>Absolute return</th>
<th>Percentage return</th>
<th>Annual return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best technical analysis</td>
<td>20 563</td>
<td>751 %</td>
<td>53%</td>
</tr>
<tr>
<td>Buy and hold</td>
<td>-755</td>
<td>-28 %</td>
<td>-6%</td>
</tr>
</tbody>
</table>

Graph 14. Profit accumulation of buy and hold and best MA strategy.
From the results above it can be seen that in subset 1 MA strategy (5,10) could produce far superior profits compared to buy and hold strategy. While it managed to avoid making losses it even produces clear profits.

Graph 15. Profit per trade distribution

As seen from profit distribution profits are quite low per trade, average being slightly positive as positive returns have fatter tail. In this framework it can be seen that reduction of 0.1% in profit to transaction costs would tilt the distribution heavily to negative. Slight differences make big results in the end when large number of trades cumulates to large profits as seen in graph earlier.
All three hypotheses were tested, if buy signals differ from zero, if sell signals differ from zero and if buy and sell differ from each other (i.e. buy-sell=0). For all the best strategies it is evident that all hypotheses can be confirmed and these strategies indeed can separate random walk to positive and negative returns in meaningful way.

Table 3. Tstat values for strategy (5,10) in subset 1

<table>
<thead>
<tr>
<th>Mean return</th>
<th>Buy Signal</th>
<th>Sell Signal</th>
<th>Tstat Buy</th>
<th>Tstat Sell</th>
<th>Tstat Buy-Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy and hold</td>
<td>-5.05301E-07</td>
<td>2.86463E-05</td>
<td>-3.0005E-05</td>
<td>25.29926404</td>
<td>-24.80678941</td>
</tr>
<tr>
<td>Variance</td>
<td>2.92477E-07</td>
<td>2.79566E-07</td>
<td>3.038E-07</td>
<td>25.29926404</td>
<td>-24.80678941</td>
</tr>
</tbody>
</table>

From table 3 it can be seen that this strategy and buy and sell signals it produces are statistically significant at 99% confidence level. As such it can be concluded that buy signal returns are statistically significant from zero, sell signal returns are statistically significant from zero and difference of these two returns is statistically significant from zero.

It should be noted that results found here would have been hard to achieve in real world scenario as these results are exposed to data snooping bias. However as seen on next chapter best strategy for subset 2 is also the same as for subset 1 (5,10). Theoretically these results could have been achieved if subsets were reversed and this MA trade strategy would have been applied in this simulated bear market.
5.1.2 Subset 2

While subset 1 buy and hold returns were negative they were positive for subset 2. Best MA strategy manages to outperform buy and hold but gap in returns is much smaller than compared to bear market results of subset 1 (Table 4). Strategy applied here is formed based on subset 1 information but closer inspection of subset 2 returns also revealed that (5,10) strategy is also the best for subset 2.

Table 4. Returns of best MA strategy compared to buy and hold in subset 2.

<table>
<thead>
<tr>
<th></th>
<th>Absolute return</th>
<th>Percentage return</th>
<th>Annual return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best technical analysis</td>
<td>8 663</td>
<td>436 %</td>
<td>40%</td>
</tr>
<tr>
<td>Buy and hold</td>
<td>1 516</td>
<td>43 %</td>
<td>12%</td>
</tr>
</tbody>
</table>

Graph 16. Profit accumulation of buy and hold and best MA strategy.
It can be seen from graph above that at the start of the period profit pattern seems to follow the buy and hold returns, 2012 downturn in economy caused losses for both strategies but MA strategy suffered smaller losses and after that continues to outperform buy and hold by producing excellent returns.

All three hypotheses were tested, if buy signals differs from zero, if sell signals differ from zero and if buy and sell differ from each other (i.e. buy-sell=0). For all the best strategies it is evident that all hypotheses can be confirmed and these strategies indeed can separate random walk to positive and negative returns in meaningful way.

Table 5. Tstat values for strategy (5,10) in subset 2.

<table>
<thead>
<tr>
<th></th>
<th>Buy and hold</th>
<th>Buy Signal</th>
<th>Sell Signal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean return</td>
<td>8,88089E-07</td>
<td>2,8646E-05</td>
<td>-3,00054E-05</td>
</tr>
<tr>
<td>Variance</td>
<td>2,15255E-07</td>
<td>2,7957E-07</td>
<td>3,038E-07</td>
</tr>
</tbody>
</table>

| Tstat Buy      | 25,26739773  | -27,165161 | 43,39869279 |

From table 5 it can be seen that this strategy and buy and sell signals it produces are statistically significant at 99% confidence level. As such it can be concluded that buy signal returns are statistically significant from zero, sell signal returns are statistically significant from zero and difference of these two returns is statistically significant from zero.

Because subset 2 strategy was formed based on subset 1 data snooping can be avoided and this strategy could have been implemented based on results observed in subset 1.
5.1.3 Total returns whole period

Total returns for whole period using strategy formed in subset 1 (5,10) is shown in table 6. It can be seen that total profits are clearly above buy and hold strategy.

Table 6. Total return for whole period using strategy (5,10)

<table>
<thead>
<tr>
<th></th>
<th>Absolute return</th>
<th>Percentage return</th>
<th>Annual return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best technical analysis</td>
<td>29 226</td>
<td>1 067 %</td>
<td>28%</td>
</tr>
<tr>
<td>Buy and hold</td>
<td>761</td>
<td>28 %</td>
<td>2,5%</td>
</tr>
</tbody>
</table>

Graph 17. Cumulative profit of the trading strategy compared to value accumulation of buy and hold.

From graph 17 above we can see the accumulation of profits compared to buy and hold. Results obtained here are in line with observations made earlier in chapter 4 regarding effects of changes in MA strategies. Short MAs produce highest amount of trades and
lowest per trade profit. However due to exponential reduction in number of trades when longer MAs are used while per trade profit reduces only in linear fashion causes strategies using short MAs to outperform ones using longer MAs. Even so all 1002 tested MA strategies outperformed buy and hold returns.

Subset 1 was used to form trading strategies and they were then applied to subset 2 to see how formed strategies would have performed. While subset 1 encountered financial crisis of 2008 subset 2 mainly captured rising market. Regardless of market differences MA strategies seem to outperform buy and hold strategies when transaction costs are not considered. Effect of transaction costs are examined in next chapter to produce more realistic results in case strategy was really implemented in trading.

5.2 Transaction costs
Transaction costs play major role in returns of the strategies and this chapter focuses on inspecting effects of transaction costs and their effect on viable strategies. Very high frequency trading can produce very good results when transaction costs are assumed to be zero. However in real world setting every trade would have transaction cost causing very high frequency and low profit to produce losses instead of profits.

Transaction in this case is defined purely by the bid ask spread as time value of the money is ignored. This is due to the fact that most of the time our resources are in full use, with high trade frequency time of free cash is also limited. Use of interest bearing instruments would also heavily increase our transaction costs as well as new trades would be needed between interest instruments as well.

Previous research such as Pätäri&Vilska 2014 have used 0,1% as their transaction cost level and same level is used in this research as well. This level is also supported by the evidence gathered from the data provided by the Vanguard group. Vanguard group is one of world largest ETF issuer in the world. According to their data typical bid ask spread is ranging from 0,01% of the S&P 500 ETF which can be considered as one of the most traded ETF to around 0,1% of some less common ones (Vanguard 2018a).
Effect of transaction costs to best non transaction cost strategy (5,10) are presented in above graph in which it can be seen when transaction costs are introduced strategy changes from excellent return producing one to severely value destroying one. This is due to nature of (5,10) strategy, it produces extremely high number of trades with low profit and these profits turn to losses when transaction costs are introduced. Seemingly low transaction cost of 0.05% already causes strategy to produce losses. This result was already expected from results gained in chapter 4 where relation in number of trades and durations of MAs were observed. These results indicate that in order to make profit strategy needs to produce profit exceeding transaction costs while maintaining sufficiently high number of trades to produce profit. Balance between number of trades and average of profit per trade needs to be found.
When considering transaction costs, the nature of the best strategy shifts significantly compared to zero transaction cost. While zero transaction cost favors strategies with short MAs resulting in a high number of trades, this is reversed to some extent when transaction costs are considered as strategies with longer MAs seem to produce the best results. Results for both subsets and the entire period are presented in the following subchapters.

### 5.2.1 Subset 1

Best strategy found using subset 1 was one with a short MA of 45 minutes and a long MA of 705 minutes (45,705). This strategy will be applied to subset 2 to see if it remains effective. This strategy managed to beat buy and hold returns quite clearly, managing to make a profit (+43%) while buy and hold investors would have suffered significant losses (-28%). Total of 474 strategies of the tested 1002 strategies beat buy and hold return. So even ignoring the data snooping bias, investors could have picked any strategy and still beat the market on almost 50% chance. Previous research has found evidence that technical analysis can perform well in falling markets and results gained here further support that finding in intraday setting as well.

Table 7. Best MA strategy (45,705) returns with 0.1% transaction cost.

<table>
<thead>
<tr>
<th></th>
<th>Absolute return</th>
<th>Percentage return</th>
<th>Annual return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best technical analysis</td>
<td>1 169</td>
<td>43 %</td>
<td>7%</td>
</tr>
<tr>
<td>Buy and hold</td>
<td>-755</td>
<td>-28 %</td>
<td>-6%</td>
</tr>
</tbody>
</table>
From graph above it can be seen that strength of MA strategy is realised especially when market takes a dive. While index value reduced significantly during 2008 crash MA strategy manages to reduce the exposure to it resulting in lower hit to value. Gap in profit remains wide as when market starts to rise MA strategy also starts to produce profits but they are somewhat in line with buy and hold returns.

All three hypotheses were tested, if buy signals differs from zero, if sell signals differ from zero and if buy and sell differ from each other (i.e. buy-sell=0). For all the best strategies it is evident that all hypotheses can be confirmed and these strategies indeed can separate random walk to positive and negative returns in meaningful way.

Table 8. Tstat values for best subset 1 strategy (45,705)

<table>
<thead>
<tr>
<th></th>
<th>Buy and hold</th>
<th>Buy Signal</th>
<th>Sell Signal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean return</td>
<td>-5,053E-07</td>
<td>4,21E-06</td>
<td>-5,5935E-06</td>
</tr>
<tr>
<td>Variance</td>
<td>2,92477E-07</td>
<td>2,24E-07</td>
<td>3,66606E-07</td>
</tr>
<tr>
<td>Tstat Buy</td>
<td>4,422226946</td>
<td>-3,956089</td>
<td>7,160798863</td>
</tr>
<tr>
<td>Tstat Sell</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tstat Buy-Sell</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
From table 8 it can be seen that this strategy and buy and sell signals it produces are statistically significant at 99% confidence level. As such we can conclude that buy signal returns are statistically significant from zero, sell signal returns are statistically significant from zero and difference of these two returns is statistically significant from zero.

5.2.2 Subset 2
Subset 2 captures mostly rising market. When transaction costs are included MA strategies struggle to beat buy and hold results. From tested 1002 strategies not a single MA strategy could exceed buy and hold returns. While in market downturn MA strategy reduces exposure to crashing market same also applies for boom in market, investor loses part of the profit when not fully exposed to market movement.

Table 9. Returns of best MA strategy formed based on results of subset 1.

<table>
<thead>
<tr>
<th></th>
<th>Absolute return</th>
<th>Percentage return</th>
<th>Annual Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best technical analysis</td>
<td>1 116</td>
<td>56 %</td>
<td>9%</td>
</tr>
<tr>
<td>Buy and hold</td>
<td>1 516</td>
<td>76 %</td>
<td>12%</td>
</tr>
</tbody>
</table>

Graph 20. Profit accumulation of best strategy and buy and hold 0.1% transaction cost.
Graph 20 illustrates the weakness of MA strategy, while it does capture profit on rising market it loses to market returns and cannot produce any excess return compared to buy and hold.

All three hypotheses were tested, if buy signals differs from zero, if sell signals differ from zero and if buy and sell differ from each other (i.e. buy-sell=0). For all the best strategies it is evident that all hypotheses can be confirmed and these strategies indeed can separate random walk to positive and negative returns in meaningful way.

Table 10. Tstat values for strategy (45,705) in subset 2

<table>
<thead>
<tr>
<th></th>
<th>Buy and hold</th>
<th>Buy Signal</th>
<th>Sell Signal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean return</td>
<td>8,88089E-07</td>
<td>4,21E-06</td>
<td>-5,5935E-06</td>
</tr>
<tr>
<td>Variance</td>
<td>2,15255E-07</td>
<td>2,24E-07</td>
<td>3,66606E-07</td>
</tr>
<tr>
<td>Tstat Buy</td>
<td>3,294775017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tstat Sell</td>
<td></td>
<td>-5,234485</td>
<td></td>
</tr>
<tr>
<td>Tstat Buy-Sell</td>
<td></td>
<td></td>
<td>7,160798863</td>
</tr>
</tbody>
</table>

From table 10 it can be seen that this strategy and buy and sell signals it produces are statistically significant at 99% confidence level. As such it can be concluded that buy signal returns are statistically significant from zero, sell signal returns are statistically significant from zero and difference of these two returns is statistically significant from zero.

When observing only subset 2 strategy beating (45,705) was also found. For subset 2 best strategy was (120,655) making absolute profit of 1289. Result is slightly better than (45,705)’s but is exposed to data snooping while still failing to beat buy and hold. Due to these reasons this strategy is no further examined.
5.2.3 Total returns whole period

Strategy formed based on subset 1 (45,705) was also best yielding strategy for whole period thanks to clear market beat in subset 1 and decent performance in subset 2 as well. Return for whole period are presented in table 11 below.

<table>
<thead>
<tr>
<th></th>
<th>Absolute return</th>
<th>Percentage return</th>
<th>Annual Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best technical analysis</td>
<td>2285</td>
<td>83 %</td>
<td>6%</td>
</tr>
<tr>
<td>Buy and hold</td>
<td>761</td>
<td>28 %</td>
<td>2,5%</td>
</tr>
</tbody>
</table>

Graph 21. Profit accumulation of best strategy and buy and hold 0,1% transaction cost.
As noted before that while MA strategy manages to avoid market crash in 2008 it fails produce good results in bull market. Thanks to profit cap achieved in 2008 crash MA manages to beat buy and hold returns when examining the whole period as seen in graph 21.

![Image 3. MA strategies beating buy and hold returns, transaction costs 0,1%](image)

From Image 3 it can be seen which MA strategies would have produced excess returns compared to buy and hold strategy. Some relations can be found, increase in short MA allows wider range of MA strategies to beat buy and hold. As example with short MA 30 only strategies with long MA from 630 to 720 produced excess profit while with short MA 90 long MA ranges from 490 to 720. In total 199 MA strategies out of 1002 tested strategies could produce excess returns when compared to buy and hold. As such investor would have had around 20% chance to beat the market if strategy would have been picked randomly at the start of period.

In some settings transaction costs could be ignored. If investor would use these moving averages simply to gain insight on current market instead of actually trading the underlying asset it would be reasonable to exclude transaction costs. In cases like this
investor could monitor moving averages to gain additional support for investment decisions and as discussed above some moving average strategies seem to produce excessive returns which indicates that these tools can be used as indicators for current market movement.

Some previous research chooses to ignore transaction costs in their effort to find good MA strategies. However as illustrated in Graph 17 it can be clearly seen that transaction costs have immense effect on the viable strategies. Based on this information it is suggested that transaction costs should always be included when measuring profitability of the strategies.

5.2.4 Taxes
Making profit also leads to taxation. Taxation varies greatly among countries and form of operation also effects tax rates. Individuals typically pay capital income tax from profit but losses can be deducted from future profits. Companies pay corporate tax regardless of source of profit and can deduct several operating costs before applying of tax. These same problems regarding taxation are also true for buy and hold investors. For these reasons taxation is not taken in to consideration when examining transaction costs in this thesis.

5.2.5 Index transaction costs
While indexes typically do not have direct transaction costs instruments available for buy and hold investor wanting to invest in index does have some costs included. Passive index funds typically have very low expenses, SP500 vanguard which is typically redeemed as one of the lowest cost ETFs/instruments to invest n sp500 has expense ratio of 0,04% (Vanguard 2018b).

For smaller market such as Finnish stock exchange management fee is slightly higher. Selligson manages OMXH25 fund with management fee of 0,18% per annum. Recently 0% management fee was announced by Nordnet but as it has somewhat short history it cannot be guaranteed it will continue to be management free in the future (Nordnet 2018). Based on this evidence annual management fee is ignored for the index as its effect is only very marginal.
5.2.6 Liquidity

Helsinki is still rather small market place when considering worldwide markets. Trader implementing these strategies could possibly run into problems with insufficient liquidity. Illiquid market would cause additional transaction costs as trades would not get executed at wished levels. Indexes are also typically traded by central counter party such as fund managing the instrument or a bank. In case of market movement it could be possible that assumed liquidity is not available at all times causing further problems for trader. Modeling this possible illiquidity is not taken in to consideration in testing of this thesis as approximating it would be difficult and cause unnecessary estimation in the model. In case of real trading it is something that would need to be considered and looked out for.
6. Conclusions

Based on findings done on this thesis it could be concluded that moving average strategies are able to find and separate profitable and non-profitable moves from the white noise/random walk. To answer our research question: **Yes, moving average strategies can be used to gain excess returns compared to buy and hold strategy.** This conclusion can be reached as for all the best strategies results were statistically significant, buy and sell signals produced by the MA strategies varied from buy and hold returns making it possible to gain excess returns. However it should be noted that use of these strategies in the very high frequency environment such as used in this thesis, it is difficult to produce excess returns in the world where transaction costs also exists. As such as an answer to sub research question: **Yes, transaction costs have significant impact to profits.**

Advancement of the computers and availability of data expanding it could be said that technical analysis models are entering or have already entered new are and their use will be surely inspected more carefully in the near future. Machine based learning and access to big data in market movement can lead to big changes in trading and asset management in the future and technical analysis is most likely part of that. Machines can absorb data of the past and learn from it way faster than one person could ever in their lifetime. As such technical analysis provides interesting angle to future of trading which has been somewhat mystified in the past. Perhaps in the future most of the trading will be done by algorithms rather than humans whom are exposed to various biases.

6.1 Financial implications

While use of these strategies might not be profitable on their own it is clearly seen that these technical analysis tools provide some evidence on market direction in short time frame. As such they could be very well implemented along some other indicators to provide information to the trader looking for good time to exit and enter the market.
Especially during the bear market these strategies seem to provide excellent returns and as such could be implemented in to active trading when investors see it appropriate. Challenge of course rises when investor can determine market as bear market and start to employ these strategies. As markets have been climbing to new heights investor could use these moving averages in hedging purpose as in market downturn MA strategy losses are smaller compared to buy and hold. However would require investor to engage in active trading which can be seen odd for investor looking to get more conservative returns while limiting downside risk.

Wide use of technical analysis by the industry also implies that companies seem to have feeling that they can gain something from the use of these tools. This points out to direction that these tools are most likely effective in the daily use to some extent as it would make no sense to keep inefficient tools in use for decades.

If effective model could be created by some company or individual they could probably employ it to harness great returns. However it is totally possible that market could adjust to this new player if used in large scale making the profitability of such system complicated. This would favor the individual user as they have much smaller impact on the markets and it would be possible continue exploitation of these strategies for longer times.

Full utilization of these techniques would require very low transactions costs as they have heavy impact on returns and usable strategies. If institutional investors have access to low/nonexistent transaction costs it would certainly be possible for them to exploit strategies such as ones examined in this thesis. However this thesis has also outlined possible strategies which would be possible to use for individual investor exposed to higher transaction costs.
It should be also noted that techniques used in this thesis seemed to perform best during market downturn. Markets have been raising more or less constantly after last financial crisis in 2008 especially in the US and many investors have provided their concern on continuity of this bull market. As such use of moving averages could serve as indicator of possible down turn happening in the future providing some protection for investor against the market turns.

6.2 Further research topics

Dynamic model and variables used in creation of such a model should be further investigated as it can be seen that best strategies are changing based on current market situation. High interval data is not widely used in the research and similar studies could be performed in other markets as well. It would be interesting to see if there are differences in profitability of the market in more active and liquid markets such as US ones to see opportunities for profit making appear also in more advanced markets. Helsinki stock exchange is quite small one in the world scope and it could be speculated that it could offer more arbitrage opportunities as probably not as many big investment banks and other major players of the market put resources in the rather small Finnish market.

Data could be also used in framework of other strategies such as neural networks and other machine based learning systems. These system could possibly find strategies which cannot be found using moving averages. Neural network could find pattern in time of the day or weekday to execute deals in order to produce excess returns.

Data could also be further examined based on more finely tuned rules. Trading could be narrowed to smaller time windows such as excluding first hour of market open as it seems most radical movements in the market seem to happen right at start of market as Helsinki stock exchange adjust to changes in the USs stock market or other major political news (such as Brexit or Greece’s debt crisis). Weekdays could also be isolated to see if it makes any difference as some studies have found evidence on variance in market returns based on weekday. Other moving average strategies could also be implemented such as ribbon and Moving average convergence divergence (MACD).
This research has attempted to shed more light to widely debated technical analysis debate still going on. However these tools are widely used in investment banking world which implies that they have some value to their users. This could also be due to fact that when everyone uses them it becomes self-fulfilling fallacy and everyone wants to have as many indicators available as possible as competitors are possibly also using them. As computation power keeps increasing and analysis techniques become more and more complex such as neural networks it is possible that in the future markets are dominated by machined based trading systems trained based on all available historical data.
References


Nasdaq (2018) Overview of OMXH25
https://indexes.nasdaqomx.com/Index/Overview/OMXH25

https://www.nordnet.fi/kampanjat/superrahasto-suomi.html


Roberts S. W. (1959) Control Chart Tests Based on Geometric Moving Averages, Technometrics, 1:3, 239-250


https://www.sec.gov/fast-answers/answersdaytradinghtm.html


