



**UNIVERSITA' DEGLI STUDI DI PADOVA**

**DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI  
"M.FANNO"**

**CORSO DI LAUREA MAGISTRALE IN ECONOMIA E FINANZA -  
ECONOMICS AND FINANCE**

**TESI DI LAUREA**

**"Trading strategies based on moving averages: an empirical application  
with high frequency data"**

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**ANNO ACCADEMICO 2015 – 2016**

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## **Acknowledgments**

Foremost I would like to express my sincere gratitude to my advisor, Prof. Massimiliano Caporin, for his continuous support and availability. His guidance helped me during the writing of this thesis.

Next I would like to thank my family, for all the support and sacrifices they made for me, my mother, my brother and Ina. In particular, this thesis, and all my achievements are dedicated to the most special person, my dad, who is no longer with me for many years now, but I know he is always watching over me. Hoping he would be proud of every choice I made.

Finally, I would like to thank all my friends for the support and patience they have shown to me during the writing of this thesis, I could not have made it without them.

## **Abstract**

Many empirical studies have investigated the profitability of trading strategies based on the technical analysis. Some of them find these strategies profitable while others do not, and this issue is still a topic of debate. In this study I try to test the profitability of trading strategies based on moving averages applied to high frequency data. I build my trading strategies using price data of 1-second intervals. The strategies mainly yield positive returns when transaction costs are not considered. When I account for transaction costs the strategies do not generate positive returns, the presence of transaction costs drives away the profitability.

## Table of contents

	Page
<b>Introduction</b> .....	1
<b>Background Information</b> .....	3
Technical analysis definition and development .....	3
The nature and instruments of technical analysis .....	5
<b>Literature Review</b> .....	15
Main studies that support the profitability of the technical analysis .....	15
Efficient Market Hypothesis .....	31
<b>Data and Methodology</b> .....	45
Data used .....	45
Model description .....	46
<b>Empirical Results</b> .....	55
Strategy results .....	55
Comparisons among strategies .....	62
Regression analysis .....	71
<b>Conclusions</b> .....	93
<b>References</b> .....	97
<b>Tables and Figures</b> .....	101
<b>Appendix</b> .....	103

## 1. Introduction

Technical analysis has been widely used in the stock market since the early 1900s. What has been and still remain long-debated is its profitability. The predictive power of the technical analysis has always been questioned by the academics since it contradicts the Efficient Markets Hypothesis. This theory first developed by Fama (1970) suggests that, prices represent all the available information, hence it is not possible to predict future movements in prices.

Even though, this contradiction, the technical analysis has always been present in financial markets, and there are a number of studies that support its profitability (see for example Brock Lakonishok and LeBaron, 1992; Blume, Easley and O'Hara 1994; Gencay 1998; Lo, Mamaysky and Wang 2000; Hsu and Kuan 2005)

Except the studies mentioned above, many other studies all based on daily data such as Sullivan, Timmerman and White (1999) find that the profitability of the technical analysis has declined and ceased to exist in the stock market in the recent years.

My study contributes to the literature since differently from most studies based on daily data, I try to test the profitability of the technical analysis, constructing trading strategies based on high frequency data. Market nowadays have become more efficient, and information about stock prices is not available only for daily intervals, but also for one-minute or even one-second intervals.

In this study I use moving averages as an instrument to construct intra-day trading strategies. I use different moving averages to construct different trading strategies. Each strategy is composed by a short term and a long term moving average, the pairs of moving averages used are the following: (5,200), (50,150), (5,150), (5,100), (50,100). The data I use are the price data for every second of the Intel for a period from September 28<sup>th</sup> 2009, to June 9<sup>th</sup> 2015. The position of the short term moving average with respect to the long term moving average determines whether the trader should take a long or short position. All positions are closed at the end of the day; none is carried over night.

The main purpose of this study is to determine whether there is some predictability present in the high frequency price data, a predictability that could be exploited to generate positive returns. The results of this study show mainly positive returns for all the strategies mentioned above when transaction costs are not considered. I also include the impact of transaction costs in this study, and what the results show is that the moving averages strategies lose their

profitability once transaction costs are taken into account. It can be said that, even though there is some predictability in stock prices I am not able to profit from it once transaction costs are considered.

The paper is organized in the following way: Section 2 presents some background information on the technical analysis and its instruments; Section 3 reviews the relevant literature, where the main studies that support or contradict the profitability of the technical analysis are presented; Section 4 describes the data used by the study and defines the model constructed for the trading strategies; Section 5 presents the main empirical results obtained and compares the results among different strategies. Also in this section I run a regression analysis in order to understand the relation between the daily returns of the strategies and the other variables produced by the model; Section 6 summarizes the main conclusions of this paper.

## **2. Background Information**

### **2.1 Technical analysis definition and development**

Technical analysis is the term used to describe the study of patterns in historical stock market series generated by day-to-day market activities, with the purpose to forecast future market movements. It is considered one of the primary investment analysis tools, and it has been an important part of the financial practice since the 1800s.

This type of analysis has a long history and dates back to the Japanese rice traders trading on the Dojima Rice Exchange in Osaka as early as the 1600s. It evolved into chartism in the early 20th century with mechanical trading rules to generate signals. This development has since been aided by the introduction of electronics which took the tedium out of complex mathematical manipulations. As computers have become more powerful and their use more widespread, analysts have begun to combine fundamental economic data with the more traditional price and volume data to produce new indicators.

The key information that technical analysis uses is volume and price. Technical traders base their analysis on the assumption that patterns in the market prices will recur in the future, and thus, these patterns can be used for forecasting purposes. The motivation of the technical analysis is the ability to identify changes in trends at the first stage and to construct an investment strategy until evidence shows a reversion of the trend.

It uses only historical data, usually consisting of only past prices but sometimes also includes volume, to determine future movements in financial asset prices. This method of forecasting is commonly used by foreign exchange dealers, who are mostly interested in the short term movements of currencies. However, technical analysis is also used to forecast share prices. A survey by Carter R. B., Van Auken H. E. (1990) reveals that investment analysts consider technical analysis as an important tool for forecasting the returns to different classes of assets.

In fact, depending on the trading horizon, between 12.8 and 40.8 per cent of foreign currency exchange traders in Hong Kong, Tokyo, and Singapore use technical indicators as the basis of their trades (Cheung and Wong, 2000). Also, technical analysis is used as the primary or secondary source of information for approximately 90 per cent of traders in London, while 60 per cent of these traders also hold technical analysis as at least as important as fundamental analysis (Allen and Taylor, 1992).

In a study by Menkhoff (2010) he analyzes survey evidence from 692 fund managers in five different countries including US and finds that 87% of fund managers use technical analysis to

some extent, with a range between the five countries of 68% to 94%. The study also shows that the technical analysis is mostly used to complement the fundamental analysis, although when referring to forecasting horizons technical analysis is the main instrument in decision making for short-term time periods.

On the other hand, as recent studies show the use of the technical analysis goes beyond the simple mean of short-term trading as Zhu and Zhou (2009) offer theoretical reasons for an investor to use technical analysis in a simple asset allocation problem and also show that it adds value to allocation methods that invest fixed proportions of wealth in equities.

Basically all the studies mentioned above believe that technical analysis generates profits because of market inefficiency. With markets being inefficient traders could find opportunities to exploit in order to make profits. This belief is in contradiction with the Efficient Market Hypothesis developed by Fama (1970), which assumes that markets are efficient and all the available information is included in the prices, making it impossible to generate profits on the basis of this information. The main models that support the Efficient Market Hypothesis are the martingale model and the random walk model, which will be explained later in the third section.

There are on the other hand a lot who believe that the technical analysis is profitable for other reasons. One of these reasons can be found in the field of behavioral finance, which suggests that investors may not be completely rational and that their psychological biases could cause prices to diverge from the 'right' level (e.g., DeBondt and Thaler (1985), and Barberis, Shleifer and Vishny (1998)). In that case speculators will not trade only on the basis of the pure economical fundamentals, but will also aim to exploit market movements generated by less sophisticated, 'noise traders'.

Technical analysis is based on three main assumptions, which are are described below.

1. The market discounts everything. A major criticism of technical analysis is that it only considers price movement, ignoring the fundamental factors of the company. However, technical analysis assumes that, at any given time, a stock's price reflects everything that has or could affect the company - including fundamental factors. As such, there is no need to study each factor individually, but instead just need to focus on the price movements only.

2. Prices tend to move in trends In technical analysis, price movements are believed to follow trends. This means that after a trend has been established, the future price movement is more likely to be in the same direction as the trend than to be against it. Most technical trading strategies are based on this assumption.
3. History repeats itself The price patterns tend to repeat, offering investors a possible prediction of where prices might be heading. The repetitive nature of price movements is attributed to market psychology; in other words, market participants tend to provide a consistent reaction to similar market stimuli over time. Technical analysis uses chart patterns to analyze market movements and understand trends. Although many of these charts have been used for more than 100 years, they are still believed to be relevant because they illustrate patterns in price movements that often repeat themselves.

## **2.2 The nature and instruments of technical analysis**

Technical analysis or, as it is also sometimes called, “chartist analysis,” is a set of techniques for deriving forecasts of financial prices exclusively by analyzing the history of the particular price series plus perhaps transactions volumes. This analysis can be performed in a qualitative form, relying mainly on the analysis of charts of past price behavior and loose inductive reasoning, or it can be strictly quantitative, by constructing trading signals or forecasts through a quantitative analysis of time series data. In practice, technical analysts often employ a combination of both qualitative and quantitative techniques.

The more widely used quantitative forms of technical analysis generally involve methods such as filter rules, moving average rules and oscillators. All these methods mentioned will be described briefly in the following pages.

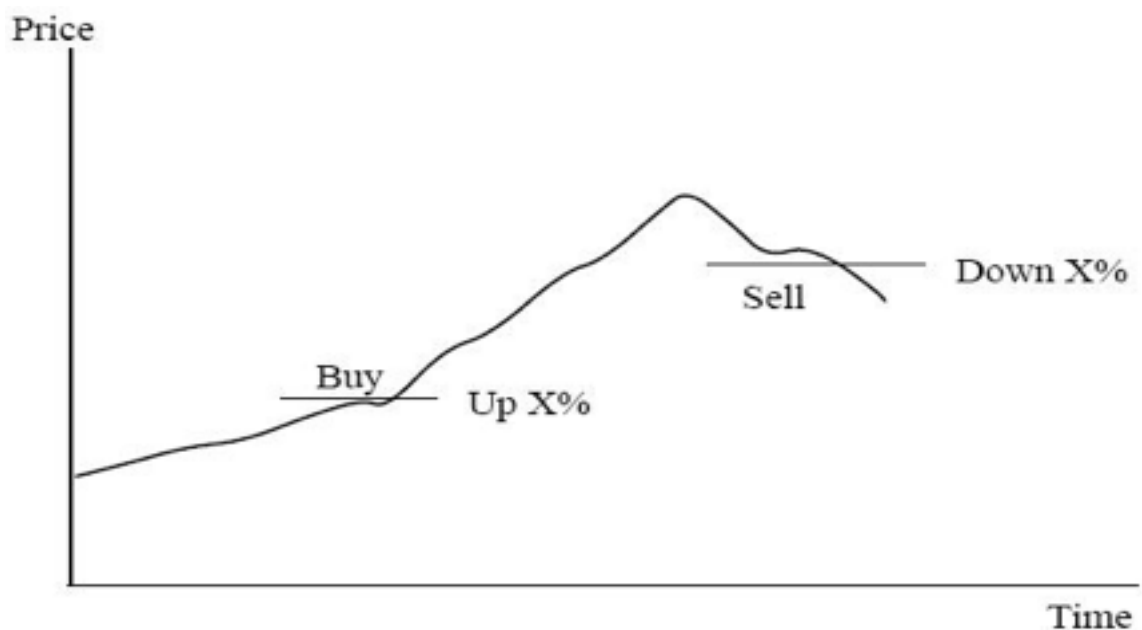
### *Filter rules*

The filter rule represents a trading strategy where technical analysts defines certain rules for when to buy and sell securities, based on the amount of percentage changes in price from previous lows and highs. It is based on a certainty in price momentum, or the idea that increasing prices tend to continue to increase and decreasing prices tend to continue to decrease. One of the most notable uses of filter rules is by Sidney S. Alexander (1961). His filter technique is a simple trading rule which tries to apply improved criteria in identifying price movements. An x per cent filter is described as follows: If the daily closing price of a certain

stock moves up by at least  $x$  per cent, take a long position and hold the position until the price goes down by  $x$  per cent from the previous high, which in this moment close the long position and at the same time take a short position. The short position is maintained until the daily closing price increases by at least  $x$  per cent above the previous low and at this moment one cover the short position and goes long.

The graph below shows an example of filter rules, where the buy line represents an increase of  $x\%$  of the daily closing price and the sell line represents a decrease of again  $x\%$  of the daily closing price of the stock.

Fig.1 Filter rules graph



Source: [www.finance-trading-times.com](http://www.finance-trading-times.com)

### *Moving average rules*

The moving average represents the average of a certain quantity of prices. If you want to calculate the moving average of 20 prices, you sum the last 20 prices and divide it by 20. The term “moving” is referred to indicate the fact that the average is calculated in the last 20 prices, so the block on which the average is calculated moves by 1 each time. There are different types of moving averages explained below.

First one can distinguish between the simple moving average and the exponentially weighted moving average. The simple moving average gives an equal weight to every price, meanwhile the exponentially weighted moving average gives more weight to the last prices, also the exponentially weighted moving average includes all prices differently from the simple moving

average. The simple moving average is the easiest and the most used one, but the exponentially weighted one is more sophisticated and reliable though is more complicated to calculate.

Moving averages can be used to create different trading strategies. Below I am going to analyze the moving average crossover and the Bollinger bands.

*The moving average crossover* is a strategy built by using two moving averages, one short term and the other of a longer term. The short term moving average is more sensitive to price changes while the long term one is more smoothed out. How are buy/sell signals generated through this strategy? The buy signal is generated when the short term moving average is above the long term one, meaning that the recent price level is above the long term price level which suggests that there is an upward trend. On the contrary the sell signal is generated when the short term moving average is below the long term one, in this case the trader should take a short position.

Below there is a graph that shows the dual moving average crossover and a summary of how the rule works.

STMA > LTMA    s = 1 (buy signal)

STMA < LTMA    s = -1 (sell signal)

Fig. 2 A simple moving average crossover



*The Bollinger bands* are a powerful instrument used by many traders. The Bollinger bands are composed by 3 different bands: the upper band, the middle and the lower one. Firstly, I construct the middle band which is basically a moving average of a certain smoothing period. Then the upper and the lower bands are constructed as plus/minus two standard deviations from the middle band.

Upper Band = Middle Band + 2 standard deviations

Middle Band = Moving average of n periods

Lower Band = Middle Band - 2 standard deviations

The trading strategies using Bollinger bands are simple. When the price level crosses and goes above the upper band this represents the start of an uptrend and the trader takes a long position, meanwhile when the prices level goes below the lower band the trader takes a short positions selling the security.

Another strategy that could be adopted is the contrarian strategy, traders believing that the price level will decrease after it goes above the upper band consider this moment as a sell signal and take a short position. On the contrary when the prices level goes below the lower band the contrarian trader takes a long position. The graph below shows an example of Bollinger bands.

Fig. 3 Bollinger bands



Source: [www.bollingerbands.com](http://www.bollingerbands.com)

Another way to use the Bollinger bands is to construct two upper bands and two lower bands, plus/minus one standard deviations and plus/minus two standard deviations respectively. In this case when the price level is between the interval of plus/minus one standard deviation from the middle band the trader takes no positions.

The trader takes a long position when the price level goes above the band that is two standard deviations above the middle band, and goes short when the price level is below the band that is two standard deviations below the middle band. Also in this example the contrary trading could be applied taking opposite positions with respect to the strategy described above. The graph below shows an example of Bollinger bands with four bands.

Fig. 4 Bollinger bands channels



Source: FXtrek Intellicharts

## *Oscillators*

Oscillators are indicators used in the technical analysis as a source of additional information. They are extremely useful especially in markets without a defined trend, where the price level moves horizontally, they are also used in markets with well-defined trends to determine situations of over-bought or over-sold.

They provide information useful to identify momentum, volatility, trends and other aspects of a security. The momentum of a market is identified by recording the persistent price variations on a predetermined time range. To construct a momentum line of 10 days one needs to subtract from the last closing price the closing price of ten days before.

$$M = V - V_x$$

where:

V = last closing price

$V_x$  = closing price of 10 days before

Oscillators have a range of values for example between 0 and 100, but also could be between -1 and +1 depending on how the oscillator is calculated. Below I am going to describe some of the most used oscillators.

### *The moving average convergence divergence (MACD)*

The moving average convergence divergence is one of the most used indicators. It is used to identify and measure momentum in a security. The MACD is composed by two exponential moving averages and is equal to the difference of these moving averages with respect to a centerline. The centerline is a point where both moving averages are equal. What is obtained, is two moving averages moving between the zero line.

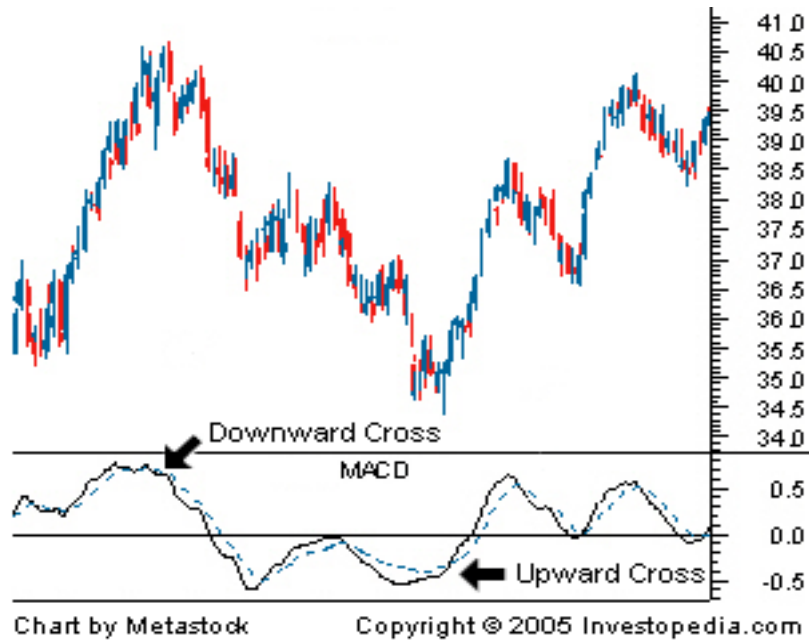
MACD = short term moving average – long term moving average.

In this way, I get a buy signal when the short term moving average crosses from below and goes above the long term moving average, basically when the difference expressed above becomes positive.

On the contrary when the opposite happens I get a sell signal and the trader should take a short position.

The figure below shows the estimation of the MACD on the daily prices graph.

Fig. 5 MACD



*The relative strength index (RSI)*

The relative strength index is also one of the most used indicators. The RSI is used to better identify and understand the over-bought or over-sold positions. There has been confusion between the RSI and the relative strength term which measures two different entities. The RSI take a range of values from 0 to 100 and is calculated as following:

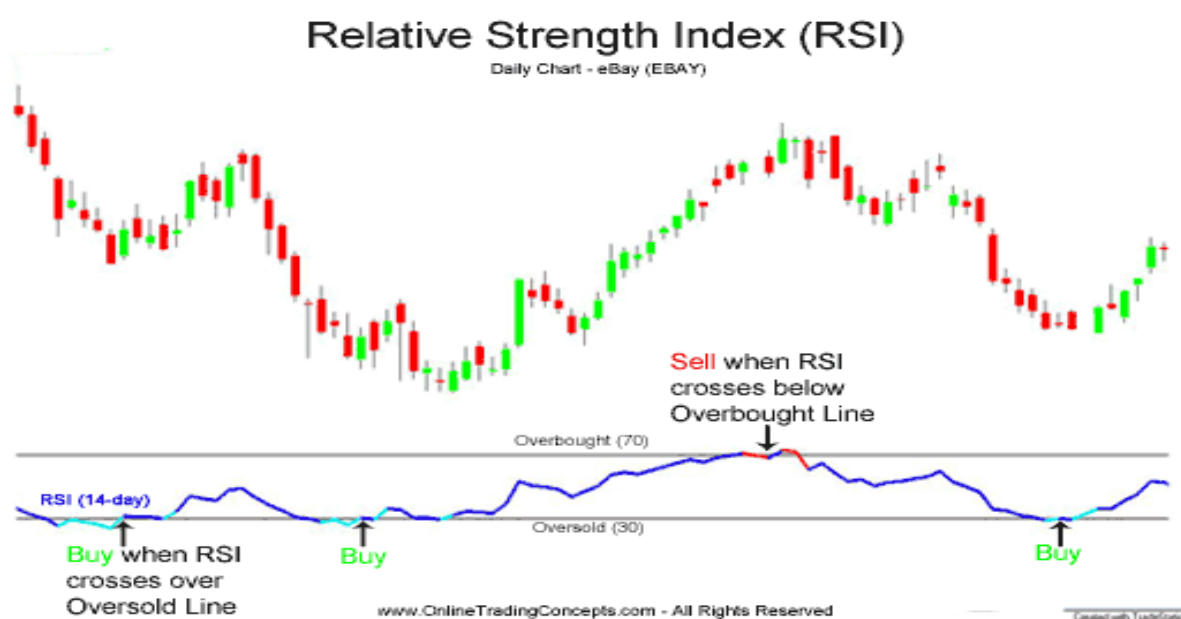
$$RSI = 100 - \left\{ \frac{100}{1+RS} \right\}$$

where:

$$RS = \frac{(the\ average\ of\ increasing\ closing\ prices\ for\ x\ days)}{(the\ average\ of\ decreasing\ closing\ prices\ for\ x\ days)}$$

As can be seen also by the formula used to calculate the RSI, it takes values in the interval [0,100], and the over-bought position is indicated by the level 70, meanwhile the over-sold level is determined at 30. Some other traders use the values 80 and 20 to identify over-bought or over-sold positions. The midrange is 50 which is used as a support or resistance benchmark. The trader gets a buy signal when the RSI line is below the over-sold line and gets a sell signal when the RSI line is above the over-bought line. The figure below shows the 14 days RSI line constructed on the daily price data of eBay.

Fig. 6 RSI example



Source: [www.onlinetradingconcepts.com](http://www.onlinetradingconcepts.com)

The RSI works best when compared to a short-term moving average crossover. If there are used two moving averages of different lag periods one will see that the crossovers of these moving averages will happen close to the 70/30 level or the 80/20 level depending on which levels, the the over-bought and over-sold lines are established. Simply said the RSI can forecast earlier the reversal of a trend either upwards or downwards.

### *The Stochastic Oscillator*

The stochastic oscillator is as well one of the most used oscillators. The main concept of this indicator is that in an uptrend prices should close at the highs of the price range, meanwhile in

a downtrend prices should close near the lows of the price range signaling upward and downward momentum respectively.

This indicator basically uses two lines, the %K and the %D, where the %D is the most important line since it gives more precise signals. The %K is calculated as follows:

$$\%K = 100 \left[ \frac{(C-L5)}{(H5-L5)} \right]$$

where:

C = last closing price

L5 = lowest closing price in the last 5 days

H5 = highest closing price in the last 5 days

This line takes values from 0 to 100 and measures the relation between the closing price and price range of a given number of days.

The %D line which is simply a moving average of the %K is calculated as follows:

$$\%D = 100 \times \left( \frac{H3}{L3} \right)$$

where:

H3 = the sum of 3 days of (C – L5)

L3 = the sum of 3 days of (H5 – L5)

As mentioned above the stochastic oscillator is plotted in the range 0 to 100 and signals over-bought situation at the level above 70, and over-sold situation at the level below 30. The best buy signal is generated when the line is at the interval 10-15, the best sell signal on the other side is generated at the level 85-90.

The stochastic oscillator can be used in long-term graphs as weekly or monthly charts, as it is recommended by its creator, but it can also be used in intra-day charts for short-term trading operations.



### 3. LITERATURE REVIEW

#### 3.1 Main studies that support the profitability of the technical analysis

Below I am going to analyze the main academic papers and studies that provide positive results for the profitability of technical analysis trading rules. Following different empirical studies, the models used and the results of each study are described.

**Brock W., Lakonishok J., LeBaron B (1992)** in their paper “Simple technical trading rules and the stochastic properties of stock return” analyze the trading returns generated by two simple trading rules on the Dow Jones Index data from 1897 to 1986.

*Data used:* As mentioned above the data used by this study is a 90 years daily data of the Dow Jones Industrial Average (DIJA). As the authors say all the stocks on the DIJA index are actively traded and so there are no concerns related with nonsynchronous trading of the stocks.

The results of the study are also presented in four different subsamples, which represent different time periods: World War I, Great Depression period, World War II and the last subsamples has data from June 1962 when the Center for Research in Securities begins its daily price series.

*Trading rules:* In this study the authors chose to test two simple trading rules: moving average crossover and the trading range break-out (resistance and support levels). As the authors say the idea behind using moving averages is to smooth out an otherwise volatile series. The moving average rule is composed by two moving averages, one of short term and the other long term. The buy (sell) signal is generated when the short term moving average is above (below) the long term one. This study considers five variations of this rule which are: 1-50, 1-150, 5-150, 1-200, and 2-200. The authors introduce also a one percent band around the moving average which reduces the number of buy and sell signals.

The first rule they consider is the variable length moving average (VMA) which works as follows: it gives a buy (sell) signal when the short term moving average is above (below) the long term moving average by an amount larger than the one percent band. If the short term moving average is inside the band, then no signal is generated. Another variation of the moving average crossover rule that is considered by the authors is the fixed length moving average (FMA) which generates a buy (sell) signal when the short term moving average cuts the long

moving average from below (above). The return of the next ten days is then recorded, and other signals generated in this ten-day period are not taken into account.

The last technical rule the study considers is the trading range break out. This rule generates a buy signal when the price penetrates the resistance level, which represents the local maximum. It is believed by the technical analysts that traders will sell at the peak, so the selling pressure will cause resistance to an increase in price. If the price goes above the previous peak it has broken the resistance level and it is considered a buy signal. With the same logic the authors explain how the sell signal is generated when the price penetrates the support level which represents the local minimum.

*Results of the study:* The results of this study on the first rule (VMA) are presented on a table composed by different columns, where each column represents the rule applied, the mean return of the buy days, the mean return of sell days, and the difference between these two. The VMA rule is composed by 10 rules since there are 5 different moving averages with and without the one percent band. The results are remarkable.

All the buy-sell differences are positive and the t-statistic for these differences is highly significant. For each rule the addition of the one percent band increases the spread between the buy and sell. The buy returns are all positive with a mean of 0.042 percent of daily return, which corresponds to a 12 percent of annual return rate. On the other side all sell returns are negative with a mean of -0.025 of daily return, which corresponds to a -7 percent of annual return rate. Six tests reject the null hypothesis of the returns being equal to the unconditional returns. Another thing to notice is that there are around 50 percent more buy signals than sell signals, which is persistent with the upward trend.

The results of each rule are then presented for each sub-period and the authors found no evidence of results being different across the sub-periods.

The second moving average rule (FMA) analyzes a ten day holding period after the crossover of the moving average. As in the first rule also in this case the introduction of the one percent band increases the difference between the buy and the sell return.

For all the tests the difference between the buy and sell are positive, and the mean difference is 0.77 percent while with the one percent band the mean difference is 1.09 percent. Both results are significantly different from the unconditional mean which is equal to 0.17 percent. Seven out of ten test reject the null hypothesis of the returns being equal to the unconditional return, and the remaining 3 tests are only marginally significant the authors find out.

The last rule the authors consider is the Trading range breakout (TRB) which gives buy or sell signals when the price level moves above or below the local maximum or minimum. The local maximum and minimum are calculated by the authors over the previous 50, 150 and 200 days. Also the one percent band is added to these rules, so for example the price level must exceed the local maximum by one percent in order for a buy signal to be generated. For the TRB the authors calculate the ten day holding period returns.

The results of these rules show positive buy-sell differences with an average of 0.86 percent. All the six tests reject the null hypothesis of the difference between the buy-sell return and the unconditional 10-day return being equal to zero. The buy return is positive for all rules with an average of 0.55 percent, and for three out of six rules the buy return is significantly different from the unconditional 10-day return, while for the other three rules is only marginally significant. The sell returns are negative across all rules with an average of -0.24 percent.

The authors after obtaining these results apply the bootstrap method introduced by Efron (1979), which is a resampling procedure for estimating the distribution of statistics based on independent observations. Several issues regarding stock returns distributions such as: leptokurtosis, autocorrelation, conditional heteroskedasticity, and changing conditional mean are addressed using this methodology (Brock, Lakonishok, LeBaron 1992). The returns produced by the buy (sell) signals using the raw Dow Jones data are compared to conditional returns produced by the simulated series. In this study the models used to generate the representative price series are the following: a random walk with a drift, an autoregressive process of order one (AR(1)), a generalized autoregressive conditional heteroskedasticity in mean model (GARCH-M), and the Exponential GARCH (EGARCH). When the returns from the actual Dow Jones series are compared to returns from the simulated series, the results provide strong support for the technical trading strategies. The returns obtained from the buy (sell) signals are not likely to be generated by any of the four popular null models (Brock, Lakonishok, LeBaron 1992). The small positive autocorrelation observed in returns is not enough, as it explains only 10 percent of the difference between the buy and sell returns. The GARCH-M model also cannot explain the returns that are generated by the different rules applied by the authors of the paper, and also is not able to predict volatility. EGARCH model also shows similar problems as the GARCH-M, and although it performs better it fails to predict volatility in sell periods. The main conclusion the authors draw is that their results are persistent with the technical analysis having a predictive ability.

**Gunasekarage A., Power D. M. (2001)** in their paper “The profitability of moving average trading rules in the South Asian stock markets” test the profitability of the simple moving average trading rules using data from four emerging countries of South Asia, in particular they analyze data from Bangladesh, India, Pakistan and Sri Lanka over a period of 10 years from January 1990 to March 2000.

This study is of particular interest for different reason explained as follows. First it’s one of the first study that conduct research on the above mentioned markets data. Second, there is a large variety of exchanges inside the sample of the four different countries. Third, as the authors point out the four stock market are considered emerging and represent an important source of financing for the companies. Last it can be said that this study is important since it applies the same trading rules applied on developed stock market data, and its results contribute on the controversial debate on the profitability of technical analysis. Analyzing this paper is also interesting because it tests the same technical trading rules as those used by Brock et. al. (1992), so the results provided by this paper can be compared to the ones by the previous paper I analyzed.

Data on four market indices used in this study are: (I) the Bombay Stock Exchange National Index of Equity Prices (BSENAT); (II) the Colombo Stock Exchange All Share Price Index (CSEALL); (III) the Dhaka Stock Exchange All Share Price Index (DSEALL); and (IV) the Karachi Stock Exchange 100 Index (KSE100). BSENAT is composed using a ‘weighted aggregates’ method employing information for 100 equity shares from five major Indian stock exchanges (Mumbai, Calcutta, Delhi, Ahmedabad and Madras) on the basis of market activity, industry representation and trading activity on exchanges (Gunasekarage A., Power D. M. 2001). The other indices CSEALL and DSEALL are comprehensive indices that record the movements of all the securities being traded on the corresponding markets, while KSE100 is an index that comprises the largest 100 companies in the exchange (27 companies representing 27 sectors and 73 companies representing the entire market) and it is measured on a value-weighted basis.

The trading rules applied as I mentioned earlier are the same as in Brock et. al. (1992), meaning the different types of moving averages strategies with and without the one percent band. The moving average strategies are each applied for every rule: the variable length moving average rule (VMA), and the fixed length moving average rule (FMA). Each of these rules are described in the previous paper so they will not be described here also.

The sample statistic the author conduct on the data show that the index that performed the best was BSENAT, while the index that performed more poorly was the DSEALL which was also

associated with high risk. Other information on the data the authors found out was that the returns on the four markets did not follow a normal distribution, all of them were strongly leptokurtic, and three of these markets showed positive skewness. Also the one-day returns and the ten-day returns showed high dependence, with most of autocorrelations being positive at a level that was significantly different from zero.

Next the results of the VMA rules are analyzed. The buy returns for every market is positive, while the sell return for each market is negative. Most of these buy and sell returns are significantly different from the returns of a simple buy and hold strategy. The number of buy signals is slightly higher than the number of sell signals for the KSE100 and BSEAT, while the number of sell signals is higher than the number of buy ones for DSEALL and CSEALL.

The average one-day (annual) buy return for all the VMA strategies on these markets are: BSEAT 0.21% (54.60%), CSEALL 0.17% (44.20%), DSEALL 0.21% (54.60%), and KSE100 0.17% (44.22%). The average one-day (annual) sell returns are: BSEAT -0.14% (-36.40%), CSEALL -0.12% (-31.20%), DSEALL -0.16% (-41.60%) and KSE100 -0.08% (-20.80%). These results clearly reject the null hypothesis that the returns to be earned from VLMA rules are equal to those from a naive buy and hold strategy and thus offer degrees of predictive ability in South Asian markets (Gunasekarage A., Power D. M. 2001). The fact that the null hypothesis is rejected for all four countries provides evidence that any market inefficiency is not specific to one size or age of market studied. One thing to notice is that different strategies provide different results, so the selection of the short term moving average, the long term moving average and the one-percent or more band could increase profitability. Another interesting result the authors point out is that the strategies with the bandwidth of one percent are the most profitable one, presumably because it generates less signals.

Now I see the results the study provides on the fixed length moving average rules. All the buy-sell differences are positive for each of the markets except for DSEALL where two of them are negative: (1,150,0) and (2,150,0) rules achieved returns of -0.0051 and -0.0045, respectively, for the Dhaka all. The average 10-day buy sell returns across nine strategies are 1.61 (-0.64%) for BSEAT, 1.98 (-2.19%) for CSEALL, 0.43 (-1.23%) for DSEALL and 2.93 (-1.49%) for KSE100. On an annualized basis these indices generated the following average buy sell returns for FLMA rules: 41.86 (-16.64%) for BSEAT, 51.48 (-56.94%) for CSEALL, 11.18 (-31.98%) for DSEALL and 62.14 (-38.74%) for KSE100. It is important to notice that most of these average buy and sell returns are significantly different from the performance achieved by the simple buy-hold strategy. However, as the authors observed, when individual strategies are tested most of the buy and sell returns did not differ significantly from their 10-day

unconditional counterparts. Another evident result is that for all the markets the number of buy and sell signals is far less than the signals produced by the VMA rule and these signals are evenly distributed across the nine strategies for the four countries examined. The smaller number of signals for the FLMA rules actually generated higher profits, on average, than their VLMA counterparts, the authors say.

Overall the results of this study agree with the ones from the previous paper analyzed of Brock et. al. (1992). The main conclusion that come up in this study is that technical trading rules have predictive power over the South Asian markets. Buy signals generate positive returns, sell signals generate negative returns, and both are significantly different from the returns generated by a simple buy and hold strategy.

This study differs from the previous study in two aspects. First, in the previous paper is seen evidence of an upward trend in the market, where the number of buy signals were higher than the number of sell signals, in this paper though the number of buy signals is not significantly higher than the number of sell signals. Second, the previous study suggests that long periods are needed to expose predictive abilities, while in this paper the authors show that short periods may also be useful for detecting forecast abilities of technical rules.

In an attempt to examine the ability to earn excess returns by exploiting these predictable patterns, the authors compared the average annual return on FLMA (1,50,0) strategy with the annual return generated by the simple strategy of buying and holding the market index. These findings indicated that the technical trading rules generate returns in excess of the average market for the investors in CSEALL, DSEALL and KSE100. The Indian market underperformed this strategy while the other three did not, probably because India is the largest market in the region, with the largest number of foreign investors and therefore possibly the most efficient one in the region (Gunasekarage A., Power D. M. 2001).

**Hsu P.-H., Kuan C.-M. (2005)** in their paper “Re-Examining the Profitability of Technical Analysis with White’s Reality Check” re-examine the profitability of technical analysis using the White’s Reality Check, which adjusts the data snooping bias.

This study considers a larger sample of trading techniques including not only simple technical trading rules but also investor’s strategy, and tests the profitability of these strategies applied to four main indices. The four indices chosen are the NASDAQ Composite, S&P500, DIJA and Russell 2000. In this paper White’s Reality Check is applied to a large variety of 39, 832 simple trading rules, “contrarian” rules, and investor’s strategies.

Data snooping is a very common issue in empirical economic studies. As known, that economic activities in the real world are not experimental in nature, so researchers often, have no choice but to count on the same data set. In the literature, there are essentially two different approaches to deal with the data snooping bias. The first approach focuses on data and tries to avoid re-using the same data set. This may be done by testing a model with a different but comparable data set; see e.g., Lakonishok, Shleifer, and Vishny (1994) and Chan, Karceski, and Lakonishok (1998). When such data are not available, a large data set can be used in order to test the model using different subsamples; see e.g., Brock, Lakonishok, and LeBaron (1992), Rouwenhorst (1998, 1999), and Gencay (1998). Such sample division is, however, kind of arbitrary and hence may lack desired objectivity.

A more formal approach, the authors say, is to consider all possible models and construct a test with properly controlled test size (type I error). Lakonishok and Smidt (1988) suggested using the Bonferroni inequality to bound the size of each individual test, but this method is not appropriate when the number of hypotheses being tested is large, as in the case of testing the profitability of technical analysis. The Reality Check proposed by White (2000) follows the latter approach but does not suffer from this problem.

In this study the authors test a large sample of 39,832 rules and strategies, of which 18,326 simple trading rules, 18,326 corresponding contrarian rules, and 3,180 investor's strategies.

The simple trading rules studied in this paper are divided in 12 classes, which are the following: filter rules (FR), moving averages (MA), support and resistance (SR), channel break-outs (CB), on-balance volume averages (OBV), momentum strategies in price (MSP), momentum strategies in volume (MSV), rectangle (RA), head and shoulders (HS), triangle (TA), broadening tops and bottoms (BTB), double tops and bottoms (DTB).

As regards the contrarian rules, each of them corresponds to the simple trading rules, but a buy signal on the simple trading rules suggests taking a short position and the contrary. Contrarian traders believe that signals of some trading rules are caused by prices moving too far from their current state, and thus suggesting a change in the trend.

Next I see the investor's strategies applied in this paper. These strategies, which amount to a total of 3,180, are divided in three classes as follows: learning strategies (LS), vote strategies (VS), and position changeable strategies (PCS).

The strategies of the LS class give the investor's the possibility to switch position following the best-performing rule from a class of rules. In the LS class there are 1,404 strategies. The VS class strategies as the authors say are based on the 'voting' results of the trading rules in a

rule class, where each rule has one vote based on its suggested position. The strategies of the PCS class are different from those in the VS and LS class since they allow for non-integral positions. In this study the authors use the voting results of the VS class as an evaluation index to determine how a position can be divided.

In this study the rules described previously are applied to the four main indices mentioned above. The authors' analysis is based on the daily returns computed using daily closing prices of the indices. The daily index data are the data from 1989 to 2002, where the data from 1990 to 2000 represents the in-sample period, and the 2001 and 2002 are saved for the out-of-sample evaluation.

In their next step the authors apply the White's Reality Check to the rules and strategies of their large sample based on two performance measures: average return and Sharpe ratio. The significance level of the reality check applied in this study is one percent.

The authors first find out that for data from 1990 to 2000 profitable trading rules and strategies exist for NASDAQ Composite and Russell 2000, but not for S&P500 and DIJA. The best rules, as the authors find out, for DIJA and S&P500 are a momentum strategy in volume and a contrarian rule on the OBV class, respectively. None of these rules however has statistically significant returns based on the p-values of the Reality Check.

As regards the two other indices the best performing rules in terms of mean return are, for the NASDAQ Composite the two day moving average with a one percent band, and for the Russell 2000 the two day moving average without the band. Both of these rules generate returns that are statistically significant at the one percent level. When considering the Sharpe ratio, the best performing rule for both NASDAQ Composite and Russell 2000 is the two day moving average with the one percent band.

The authors also summarize the rules and strategies that yield significant mean returns, and observe some facts presented as follows on their paper. First fact they present is that, most profitable rules for NASDAQ Composite and Russell 2000 are based on filter rules and moving averages rules. Second observation is that the authors find none of the contrarian strategies significantly profitable. Third observation is that there are much more profitable investor's strategies than simple rules. The last observation the authors make is an interesting one, they find out that there exist profitable strategies based on non-profitable simple rules.

Next on their study, the authors compare the returns of the best rules identified previously with the returns of a buy-and-hold strategy, in order to confirm the profitability of the technical analysis. They take into consideration the transaction costs at the level of 0.05% for each one-

way trade. They find out that when transaction costs are not taken into consideration the best performing rule for NASDAQ Composite and Russell 2000 outperforms the buy-and-hold strategy for the whole in-sample period. On the other hand, when considering transaction costs the best rule for NASDAQ Composite outperforms only for 7 out of 11 in-sample periods, while the best rule for Russell 2000 still outperforms in all the in-sample periods. As regards the average return over the 11 years the best rule for both indices outperform the buy-and-hold strategy. In the out of sample period the best rule for NASDAQ Composite beats the buy-and-hold strategy for both years 2001 and 2002, meanwhile the best rule for Russell 2000 beats the buy-and-hold strategy only for the first year 2001 and not for 2002.

One interesting conclusion the authors draw is that significant profitable simple rules and strategies are available for relatively young markets (NASDAQ Composite and Russell 2000), but not for the more mature markets (DIJA and S&P 500). This could be due to the fact that young markets haven't yet developed a weak market efficiency form. Another important finding, mentioned also above, is the fact that technical analysts can construct profitable strategies from unprofitable simple rules. This result shows that merely rejecting the profitability of simple trading rules does not necessarily negate the usefulness of technical analysis (Hsu P.-H., Kuan C.-M. 2005).

**Kenourgios D., Papathanasiou S. (2010)** in their paper "Profitability of technical trading rules in an emerging market" test the profitability of the technical trading rules using data of the FTSE/ASE 20 index in the Athens Stock Exchange (ASE), during the period 1995 to 2008. They focus on a less developed and efficient market due to the lack of research on these types of markets. The technical trading rules used in this paper are the simple moving averages, rules similar to those used by Brock, Lakonishok, and LeBaron (1992), using also similar t test and bootstrap methodology under the generalized autoregressive conditional heteroskedasticity model.

The authors of the study use the following approach in order to measure the profitability of the simple moving average rules. They compare the returns given by the buy signals generated by the moving averages with the returns of a simple buy-and-hold strategy. Additionally, they compare the returns yielded by the buy signals generated by the moving averages minus the returns of the sell signals generated by the moving averages with the returns of a simple buy-and-hold strategy. The returns are calculated after the transaction costs. All transaction costs assume commission as entry and exit fees, equal to 0.2 percent of the investing capital.

First the authors investigate if the simple moving averages rules perform better than the simple buy-and-hold strategy using the standard t test. The t test is used in order to check if the means of two data groups are statistically different from each other to allow the comparison of these means. The authors use the t test to compare the returns of the unconditional buy strategy with the returns of the buy signals generated by the moving averages, and also they compare the returns of the unconditional buy strategy with the returns of the buy signals of the moving average minus the returns of the sell signals generated by the moving averages. It is known though, that the results produced by the t test assume independent, stationary and asymptotically normal distributions. It is also known that most of financial time series exhibit non-linearity due to high levels of skewness, kurtosis and heteroskedasticity. To overcome these statistical issues, the authors, adopt the bootstrap methodology as in the paper of Brock, Lakonishok, LeBaron (1992). The bootstrap method is a computerized re-sampling procedure introduced by Efron (1979).

The bootstrap methodology implements the following procedures: first,  $Z$  bootstrap samples are created, each of which containing  $N$  observations by sampling with replacements from the original return series. In the second step the corresponding price series is calculated for each bootstrap sample, the moving average is applied to each artificial price series and the desired performance statistic is then calculated for each price series. In the final step the p value is determined by measuring the number of times the statistic from the artificial price series exceeds the statistic for the original prices series. A data generating process must be determined previously in order to use the bootstrap methodology. The bootstrap procedure may be used to generate a lot of different return series by sampling with replacement from the original return series. The bootstrap samples that are created, are simply artificial return series that maintain the same distributional characteristics of the original series, but are clean of any serial dependence.

The authors point out that financial series often exhibit volatility clustering, a characteristic in which large changes follow large changes and small changes tend to follow small changes. Volatility clustering, or persistence, suggests a time series model in which successive disturbances, although uncorrelated, are nonetheless serially dependent (Kenourgios, Papathanasiou, 2010). To account for the volatility clustering the authors use the model of generalized autoregressive conditional heteroskedasticity, or GARCH (1,1), a model proposed initially by Engle (1982).

In order to use bootstrap under GARCH (1,1), the authors first compute the GARCH (1,1) by using maximum likelihood and apply the bootstrap procedure to the standardized residuals.

Then, as Kenourgios and Papathanasiou describe, the GARCH series are calculated using the estimated parameters and the disintegrated residuals.

The data used in this study as mentioned at the beginning, include the daily closing prices of the FTSE/ASE 20 index from 1/1/1995 to 31/12/2008, and the dataset consists of 3,249 observations. The FTSE/ASE 20 is one of the most famous indices of the Athens Stock Exchange and includes 20 companies with the largest capitalization.

The moving average rules tested in this study are the following: (1, 9), (1, 15), (1, 30), (1, 60), (1,90), (1, 120), (1, 150), where the first number in the brackets represents the days of the short term moving average and the second number is the number of days of the long term moving average.

The first results the authors compute are the standard statistical results. They compute the returns of buy signals, sell signals and the difference between these two for each of the rules mentioned above. What they observe is that the buy-sell differences are significantly positive for all rules. The mean buy-sell returns are all positive with a daily average of 0.0987 percent, which is equivalent to 24.675 percent of yearly average return. The mean returns of the buy signals are all positive with a daily average return of 0.0669, which corresponds to 16.725 percent on a year basis. The null hypothesis is rejected, given that the daily return of buy signals is significantly different from the average return of the simple buy-and-hold strategy which is equal to 0.020439 percent. Six out of seven tests reject the null hypothesis that the returns equal the unconditional returns at a five percent significance level. Overall it can be said that the strategies built by the buy and sell signals generated by the moving averages outperformer the buy-and-hold strategy, with an average yearly return of 24.675 percent with respect to the 5.10975 percent the buy-and-hold strategy produces.

Following Brock, Lakonishok, LeBaron (1992), the authors create 500 bootstrap samples, each consisting of 3,249 observations by resampling with replacement the standardized residuals of the GARCH (1,1) model. After that GARCH price series are generated, on which the moving averages are applied and at the end the p-values are calculated.

When observing the results of the GARCH price series the authors point out the in most of the simulated GARCH (1,1) series are greater than those from the original FTSE/ASE 20 series. In most of the simulated series the buy-sell positions generate average returns which are higher than the one generated by the original series. All the results for the returns of the buy signals, sell signals and the buy-sell positions are highly significant, which leads to the acceptance of the null hypothesis. What this means, Kenourgios and Papathanasiou say, is that the trading

rule excess return calculated from the original series is less than or equal to the average trading rule return for the pseudo data samples.

Overall, Kenourgios and Papathanasiou say, the results indicate that making trading decisions based on moving average rules lead to significantly higher returns than the buy and hold strategy, even after transaction costs. They add that, as the results show, technical rules produce useful signals and can help to predict market movements.

Their findings contradict the efficient market hypothesis, since traders can actually gain abnormal returns by using moving average trading strategies. The results of this study are consistent with the ones by Brock, Lakonishok, LeBaron (1992), and in agreement with evidence that technical trading strategies are profitable in emerging and less developed stock markets. The results of the study are also consistent with the simple technical rules having predictive power.

This research indicates that the benefits of technical trading strategies, such as prediction of price movements and the identification of trends and patterns, can be exploited by traders to earn significant returns of the Athens Stock Exchange (Kenourgios, Papathanasiou, 2010).

**Pavlov V., Hurn S. (2012)** in their paper “Testing the profitability of moving average rules as a portfolio selection strategy”, the popular moving average rules are applied to a cross-section of Australian stocks and the signals from the rules are used to form portfolios. Pavlov and Hurn say that the performance of the trading rules across the full range of possible parameter values is evaluated by means of an aggregate test that does not depend on the parameters of the rules.

There are several contributions of this paper mentioned as follows. One of the main contributions is that it overcomes potential limitations in time-series data by applying the technical trading rules to cross-sections of stocks and then use the buy and sell signal generated to create the portfolios. Another contribution of this paper is the reduction of the data snooping bias by the use of several tests that assess the statistical significance of portfolio returns while allowing freedom in choosing the parameter settings.

The database for this study is composed by monthly observations regarding prices, returns, dividends and capital reconstructions for all stocks listed on the Australian Stock Exchange in the period from December 1973 to December 2008.

To avoid possible issues due to delisting and illiquidity, Pavlov and Hurn apply the trading rules only to the top 500 stocks on the Australian Stock Exchange, and include in the portfolio at time  $t$ , only stocks that have no missing observations over the three years before the portfolio

creation. Data reveals that the number of securities that fulfill the liquidity requirements ranges between 273 and 411 with the average being 342 securities.

The buy and sell signals generated by the trading rules are used to construct equally weighted share portfolios. To construct these portfolios, signals are generated by the moving average crossover, and the authors use the exponentially weighted moving average, not the simple moving average. Pavlov and Hurn say that, the reason behind choosing the exponentially weighted moving average is because it provides continuous dependence on the averaging parameter, and therefore produces sharper statistical results. The portfolio is created buying one unit of the long portfolio, a purchase which is financed by selling one unit of the short portfolio. The return of the portfolio is nothing but the difference between the return of the long portfolio with the return of the short portfolio. In their study the authors assume that the portfolio is held for one month and then sold.

The authors propose different tests to assess the performance of the portfolios created on the basis of the trading signals generated. The first test they propose is the cross-sectional test which aim is to compare the long or short positions of the portfolio with a randomly chosen portfolio composed by the same number of stocks as the number of the long or short trading signals generated by the trading rule. A large positive or negative value of the cross-sectional test suggest that related leg (long or short) of the portfolio performs better than the randomly chosen portfolio. The second test proposed is the time-series test. This test estimates the performance of the long or short leg of the portfolio over 36 months before the portfolio creation, but using the fixed weights generated and selected by the trading rule at the current moment of time. A large values of the time-series test would suggest that the trading rule is selecting reversals. The last test the authors propose is the composite test. Since the test statistics mentioned above are depended on the averaging parameter, the composite test proposes the elimination of this dependence of the parameter by averaging the test over a range of different values of the averaging parameter. The statistical significance of each of these tests are established by the bootstrap procedure, since the tests proposed are not standard.

The fundamental assumption underlying the generation of bootstrapped panels of equity returns is that the returns are generated by time-varying risk exposure to economy-wide risk factors (Pavlov, Hurn 2012). All the stocks that are taken into consideration in this study were ordered by size and divided into 20 portfolios, each of which had the same number of stocks. Size sorting was done on the basis of the last recorded price before the portfolio creation. The identification of the relevant factors to include was done by undertaking a principle-component analysis of size-sorted portfolio returns.

There are a few things to notice from the results of the cross-section and time-series tests as a function of the averaging parameter. The first thing is that both the long and short leg includes a large number of shares, and at small levels of the averaging parameter the performance of the trading rules is not significantly different from the performance of the equally-weighted portfolio of all shares. Second, what is interesting, is that the portfolio generated by the sell signals outperforms the one generated by the buy signal for every level of the averaging parameter. This means that the contrarian strategy is actually the most profitable strategy for undertaking with the moving average rules, which suggests buying on a sell signal and selling on a buy signal.

Next the authors plot both the cross-section arbitrage portfolio test and the time-series arbitrage portfolio test together with the 90 percent bootstrap confidence intervals for the test. What is obvious is that none of the bootstrap models can reproduce the size of the performance statistic of the test, and both cross-sectional and time-series arbitrage portfolios are outside the confidence levels.

Another observation the authors make is that the median of the bootstrap distributions of both tests are positive when the factors are fixed at their estimated sample realizations. This is consistent, also shown in other studies as Brock et. al. (1992), with the tendency of moving average crossover to generate positive returns when applied to aggregate indices.

The research reported in this paper has examined the returns to portfolios formed on the basis of the popular moving-average trading rules and some of the aggregate properties of these portfolio returns have been documented. Over a significant range of values for the smoothing parameter used in the specification of the moving-average trading rules, portfolios constructed on the basis of the buy and sell signals generated by the rules appear to generate substantial contrarian profits (Pavlov V., Hurn S., 2012). Furthermore, simple models of the returns generating process prove inadequate to explain these profits which are largely driven by the abnormal behavior of the stocks selected in the long leg of the portfolio. One of the more intriguing results generated by the moving-average trading rules pertains to the returns on the portfolio corresponding to the largest contrarian profit over the full sample. The performance of the arbitrage portfolio is not explained by the exposure to systematic factors in returns but is fairly strongly correlated with nominal interest rates and inflation (Pavlov V., Hurn S., 2012).

**Schulmeister S. (2009)** in his paper “Profitability of the technical stock trading: Has it moved from daily to intraday data?” tries to investigate the performance of the technical analysis on

both daily and intraday data of the S&P 500 spot and future markets. The purpose of this paper is to provide new information on the profitability of the technical analysis in the stock market. In particular, this study re-examines the declining profitability of the technical analysis over the 1990s by analyzing the ex-post-profitability of 2580 moving average rules, momentum strategies and relative strength indices using data from the S&P 500 spot market from 1960 to 2007, and the stock index futures market data from 1983 to 2007. The model includes both trend-following and contrarian strategies, and it uses both daily and 30-minute data.

This study includes a large variety of technical analysis models as mentioned above. As regards the moving average rules, a large number of combinations is studied, with the short term moving average ranging from 1 to 12 days, and the long term moving average ranging from 6 to 40 days, with the restriction that the difference between the short term and the long term moving average should be at least 5 days. While as regards the momentum strategies and the relative strength index the time range is between 3 to 40 days. The criteria used to select the ranges of the rules was to analyze the most frequently used models.

The author describes the assumptions on which the simulated trading is constructed. As regards the market for stock index futures the most liquid contract is traded. So what this means is that the trader rolls over his open position on the 10<sup>th</sup> day of the expiration month from the near by contract to the contract whose expiration is three months later. In order to avoid any break in the price signal generation, the author says, the price of the contract which expires in the following quarter is indexed with the price of the near-by contract as a base.

The author uses the open price for both signal generation and for calculating returns for each position. It is also assumed that the technical model is used by a professional trader, trading in electronic exchanges, so the commissions and slippage costs are the following, 0.002 percent for commissions and 0.008 percent for slippage costs. The model overall assumes transaction costs of 0.01 percent.

The return of each model is estimated on the basis of the number of profitable/unprofitable position, the daily return of the profitable/unprofitable positions and the duration of profitable/unprofitable positions.

The empirical results of the study when using daily stock prices are described below. As regards the spot market, when the S&P 500 spot market is traded between 1960 and 2007, 8.6% of all models achieve a t-statistic greater than 3 and the average yearly return of these models is 8.3%. The t-statistic of 25.8% of all models is between 1.0 and 3.0, while 31.1% of the models generate a t-statistic between 0.0 and 1.0, and the remaining part of the models which

corresponds to 34.4% is unprofitable. What is worth noticing is that the average rate of return is declining with time, where the return was 8.6% in the time period 1960-1971, 2% in 1972-1982, 0.0% in 1983-1991, 5.1% in 1992-2000 and finally 0.8% in 2001-2007. Meanwhile in the futures market, the 2580 trading systems are also unprofitable. When the S&P 500 trading is based on daily data from 1983 to 2007 it yields an average return of 3.7% per year. In both spot market and futures market, the best performing models are those that exploit the short term stock price trends.

Schulmeister says that the declining profitability of the technical analysis using daily data can be explained in two ways. One is the “Adaptive market hypothesis” (Lo, 2004), which suggests that asset markets have become more efficient, partly because of learning to exploit profit opportunities wipes out these opportunities, partly because information technologies improve market efficiency. Another possible explanation is that technical trading are using more intraday data instead of daily data. This could have led to the intraday data being more consistent and with more opportunities to be exploited by the traders.

Next I am going to analyze the empirical results of the technical analysis when applied to 30-minute data. As regards the futures market, the technical trading models produce an average gross return of 7.2% per year between 1983 and 2007. Meanwhile the net average return is significantly lower given the large number of transaction, and amounts at 2.6% per year. Over the whole period from 1983 to 2007, 97.3% of all 2580 trading models are profitable, producing positive gross rate of returns. When trading the S&P 500 futures based on 30-minute data, the momentum strategies and the relative strength index models produce higher returns than the moving average models, with the respective rates of return: 8.1%, 9.5% and 6.8%. Given the high number of transactions that happen when trading with intraday data the net rate of return is 20.5 percentage points lower than the gross return.

The author points out that the number of unprofitable positions is higher than the number of profitable ones, the unprofitable positions are more frequent, and also the return on profitable positions is not higher than the return of unprofitable ones. From this observation it can be said that the main reason for the profitability of the technical trading models based on 30-minute data, is the duration of profitable position with respect to unprofitable ones.

When comparing the trading models results based on daily data with those based on intraday data the author points out the following observations. First there is no clear sign of declining trend of the profitability of the trading models based on 30-minute data, differently from the trading models based on daily data. Second observation is that the performance of the 2580 models varies a lot across different sub-periods. The highest returns are produced in the 1989-

1991, 1986-1988 and 1998-2000 sub-periods, while the sub-periods where the models perform comparatively worse are 1992-1994 and 2003-2007.

Next the author considers the performance of the 25 best models ex-ante and ex-post. The ex post profitability of the best models is derived from two components, one is the occurrence of the trend since stock prices are not random, the other component is the selection bias. If the profitability of these models is mainly due to the normal price trends, then it can be reproduced ex ante. The author checks the performance of these models ex ante and observes the following results: The ex post performance of the best 25 models is way better than the average performance of all models, and the ex ante performance of these models is also significantly better than the average performance over all models.

### **3.2 Efficient Markets Hypothesis**

The profitability of the technical analysis has always been in contradiction with the efficient markets hypothesis. Below I am going to review some of the definitions and studies whose results are in favor of the efficient market hypothesis.

One of the earlier versions of the efficient markets hypothesis is presented by **Working (1949)**, according to his definition: “If it is possible under any given combination of circumstances to predict future price changes and have the predictions fulfilled, it follows that the market expectations must have been defective; ideal market expectations would have taken full account of the information which permitted successful prediction of the price changes.”

In his later work, he revised the definition of a perfect futures market to “...one in which the market price would constitute at all times the best estimate that could be made, from currently available information, of what the price would be at the delivery date of the futures contracts (Working, 1962).” This definition of a perfect futures market is in essence identical to the famous definition of an efficient market given by **Fama (1970)**: “A market in which prices always ‘fully reflect’ available information is called ‘efficient’.” Ever since the survey study by Fama was published, this definition of efficient markets has been used as the standard definition in the financial economics literature.

Another important work on the efficient market hypothesis was done by Jensen (1978). His definition regarding efficient markets is: “A market is efficient with respect to information set  $\theta_t$  if it is impossible to make economic profits by trading on the basis of information set  $\theta_t$ .” Given that the economic profits are risk-adjusted returns after deducting transaction costs,

Jensen's definition suggests that market efficiency may be tested by considering the net profits and risk of trading strategies based on information set  $\theta_t$ .

Timmermann and Granger (2004) expanded the definition of Jensen by identifying how the actual forecasting uses the information variables in  $\theta_t$ . Their definition is the following: "A market is efficient with respect to the information set  $\theta_t$ , search technologies  $S_t$ , and forecasting models  $M_t$ , if it is impossible to make economic profits by trading on the basis of signals produced from a forecasting model in  $M_t$  defined over predictor variables in the information set  $\theta_t$  and selected using a search technology in  $S_t$ ."

On the other hand, Jensen (1978) grouped the various versions of the efficient markets hypothesis into the following three different forms based on the definition of the information set  $\theta_t$ :

- 1) the Weak Form of the Efficient markets hypothesis, in which the information set  $\theta_t$  is considered to be solely the information contained in the past price history of the market as of time  $t$ .
- 2) the Semi-strong Form of the Efficient markets hypothesis, in which  $\theta_t$  is considered to be all information that is publicly available at time  $t$ .
- 3) the Strong Form of the Efficient markets hypothesis, in which  $\theta_t$  is considered to be all information known to everyone at time  $t$ .

From the three types of market efficiency described above, the technical analysis assumes the weak form, since it is based primarily on past prices. When testing the efficiency of markets, more specific models should be considered, models that can actually describe the process of price formation when prices reflect all the available information. Two of these models, the martingale model and the random walk are discussed below.

#### *The martingale model*

In the mid-1960s, Samuelson (1965) and Mandelbrot (1966) independently demonstrated that a series of prices of an asset is a martingale (or a fair game) if it has unbiased price changes.

A martingale stochastic process  $\{P_t\}$  is expressed as:

$$E(P_{t+1} | P_t, P_{t-1}, \dots) = P_t \quad (1)$$

or equivalently, 
$$E(P_{t+1} - P_t | P_t, P_{t-1}, \dots) = 0 \quad (2)$$

where  $P_t$  is a price of an asset at time  $t$ .

The first equation states that tomorrow's price is expected to be equal to today's price, given knowledge of today's price and of past prices of the asset. Equivalently, the second equation states that the expected price change of the asset is zero when conditioned on its price history. It is important to note that the martingale process does not imply that successive price changes are independent. It only suggests that the correlation coefficient between these successive price changes will be zero, given information about today's price and past prices.

Campbell, Lo, and MacKinlay (1997) stated that: "In fact, the martingale was long considered to be a necessary condition for an efficient asset market, one in which the information contained in past prices is instantly, fully, and perpetually reflected in the asset's current price. If the market is efficient, then it should not be possible to profit by trading on the information contained in the asset's price history; hence the conditional expectation of future price changes, conditional on the price history, cannot be either positive or negative (if short sales are feasible) and therefore must be zero."

One assumption of the martingale process which does not hold in reality is that it implicitly accepts risk neutrality. As it is known though, in general investors are risk-averse, and it is necessary to include risk factors in the model.

A version of the martingale model, is the sub martingale suggested by Fama (1970). This model is expressed as follows:

$$E (P_{j,t+1} | \theta_t) \geq P_{j,t} \quad \text{or equivalently,} \quad E (r_{j,t+1} | \theta_t) \geq 0$$

This states that the expected value of next period's price based on the information available at time  $t$ ,  $\theta_t$  is equal to or greater than the current price. Equivalently, it says that the expected returns and price changes are equal to or greater than zero. What the sub-martingale model implies is that it is impossible for any type of trading rules based only on the information available at time  $t$ ,  $\theta_t$ , to generate expected returns higher than the ones expected by a simple buy and hold strategy.

### *The random walk model*

The idea of the random walk model goes back to Bachelier in the 1900s who developed different models of price behavior for security and commodity markets. One of his models is the simplest form of the random walk model: if  $P_t$  is the unit price of an asset at the end of time  $t$ , then it is assumed that the increment  $P_{t+1} - P_t$  is an independent and normally distributed random variable with zero mean and variance proportional to  $\tau$ .

Campbell, Lo, and MacKinlay (1997) summarize several versions of random walk models, based on the distributional characteristics of increments. The simplest version of the random walk hypothesis is the following, in which the dynamics of  $\{P_t\}$  are given by the following equation:

$$P_t = \mu + P_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \text{IID}(0, \sigma^2)$$

where  $\mu$  is the expected price change or drift, and  $\varepsilon_t \sim \text{IID}(0, \sigma^2)$  signifies that  $\varepsilon_t$  is independently and identically distributed with mean 0 and variance  $\sigma^2$ . The random walk as the martingale process are both ‘fair games’, but the random walk is in a stronger sense, since the independence of the increment  $\varepsilon_t$  implies not only that increments are uncorrelated, but also that any nonlinear functions of the increments are also not correlated.

Fama (1970) stated that “In the early treatments of the efficient markets model, the statement that the current price of a security ‘fully reflects’ available information was assumed to imply that successive price changes (or more usually, successive one-period returns) are independent. In addition, it was usually assumed that successive changes (or returns) are identically distributed.” However, the assumption of identically distributed increments has been questioned for financial asset prices over long time periods because of numerous changes in the economic, technological, institutional, and regulatory environment surrounding the asset prices.

Below as mentioned earlier are presented different studies that conduct different tests in different markets, in order to assess the profitability of the technical trading rules. For each paper that is reviewed, I describe the market data used, the model implementation, the motivation of the authors for every assumption made, and the empirical results achieved. What is common for all the papers is that the results they get, are in favor of the efficient market hypothesis.

**Fang J., Jacobsen B., Qin Y., (2013)** in their study “Predictability of the simple technical trading rules: An out of sample test” use out-of-sample fresh data to measure the performance of the technical trading rules and find no evidence of predictability of stock prices in the period from 1987 to 2011. Their test safeguards from sample selection bias, data mining, hindsight bias and other common bias that might affect the results.

The authors use fresh out of sample data, which are generally considered to offer the strongest safeguard against possible statistical biases. For example, Neely and Weller (2012) consider fresh data based out-of-sample study as the most certain solution against data snooping, data mining and publication bias; Cooper and Gulen (2006) report that many features of a researcher's out-of-sample experiment such as the choice of assets, predictive variables, length of the in-sample window used to obtain forecast parameters, and model selection methods are typically exogenously determined by the researcher after having obtained familiarity with the entire data, whereas it does not induce a bias when out-of-sample tests are performed on new data.

The authors evaluate the profitability of 26 classical technical trading strategies, strategies that are applied on the Dow Jones Industrial Average (DJIA) during the period from 1987 to 2011. These trading rules are the same that are used by Brock et al. (1992), and this allows the authors of this study to perform a complete out-of-sample test by using the exact same technical trading rules on a new data set that minimizes the effect of any possible statistical biases.

The authors use data both from the Dow Jones Industrial Index (DJIA) and the S&P 500 Composite Price Index in this study. It is worth mentioning that the results generated from these two series are reliable and meaningful for several reasons. First, they both are US indices, where the market considered to be more efficient and is not subject to problems such as political instability and government intervention. Second, as the authors say, the US is also the most important and the largest economy worldwide and both of these indices are historically extensive. They study the DJIA first in order to link this study directly to the study of Brock et al. (1992). Then in order to assure that their results are not index dependent, they replicate the same evaluation on the S&P 500.

Before discussing out of sample results, the authors first provide some brief discussion on the in-sample findings of Brock et al. (1992). They reproduced the results of Brock et al. (1992) by using their methodology on the same DJIA 1897 to 1986. The Wald test statistics, rather than the original t-statistics, is used, with the conclusions drawn from these two statistical tests being basically the same. They find out that their results are not very similar to those of Brock et al. (1992). For example, the variable length moving average (1,50,0) rule generates 14,420

buy signals and 10,617 sell signals that total 25,037 signals across the 90-year sample period, according to the authors, meanwhile Brock et al. (1992) reports 14,240 buy signals and 10,531 sell signals. The mean buy (sell) return for this trading rule is 0.050% (−0.027%) while Brock et al. (1992) report 0.047% (−0.029%).

While when discussing the out-of-sample results the authors find no evidence that support the fact that technical trading rules have predictive abilities. The out-of-sample findings differ a lot from the findings of the in-sample results the authors point out. In performing the technical trading rules on the same DJIA index out-of-sample data from 1987 to 2011, the authors find that differently from Brock et al. (199), most of the sell signal returns are positive.

Over all the 26 trading rules analyzed, three of them are found to produce significantly different buy and sell returns at a significance level of 90 percent. The spread between the signals is, however, negative, which actually indicates that the buy, the sell, or both signals predict the market in the opposite direction (Fang, Jacobsen, Qin, 2013). These negative values are in contrast with the findings of Brock et al. (1992).

The authors also apply further checks. First they engage the OLS outlier robust regression in order to limit the influence that any extreme observation, such as the Wall Street crash or the recession, might have on the results. They find out that the predictability during the in-sample period is robust when the impact of outliers is limited, also in the out-of-sample the technical trading models perform poorly under the OLS.

Next since results might be driven by a certain time period the authors employ the rolling windows regression to check of the stability of the data. They perform this analysis on 10-year moving windows that roll ahead 1-month every time. The evidence of this regression suggests that both in-sample and out-of-sample results are consistent over all time periods.

The authors also perform other robustness checks and the results do not change. When the S&P 500 is considered, it also does not affect the conclusion achieved by this study.

Concluding the authors point out that they find no evidence that 26 popular technical trading rules tested by Brock et al. (1992) have statistically significant predictability out-of sample. The predictability has disappeared at the beginning of the 25-year sample, when their sample ends. They also find no evidence in an earlier fresh sample from 1885 to 1896, which it does not suggest that the market has become more efficient over time but it is more likely that statistical biases have caused the in-sample predictability result (Fang, Jacobsen, Qin, 2013).

**Bajgrowicz P., Scaillet O. (2009)** in their paper “Technical Trading Revisited: False Discoveries, Persistence Tests, and Transaction Costs” reexamine the profitability of the technical trading rules on the daily prices of the Dow Jones Industrial Index data from 1897 to 2008. Differently from other studies that apply the technical trading rules to the same data, this study uses a new approach for dealing with the data snooping bias, the False Discovery Rate (FDR). More precisely, they use the FDR+ and the FDR–, developed by Barras, Scaillet and Wermers (2009). The FDR+/- gives the proportion of false discoveries — rules with no genuine performance, separately among the rules selected as delivering significant positive and negative performance. The authors evidence that from a Monte Carlo experiment, it is shown that the FDR approach has an advantage compared to statistical methods used in previous studies, e.g., the bootstrap reality check (BRC) of White (2000) employed by Sullivan, Timmermann and White (1999), and the stepwise multiple testing method of Romano and Wolf (2005). The BRC reveals only whether the best performing rule in the sample actually performs better than the benchmark, after considering data snooping. The authors say that this method provides no information on the other strategies, and it is kind of hard to picture an investor who is willing to invest in only one strategy. The FDR approach used in this study however, by tolerating a certain (small) proportion of false discoveries, improves the chances of detecting true outperforming rules.

A second issue the authors take into consideration is how can investors choose the best performing rules ex ante. They investigate this issue by performing different persistence test, where they examining the same portfolio rebalanced every six months, not in the in-sample dataset, but using out-of-sample data. In this way, the only information used to select the best performing rules are historical data, which is similar to what investors would do. This study is the first study to implement this type of persistence tests on the technical trading rules.

The authors go further and to confirm that is not possible to select a best performing rule ex ante they examine if the performance of an investor would change if he could know the state of the economy in advance, or if he could change to specific rules depending on the market conditions.

A third element the authors consider is the introduction of transactions costs. The rules selected before transaction costs generate a lot of trading signals and their performance is entirely offset once the transaction costs are included.

The authors in order to examine whether technical trading rules produce better performance, they first specify a universe of technical rules from which investors could choose their strategies. When applied to a series of past prices, a trading rule indicates whether a long

position (buy), a neutral position (out of the market), or a short position (sell) should be taken in the next time period. Formally, I consider that to the  $k^{\text{th}}$  rule corresponds a signal function  $s_{k,t-1}$ , based on the information up to time  $t - 1$ , which returns the value 1 for a long position, 0 for a neutral position, and  $-1$  for a short position (Bajgrowicz, Scaillet, 2009). To make sure that comparison is possible with the results of Sullivan, Timmermann and White (1999) (referred as STW), the authors choose the same universe of technical trading rules which consists of 7,846 rules divided into the following five categories: filter rules, moving averages rules, support and resistance rules, channel breakouts and on-balance volume averages.

Every rule considered generates a signal over the predicting period. Bajgrowicz and Scaillet compute a statistic measure, which measures the performance of the rule relative to a benchmark. The rule is defined in a way that under the null hypothesis the trading rule does not generate any higher performance than the benchmark. In their study, STW use two simple performance criteria: the mean return and the Sharpe ratio. The authors of this study however focus only on the Sharpe ratio, which measures the average additional return per unit of total risk. They use a standard practice and compute the excess return with respect to the risk-free rate. This indicates that trading rules earn the risk-free rate on days where a neutral signal is produced.

The data used in this study are the daily prices of the DIJA index in the period from 1897 to 2008. Differently from the STW, that use data of the DIJA index from 1897 to 1996, this study adds a new period of data from 1997 to 2008.

Next I look how the authors explain their approach (FDR) for the data snooping bias.

The goal of this approach is to identify a large number of outperforming strategies for maximum diversification. The FDR allows a certain (small) proportion of false discoveries in exchange of a better chance of detecting many outperforming rules, Bajgrowicz and Scaillet say. Elaborating on the FDR, Barras, Scaillet and Wermers (2009) introduce the FDR+/-, which allows to estimate separately the proportion of false discoveries among technical rules that perform better or worse than the benchmark. They use  $R^+$  to define the number of trading rules selected as significantly positive.  $F^+$  of these rules do not truly generate excess performance, but have been selected erroneously. The FDR among the rules yielding positive returns, denoted by  $FDR^+$ , is defined as the expected ratio of  $F^+$  over  $R^+$  (Bajgrowicz, Scaillet, 2009).

The  $FDR^+$  can be estimated as

$$FDR+ = \frac{Fb+}{Rb+}$$

where  $Fb+$  and  $Rb+$  are estimators of  $F+$  and  $R+$ .

Similarly, an estimator of the FDR among the rules yielding negative returns, denoted by  $FDR-$ , can be written as

$$FDR- = \frac{Fb-}{Rb-}$$

An  $FDR+$  of 100% means that no rule is able to produce positive returns and that the seeming performance is purely due to luck, i.e., data snooping. On the other extreme, an  $FDR+$  of 0% indicates that all selected strategies do genuinely produce positive performance.

Next I see the empirical results of this study before taking into consideration transaction costs.

They firstly investigate the performance of the long term in-sample technical trading rules, periods that vary around 10 or 20 years depending on the sub-sample. The evidence show that up to the 1960s they find that a large number of rules generate higher positive performance, even when accounting for data snooping. The results also show what other studies also confirm, that the profitability of the technical rules decline over time. In fact, after 1986 not only there are no more outperforming rules, but they are replaced by underperforming ones. This declining profitability trend is also confirmed in the new sample of data from 1997-2008. This could be explained with the markets becoming more efficient thanks to information technologies, lower trading costs etc.

Next the authors investigate the performance of short term trading rules strategies. They consider short term performance because it is known that investors update their strategies frequently adapting to the changing economic and market conditions. Another reason is that once the investors become conscious about the profitability of a rule, its profitability is lost from competition. The authors test the short term performance by measuring the performance of the best trading rule over a period of 6 months. Every six months a new set of rules is selected by adjusting the  $FDR+$  at a 5% level. The in-sample short term performance is remarkable, with the Sharpe ratio exceeding 3, in three out of five subsamples. In the short term performance

is observed the same phenomena as in the long term performance with the declining trend in performance in the recent subsamples.

The authors in order to investigate how it can be possible for investors to select the best performing rules ex ante, perform a persistence test. They measure the performance of the 5%-FDR+ portfolio, that is rebalanced every six months no longer in the in-sample period, but in the out-of-sample period. Every time only historical information is used to select the trading rules. The results of the persistence test show that the out-of-sample performance is positive for the first five sub-periods (1897-1996), however the Sharpe ratio hardly exceeds the 0.5 and it also becomes negative in the last sub-period which corresponds to 1997-2008.

Even though the persistence results show that it is not possible for investors to choose ex ante the best performing rules, the authors also consider if other variables could be used to determine which trading rules would perform best. Firstly, the authors consider the business cycle as a variable and they observe that based on the knowledge of the business cycle will not help investors to select a suitable trading strategy. Secondly, they take into consideration the market environment, and the conclusion they achieve is that even with market environment information, traders would not be able to construct the adequate strategy.

Next the authors introduce the transaction costs and measure the long term and short term performance. Transaction costs have been declining over time, and so the transaction costs applied vary over different sample periods.

With the introduction of the transaction costs the positive long term performance is entirely offset. The positive return drops from 20% to 0% and 3% respectively in the first two sub-periods. In the third sub-period the drop is even higher, from 44% to 8%. Not only trading rules are not profitable but, once the transaction costs are included even in-sample profitable trading rules become un-profitable.

The in-sample and out-of-sample performance analysis of the 5%-FDR+ portfolio rebalanced every six months is repeated, including this time the transaction costs. Results show that both in-sample and out-of-sample performance disappears already with the addition of low transaction costs. For example, in the sub-period 3 (1939–1962), the in-sample Sharpe ratio drops from 3.19 to  $-0.20$  when one-way transaction costs of 50 basis percentage points (bps) and 25 bps yearly lending fees are included.

All these results lead to one important conclusion of this study, that conclusion being that the usefulness of the technical trading analysis is seriously questioned by the impact of transaction costs and the lack of persistence.

**Curcio R., Goodhart C., Guillaume D., Payne R. (1997)** in their paper “Do technical trading rules generate profits? Conclusions from the intraday foreign exchange market” test the profitability of filter rules applied to the intraday foreign exchange market data.

The data used in this study is divided in two samples. The first sample includes data from 10 April 1989 to 29 June 1989 and the second samples includes the period from 31 January 1994 to 30 June 1994. Each sample contains tick-by-tick FFX quotations series for the Mark (DEM), Yen (JPY) and Pound (GBP) against the US dollar (USD), and also observations on support-resistance and high-low trading ranges. The authors construct by using the tick-by-tick quotations an intra-daily bid, ask and midpoint quotation series for each of the three currencies, sampled at a fixed time interval of one hour. By doing so they create a time-series length for each currency of around 1400 return observations for the first sample and for the second sample around 2500 return observations.

As mentioned at the beginning the authors use filter rules, so every technical rule applied is based on the exchange rate moving outside a pre-determined trading range. The results are presented based on four different classes of trading rule definition. A first range is defined from the support and resistance levels that appear on the Reuters FXNL screen. As a second possible range is the use of HIGH-LOW data which also appears on the FXNL screen. The third range is determined by using both the support-resistance and HIGH-LOW data, where the minimum of the support and LOW data and the maximum of the resistance and HIGH represents the range. Finally, the fourth trading range is similar to the one used by Brock, Lakonishok and LeBaron (1992). At each hourly observation point, the local maximum and minimum of the exchange rate based on a given window of past hourly observations are used as the maximum and minimum of the trading range. Independently from the trading range used, a buy signal is generated when the spot rate is above the maximum level of the range suggesting to take a long position, meanwhile a sell signal is generated when the spot rate is below the minimum of the trading range. If the spot rate is within the range no position is taken.

Next the authors try to include the transaction costs. They say that the incorporation of transactions costs comes in the definition of the trading return. If one has, for example, taken a long position, the price at which currency was purchased was the market ask price. In closing out the position one sells back to the market, implying that one will receive the market bid. Therefore, in opening and closing each position, the trader pays the quoted spread to the market maker as a transaction cost.

When examining the returns made from the application of the support-resistance and HIGH-LOW rules the authors find out that in the majority of cases the returns are positive and are generally a significantly higher than the returns generated from a simple buy and hold strategy. Examining the significance of the buy and sell sides separately, they find that in 18 of the 36 cases the rules generate significant profit.

Similar results are obtained from the use of the Max-Min trading range rules proposed by Brock, Lakonishok and LeBaron (1992), although they are slightly weaker. They find positive profits for only 14 of the 36 separate buy and sell rules, and the combined buy-sell return is significantly greater than zero in 8 of the 18 cases.

These results however change when accounting for transaction costs. In fact, once spreads are taken into consideration, almost all trading rule profits are eliminated. For the support-resistance and HIGH-LOW trading range data, only 4 of the 36 buy or sell rules produce returns which are significantly greater than zero. Further, when considering the composite bid and ask rules only 2 of the 18 have significantly positive returns. Similar to the previous results, the returns from the Max-Min rules perform worse than the returns from support-resistance based rules; none of the rules has returns significantly greater than zero, while 7 of the 36 separate bid and ask rules and two of the composite rules produce significant losses.

Next the authors observe the results for the second sample. Specific observations on the application of the support-resistance and HIGH-LOW rules show that of the separate buy and sell returns only 15 of the 36 are positive and of these only 4 of them are significant. In fact, there are almost as many significantly negative returns (3 of 36) as there are significantly positive returns. Further, as regards the composite buy and sell rules only 2 of the 18 produce significant profits. Again the results from the application of the Max-Min rules are weaker. Only 9 rules generate positive returns, out of which only 2 significantly positive and there are 7 significantly negative returns, which is far more than the significantly positive ones. This leads to the result that only one composite return produces excess returns significantly greater than zero, while 4 of the 18 yield significantly negative returns.

When accounting for transaction costs, results get worse. Simply incorporating the spread (as a transaction cost) into the calculations all significantly positive returns for the full sample is eliminated. For the support-resistance rules only 10 applications have positive returns but not significantly positive, while 14 returns are significantly negative. On the other hand, the Max-Min rules all show negative returns, with 32 out of 36 being significantly negative.

In conclusion, the main results of this study show that the set of technical rules applied cannot generate profits. The results are even more clear when transaction costs are taken into consideration. Overall, the results of this study are consistent with the efficiency in the foreign exchange market.



## 4. Data and methodology

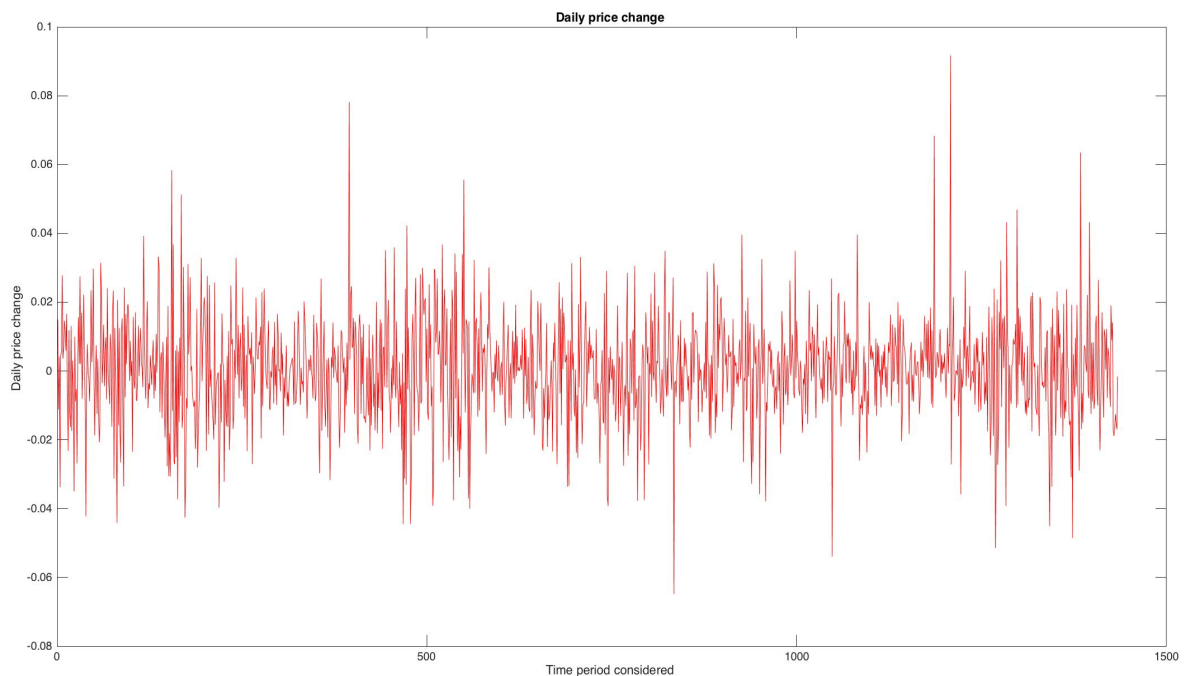
### 4.1 Data used

The data used in this study are high frequency data of the Intel stock prices. The data used represent the stock prices of Intel for every second for the period from September 28<sup>th</sup> 2009 to June the 9<sup>th</sup> 2015, for a total of 1434 trading days.

Intel is one of the world most important manufacturer of microprocessors. The company went public in 1971 with a \$6.8 million initial offer corresponding to a price of \$23.50 per share. During the period taken into study the daily percentage change of the stock has been stable with a mean percentage change very close to 0, specifically -0.02578%, equivalent to -2.578 basis points. Nonetheless, there have been days with high percentage changes, in fact the highest increase on the stock price is by 9.17% on July 15<sup>th</sup>, 2014, while the largest decrease was reached on 17<sup>th</sup> January 2013, a decrease of 6.48%.

The graph below shows the daily price changes of the stock in the time period considered in this study.

Fig.7 Daily price changes of the sock



*Source: Graph computed by the author of the study*

The raw data contain a total number of almost 18 million data from which I construct a matrix that is composed by the date, time, opening price, high price, low price, closing price and the volume traded in each moment.

The data are restricted by not considering data before 9.30 am and after 16.00 which is the opening time of the Nasdaq Stock Exchange. This restriction is essential to the trading strategy adopted. Since, the strategy developed is based only on day trading, so every open position is closed by the end of the trading time, considering any data beyond this time frame not only it would compromise the results generated, but also would be irrational.

## 4.2 Model description

The model used in this study is based on one of most used technical analysis instruments: the moving average. A moving average is a simple average over a certain period of time, and it's moving because it is recomputed in a continuous way, where the earliest value is dropped while the newest value is added. This means that I have a different value of a moving average of a certain period for each price data that I have.

The first step to constructing this trading strategy is calculating the moving averages. Since there are four different types of price data, open, high, low and close price, I must decide which price data to use in order to calculate the moving averages. Usually closing prices are considered the most important and the data from the close prices are used to built trading strategies, although this happens when there are only daily data and not intra-day ones. As mentioned earlier this strategy is built to function as an intraday trading strategy, where every position is closed by the end of the day. For these reason and given the availability of the data possessed it is decided to construct a vector of the averages of the four prices in every moment. This vector is constructed as follows:

$$Avg(n) = \sum_{i=1}^4 P(n, i)/4,$$

where  $n=1 \dots$  end of data series.

Once the vector *Avg* is constructed I have the base data on which to calculate the moving averages. The trading strategy is composed by two different moving averages, one of shorter

time period and the other of longer period, denoted as SMA and LMA for the short term and long term moving average respectively. The moving averages are calculated as follows:

$$SMA(i) = \frac{1}{n} \sum_{h=i}^{n+i-1} Avg(i)$$

$$LMA(i) = \frac{1}{m} \sum_{h=i}^{m+i-1} Avg(i) \quad m > n$$

where,

$i=1 \dots$  end of data series,

$n$  = period over which the short term moving average is calculated

$m$  = period over which the longer term moving average is calculated

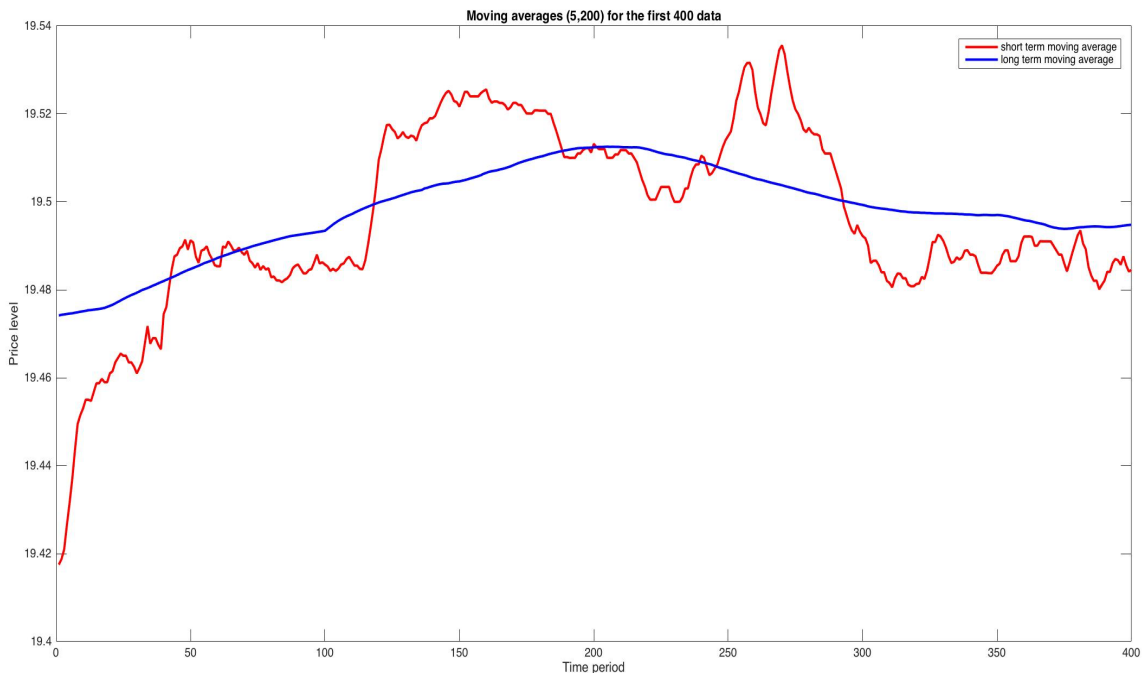
After seeing how the moving averages are constructed it is continued by deciding which values to give to  $m$  and  $n$ . During the years there have always been discussions on which moving averages rules perform better than others. In some periods, a moving average performed better than others, while this changed in the next periods. Since markets have become more efficient, and more dynamic selecting one moving average as the best with respect to others is impossible. For this reason, the trading strategies designed are based on different pairs of moving average. More precisely the pairs considered are: (5,100), (5,150), (5,200), (50,100) and (50,150), where the first number represents the short period moving average and the second one the long period moving average,  $n$  and  $m$  respectively.

Next I use the moving averages of the trading strategy to generate the buy and sell signals. Depending if the long term moving average is above or below the short term one it represents a downward or upward trend, suggesting one should take a short or long position on the market. The next step is indeed creating a vector of trading signals in each moment. This vector, called *Pos*, takes the following values:

$$Pos(i) = \begin{cases} -1 & LMA(i) > SMA(i) \\ 1 & SMA(i) > LMA(i) \end{cases}$$

The graph below shows the 5-period and 200-period moving averages for the first 400 price data present in my data set. The blue line represents the long term moving average while the red one the short term moving average. As seen from the equation above the code will generate a -1 which represents a sell signal or a short position whenever the long term moving average is above the short term one and the vice versa.

*Fig.8 The MA (5,200)*

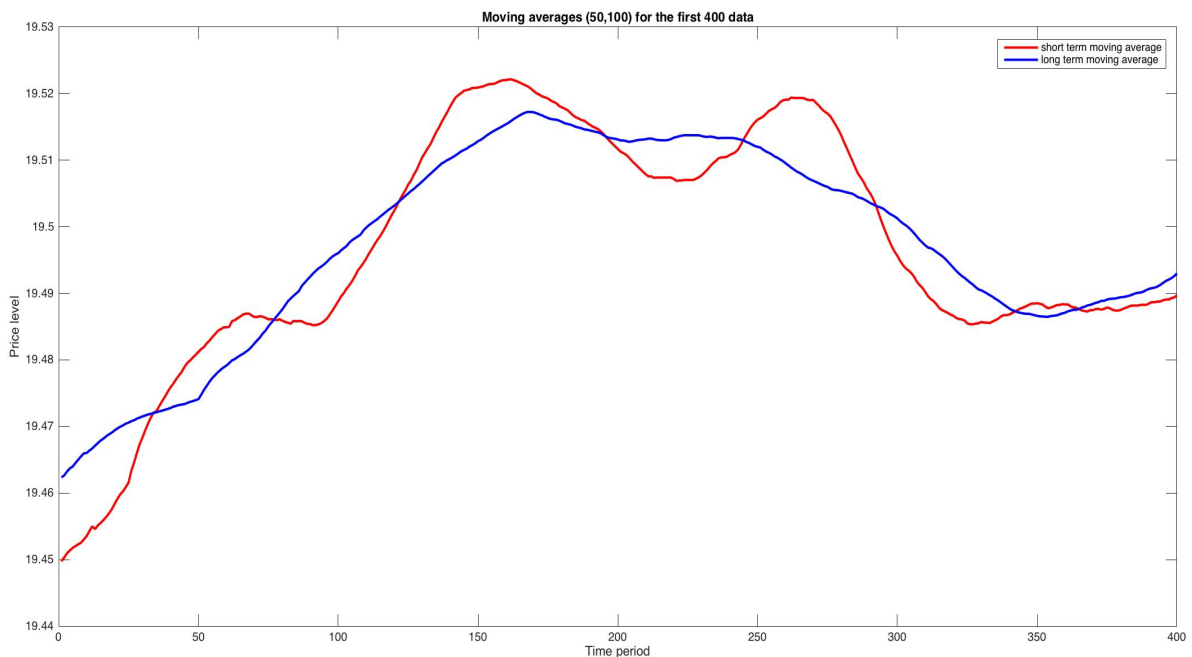


*Source: Graph computed by the author of the study*

As it can be imagined, different pairs of moving average would produce different trade signals affecting the moment of entering or closing a position. When compared with a different pair of moving averages that is used in this study it can be seen how the trading signals generated could vary from one selected rule to another. For comparison effect I look at the graph that the two moving averages of the pair (50,100) produce for the same time period as the one used in the preceding graph. As in the previous figure the red line represents the short term moving average, while the blue line the long term one.

From the two different graphs it can be seen how the for example the first buy signal is generated in diverse moments which leads the two rules to yield different strategy returns. Note that I only present the first 400 data in order to distinguish between the two moving averages, thing which would be impossible when plotting the whole set of data of almost 18 million.

*Fig. 9 The MA (50,100)*



*Source: Graph computed by the author of the study*

The next step after creating the vector of signals is giving real values to the strategy. I assume an initial portfolio budget of one million dollars and invest on the strategy 80 percent of the value. The strategy followed assumes no short-selling, so the algorithm starts buying when it receives the first buy signal. The second the first value of 1 in the vector of the signals (*Pos*) is detected, the transaction of buy is executed the following second. The long position is then kept open until I get a sell signal represented by the value of -1 in the vector *Pos*, in which case the sale of the shares previously purchased is actualized the following second. The value of the portfolio budget increases or decreases after each trade transaction depending on whether the signals produced are correct or not.

For each trade transaction, the time it happens, the cost of buying, the value when sold and the difference which gives the gain or loss is transferred in a matrix containing the strategy results.

In this manner, it is changed from a large matrix containing a lot of data into one with useful information about the trades. The data from this matrix are then used to calculate the return of each trade and the daily returns for every trading rule taken into consideration, steps that will be explained below after the introduction of the transaction cost into the model. Given the large number of trade happening every day the transaction costs affect a lot the daily returns.

### *Introduction of transaction costs*

Transaction costs are really important to investors because they represent a significant factor in calculating the net return of a trading strategy. The widely accepted definition of transaction cost is that they represent all the expenses incurred when buying or selling a good or a service in a certain market. When talking about financial markets, of course transaction costs are composed by the expenses encountered when buying or selling a financial security.

Transaction costs usually include commission fees, exchange fees, bid/ask spread, and other types of expenses. Transaction costs have a great impact especially on investors who actively trade on the market, and the amount varies depending on the firm the trader does business with.

As explained earlier with the large amount of intra-day data available, the number of trades per day is also quite significant, which means that transaction costs play a crucial role in determining the daily returns of each trading strategy applied. As known already, the number of trades that happen depend on the moving average pair selected, meaning that the transaction costs, for each strategy considered, will be quite different.

When determining the amount of the transaction costs applied to each trade I follow the approach of Schulmeister (2009), which considers that transaction costs include commissions and slippage costs. These two components are estimated under the assumptions that the technical models are used by professional traders that trade in electronic exchanges. Under this assumption commission costs are considered to be around 0.002% per transaction, meanwhile the slippage costs, which represent costs encountered due to the failure to meet expectation with regard to the execution of an order, are assumed to be roughly 0.008%. Given the values of the two components assumed, it can be said that the overall transaction costs per trade are equal to 0.01%, or 1 basis point.

These costs are introduced in the model and added to the matrix of data that represent the strategy results. For each element of the matrix, 0.01 percent is added to the cost of buying the shares, and at the same time 0.01 percent is subtracted by the amount gained by the sale of the

shares. The difference between these two values gives us the amount of gain or loss for each trade while considering transaction costs.

The new set of values obtained will be used to calculate the net daily returns of each strategy. Also these data will be used to compare the returns the strategies yield when transaction costs are not considered versus the returns when these costs are taken into account.

### *Daily returns*

After the introduction of the transaction costs the model proceeds by calculating the daily returns of each strategy with and without the transaction costs. Although the definition of the daily return of a stock is broader since it incorporates intraday return which is the return generated by the stock during the opening trading hours, and the overnight return which is the return generated by price changes from the close of one day until the open of the next trading day. In this case I focus only on intraday return, since it is used a day trading strategy and no positions are left open overnight.

The daily returns are calculated in two steps. First I calculate the return of each trade with the following formula:

$$r_i = \frac{d_i}{b_i}$$

where:

$d_i$  – the difference between the amount received when the shares are sold with the amount spent to buy the shares.

$b_i$  – the amount spent for buying the shares, or the amount invested in the shares

Secondly, I find the end of each trading day, and the daily return is then calculated as the product of all the trade returns for one day, as follows

$$r_D = \prod_{i=1}^n (1 + r_i)$$

where:

$n$  – number of trades per day

After calculating the daily return with the above formula, one is subtracted in order to obtain percentage levels of the daily returns. The formula is of course repeated for each trading day present in the dataset. At the end a vector of 1434 daily returns is obtained.

In the same manner it is calculated the returns for each trade when transaction costs are present, and convert them into daily returns as expressed earlier.

### *Standard deviation, realized volatility and number of trades*

Other important elements I include in this study are the standard deviation, the realized volatility and the number of trades. All the three factors differ from one strategy to the other so, these elements are used to compare the different moving average rules adopted.

The standard deviation is the most important measure of volatility. It is calculated simply, and for the daily standard deviation I use the returns of each trade within the day, obtaining 1434 values, one for each day. Also the standard deviation using the vector of daily returns is calculated.

The realized volatility according to the Layman's definition is the magnitude of price changes, regardless of direction, of some underlying over a specific time period. For calculating the realized volatility, I use the return of each trade within a daily period. The following formula is used:

$$RV_t = \sum_{i=1}^n r_i^2$$

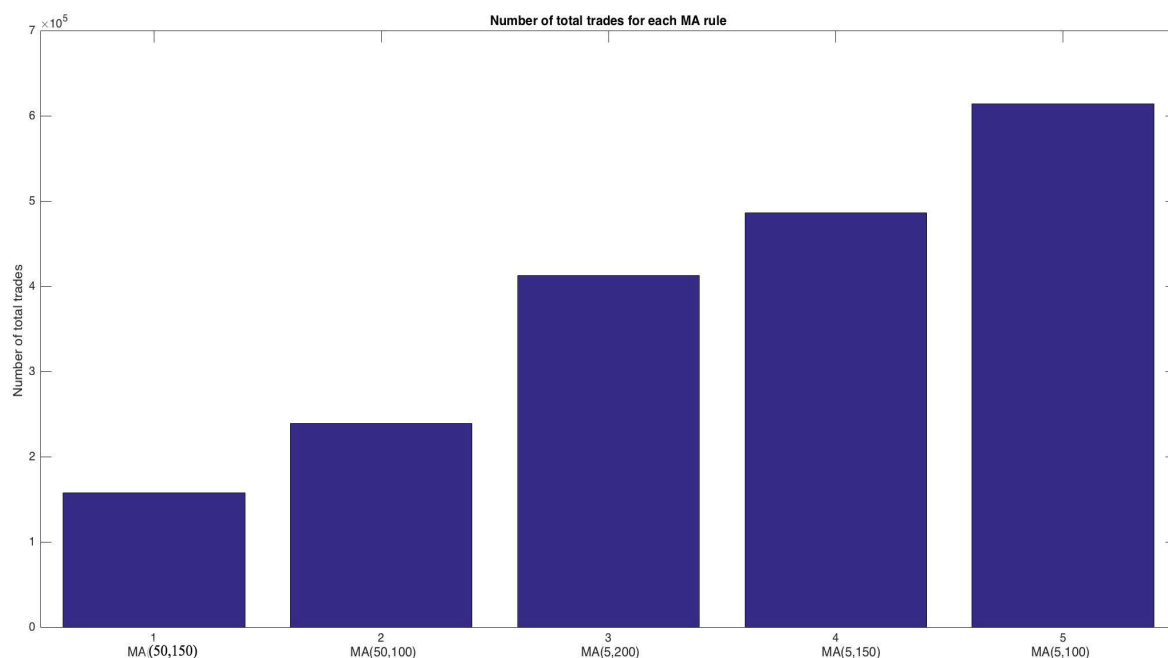
where:

$r_i$  – the return of each trade

The number of trades is simple counted for each day, but it represents an important measure, given that different moving averages rules used result in different numbers of trades per day. It is also important since the more trades there are every day, the more transaction costs are paid. Every trade is composed by two transactions, one is the buy transaction and the other the sell transaction, so a trade is defined as the complete cycle of opening and then closing a long

position, given the no short selling constraint imposed in my model. The following graph represents the total number of trades for each of the rules taken into consideration in this study. As can be seen below the moving average rule that produces less trades, is the MA (50,150), while the largest number of trades is generated by the MA (5,100) with a total number of 157,419 and 613,674 trades respectively. The daily return for each model is then regressed against different variables as the number of trades, the standard deviation, the market volatility, in order to analyze if these variables could explain the daily return values. The results will be described in the following chapter.

*Fig. 10 Total number of trades*



*Source: Graph computed by the author of the study*

### *Comparison with the daily return of the S&P500*

In this model, when comparing the strategies based on the different moving averages, it is not only considered the comparison of different strategies, but also the comparison of the returns of each strategy with the daily return of the S&P500.

The S&P 500 is widely considered as the best single measure of large-cap U.S. equities. The index of 500 stocks is chosen on the basis of market size, liquidity and industry grouping, among other factors. The S&P 500 is aimed to be a leading indicator of U.S. equities and is meant to reflect the risk/return characteristics of the large cap universe.

A team of analysts and economists at Standard & Poor's, known as the S&P Index Committee decide which companies are included in the index. The S&P 500 is a market value weighted index – where every stock's weight is proportional to its market value.

There is over USD 7.8 trillion benchmarked to the index, with index assets including approximately USD 2.2 trillion of this total. The index includes 500 leading companies and captures approximately 80% coverage of available market capitalization.

## 5. Empirical results

### 5.1 Strategy results

For each moving average rule the strategy yields different results regarding the daily return, the number of trades, the standard deviation etc. On this part of this study I am going to analyze the results of each of these rules in absolute terms and relative to one another. Below are described the outcomes of each rule to help understand if these technical analysis instruments can generate profits, by capturing, if any predictability in stock prices.

A summary of the results of each strategy is presented on the table below. The data presented in the table represent only daily data, where the first column is the average daily return when transaction costs are not taken into account, the second is the standard deviation of the daily returns, the third the average daily return when transaction cost are present, and the last column represents the average number of trades per day.

Besides the summary of data present on the table, I analyze each strategy separately considering the movements of the daily returns, the monthly returns and also the maximum and minimum returns reached by each strategy. For the maximum and minimum value, I also check the dates when these values are generated.

The results of each strategy are then compared with the results of other strategies and also with the return of the S&P 500. One interesting thing to notice from the table at first sight is that all the strategies have positive daily returns when transaction costs are not taken into account. This could be seen as signal that moving averages used as a trading rule could generate profits meaning there is some predictability in the stock prices.

*Table 1. Summary of results*

MA rule	Mean	St. deviation	Mean (tr. costs included)	Average number of trades per day
(5, 200)	0.53%	3.29%	-5.11%	288
(50,150)	0.9%	2.82%	-1.31%	111
(5, 150)	0.73%	3.51%	-5.91%	340
(50, 100)	1.47%	2.92%	-1.87%	167
(5, 100)	1.12%	3.89%	-7.22%	429
S&P500	0.05%	0.99%		

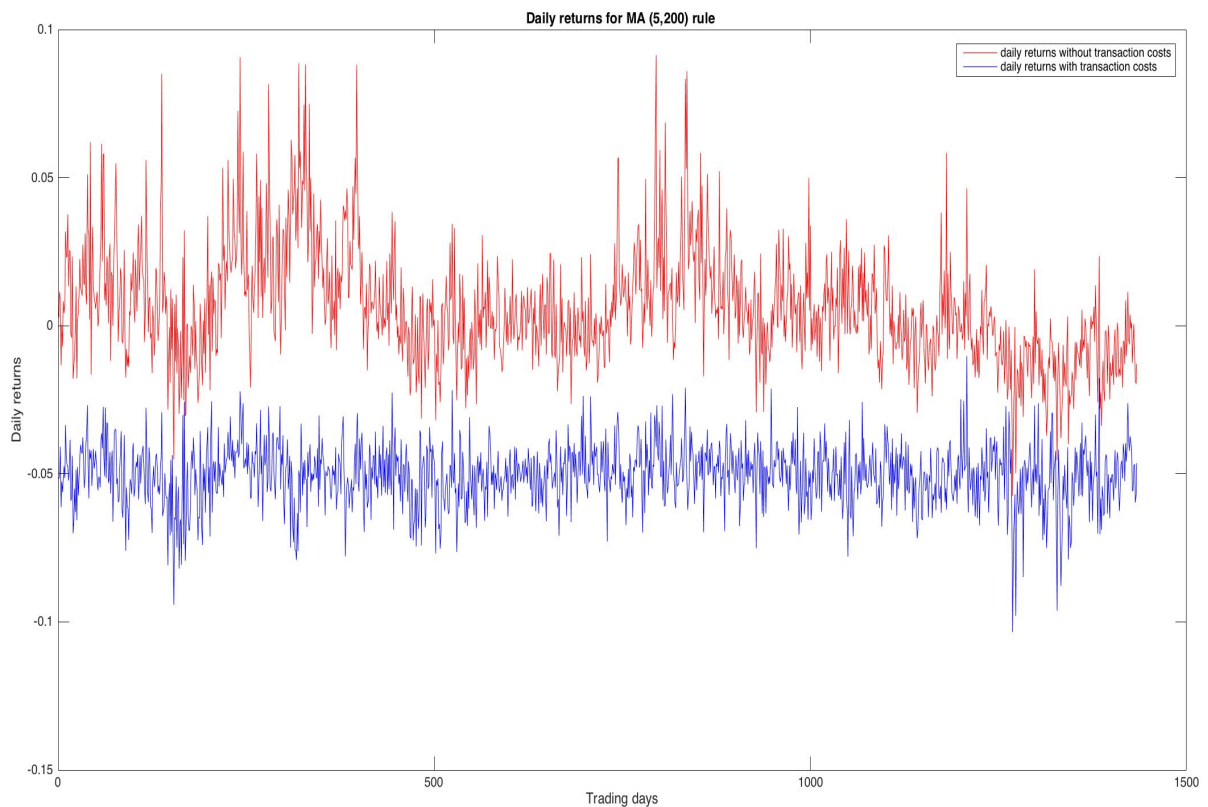
*Source: Table computed by the author of the study*

### *The MA (5,200) rule*

The strategy created using the moving averages of 5 and 200 produce a total number of 412160 trades. The mean daily returns without considering the transaction costs is 0.53% or 53 basis points. When transaction costs are taken into account the returns of each day become negative with a mean of -5.11%.

The following picture shows the daily returns of this strategy with and without transaction costs. It can be seen how daily returns when transaction costs are not considered are mostly positive, while this does not hold true when the transaction costs are added.

*Fig. 11 The daily returns of MA (5,200)*



*Source: Graph computed by the author of the study*

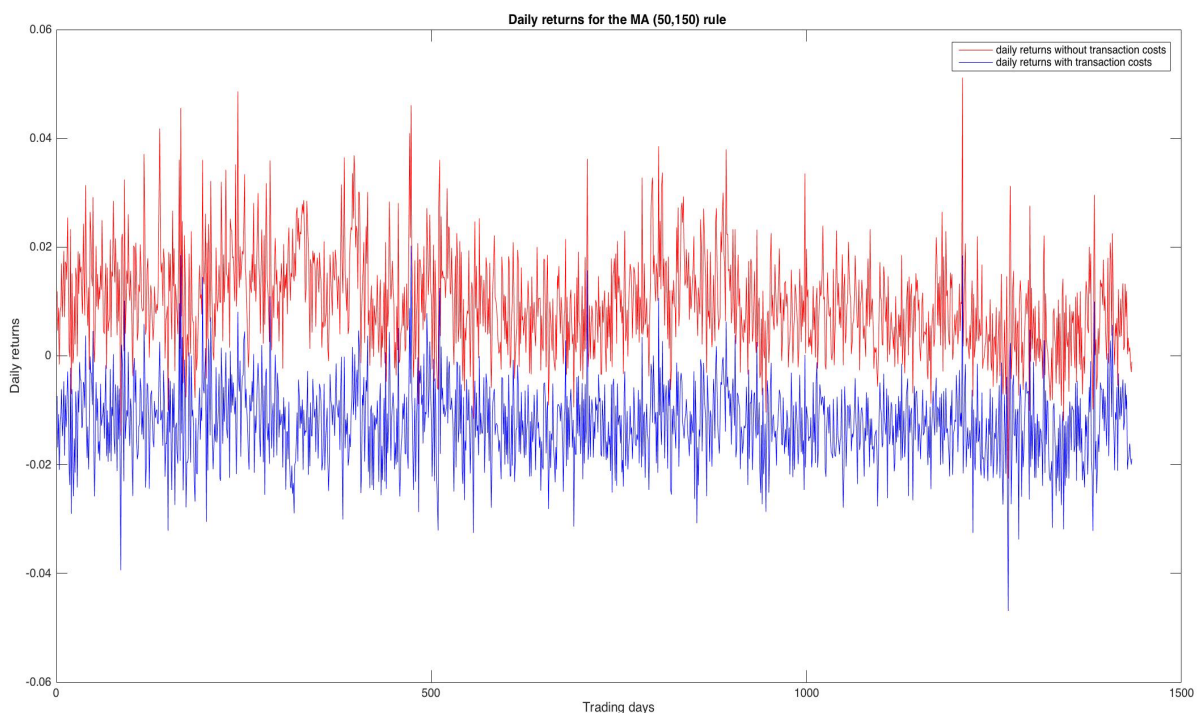
Without the transaction costs the daily returns are quite considerable and correspond to a monthly return of 16.71%. The average number of trades per day is 288 and the standard deviation of the daily returns is 3.29%.

Most profitable day considering this strategy is on November the 20<sup>th</sup> of 2012 with return of 9.13%. When considering transaction costs there are no days with positive rates of return. The minimum daily return registered is -5.75% on October the 10<sup>th</sup> of 2014.

### *The MA (50,150) rule*

The strategy constructed by the two moving averages of 50 and 150 generates the least number of total trades amounting to 157419. The mean daily return of this strategy without considering transaction costs is 0.9%, or 90 basis points. While when I add the transaction costs the daily return drops to -1.31% on average. The following graph shows the returns on a daily level with and without transaction costs. It can be seen how daily returns when transaction costs are not considered are mostly positive, while this does not hold true when the transaction costs are added, although differently from the MA (5,200) rule some of the daily returns including transaction costs are positive.

*Fig. 12 The daily returns of MA (50,150)*



*Source: Graph computed by the author of the study*

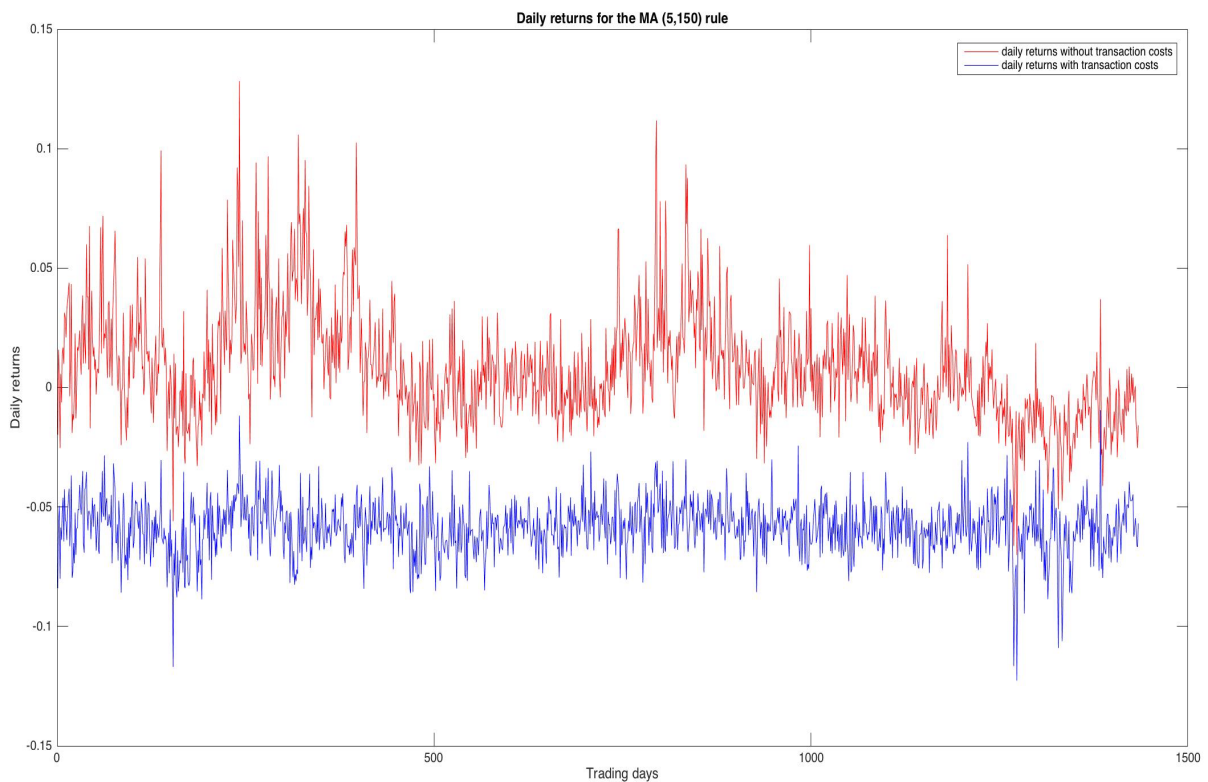
The daily returns are quite high when transaction costs are not considered, values that when converted into monthly returns have an average of 22 percent per month. The standard deviation of the daily returns for this strategy is 2.82 percent. On the average there are 111 trades each day.

The most profitable day when using this strategy is generated on July the 15<sup>th</sup> of 2014 with a return of 5.12 percent. While when considering transaction costs, the most profitable day is August the 10<sup>th</sup> of 2011 with a return 2.02 percent. The minimum level the daily return reaches, is -2.26 percent on October the 10<sup>th</sup> of 2014.

### *The MA (5,150) rule*

The strategy based on the moving average rule of 5 and 150 produce a large number of trades, a total of 486174. The average daily returns of this strategy, without counting for transaction costs is 0.73 percent, or 73 basis points. While when I consider transaction costs the daily return decreases a lot, and has a mean of -5.91 percent per day. The following graph shows the returns on a daily level with and without transaction costs. As can be seen the daily returns when transaction costs are not considered are mostly positive, while this does not hold true when the transaction costs are added, and differently from the previous strategy there are no positive values for returns that include transaction costs.

*Fig. 13 The daily returns of MA (5,150)*



*Source: Graph computed by the author of the study*

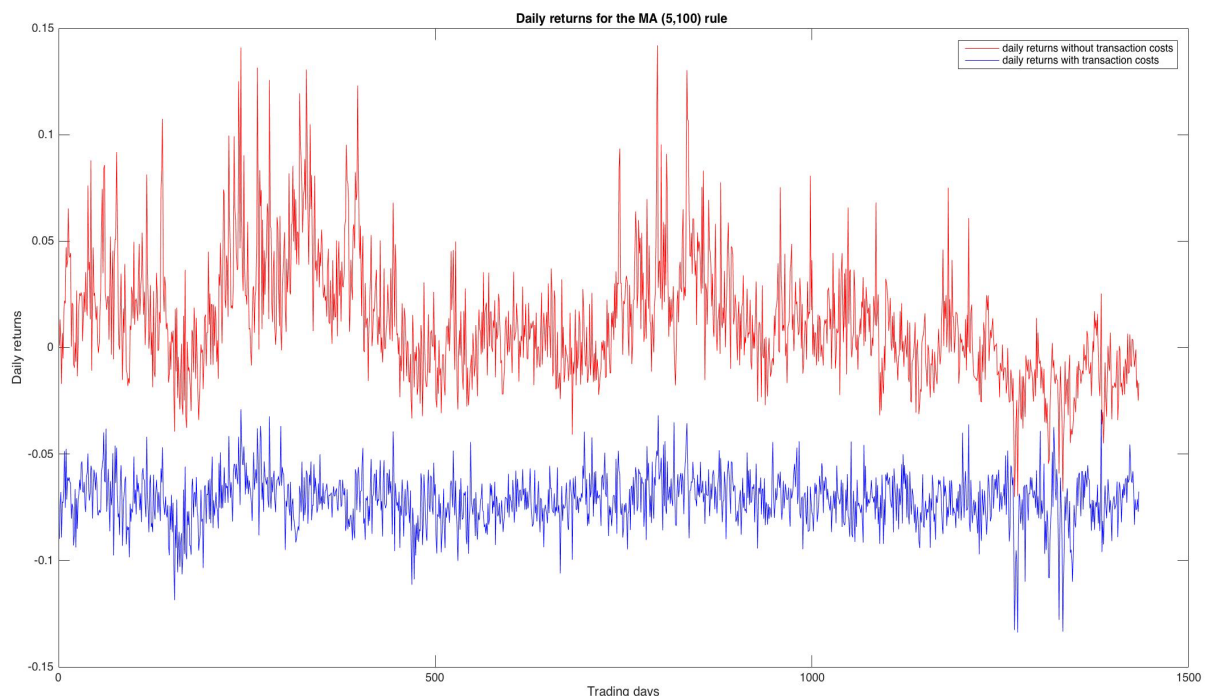
The returns of this strategy are significantly positive when transaction costs are not taken into account, and when converted in monthly returns, the average is 23.9 percent per month. The standard deviation of the daily returns for this strategy is 3.51 percent. On the average there are 340 trades each day, which explains why the daily returns when considering transaction costs are all negative. The returns of most trades are not high enough to justify the transaction costs, and more trades there are the higher the costs paid.

The most profitable day when I analyze the MA (5,150) rule is September the 10<sup>th</sup> of 2010 with a return 12.83%. Meanwhile when the transaction costs are considered, there are no days with a positive return. The minimum level of daily return is reached on October the 15<sup>th</sup> of 2014, and its value is -7.01%.

### *The MA (5,100) rule*

The strategy based on the moving average rule of 5 and 100 generate the largest number of trades, a total of 613674. The average daily returns of this strategy, without counting for transaction costs is 1.12 percent, or 112 basis points. While when transaction costs are considered the daily return decreases a lot, and has a mean of -7.22 percent per day. The following graph shows the returns on a daily level with and without transaction costs. As can be seen the daily returns when transaction costs are not considered are mostly positive, while this does not hold true when the transaction costs are added, and similarly to the previous strategy there are no positive values for returns that include transaction costs.

*Fig. 14 The daily returns of MA (5,100)*



*Source: Graph computed by the author of the study*

The returns of this strategy are highly positive when transaction costs are not taken into account, and when converted in monthly returns, the average is 39.66 percent per month. The standard deviation of the daily returns for this strategy is 3.89 percent. On the average there are 429

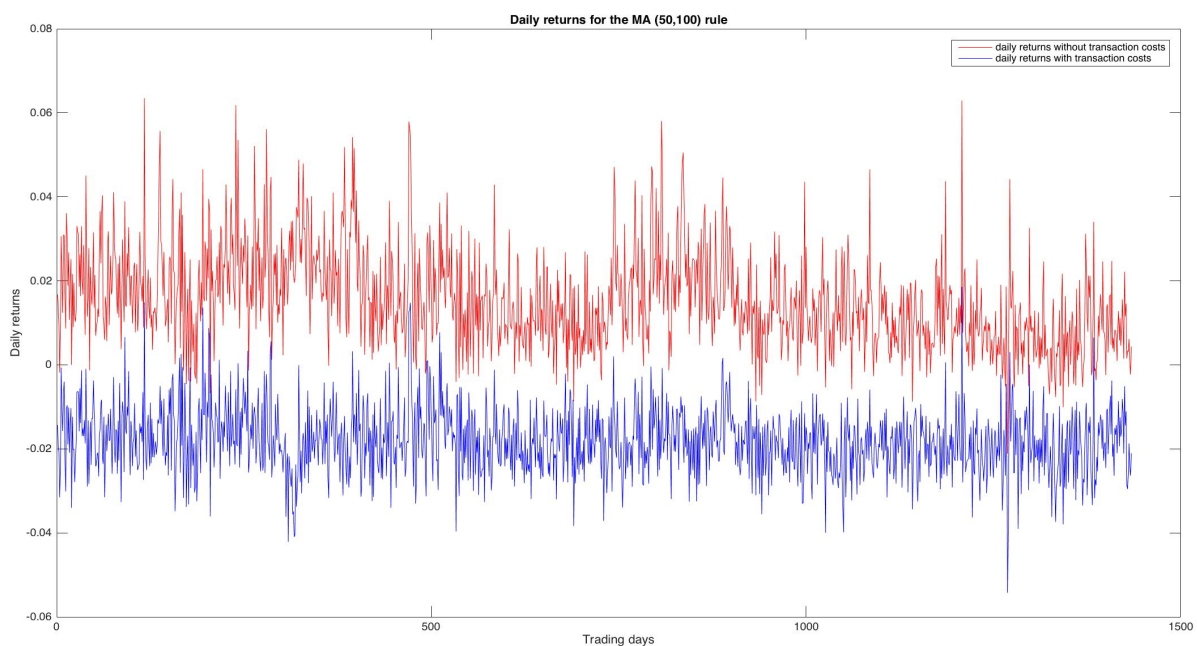
trades each day, which explains why the daily returns when considering transaction costs are all negative. The returns of most trades are not high enough to cover for the transaction costs, and more trades there are the higher the costs paid.

The most profitable day with MA (5,100) rule is on November the 20<sup>th</sup> of 2012 with a return of 14.19 percent. While when transaction costs are considered there are no days with positive rates of return. The minimum daily return reached is -7.01 percent, return generated on October the 10<sup>th</sup> of 2014.

### *The MA (50,100) rule*

The strategy based on the moving average rule of 50 and 100 generates among the least number of trades, more precisely a total of 238607. The average daily returns of this strategy, without counting for transaction costs is 1.47 percent, or 147 basis points. While when transaction costs are taken into account the daily return decreases, and has a mean of -1.87 percent per day. The following graph shows the returns on a daily level with and without transaction costs. As can be seen the daily returns when transaction costs are not considered are mostly positive, while this does not hold true when the transaction costs are added, although similarly to the MA (50,150) strategy there are some positive values for returns that include transaction costs.

*Fig. 15 The daily returns of MA (5,100)*



*Source: Graph computed by the author of the study*

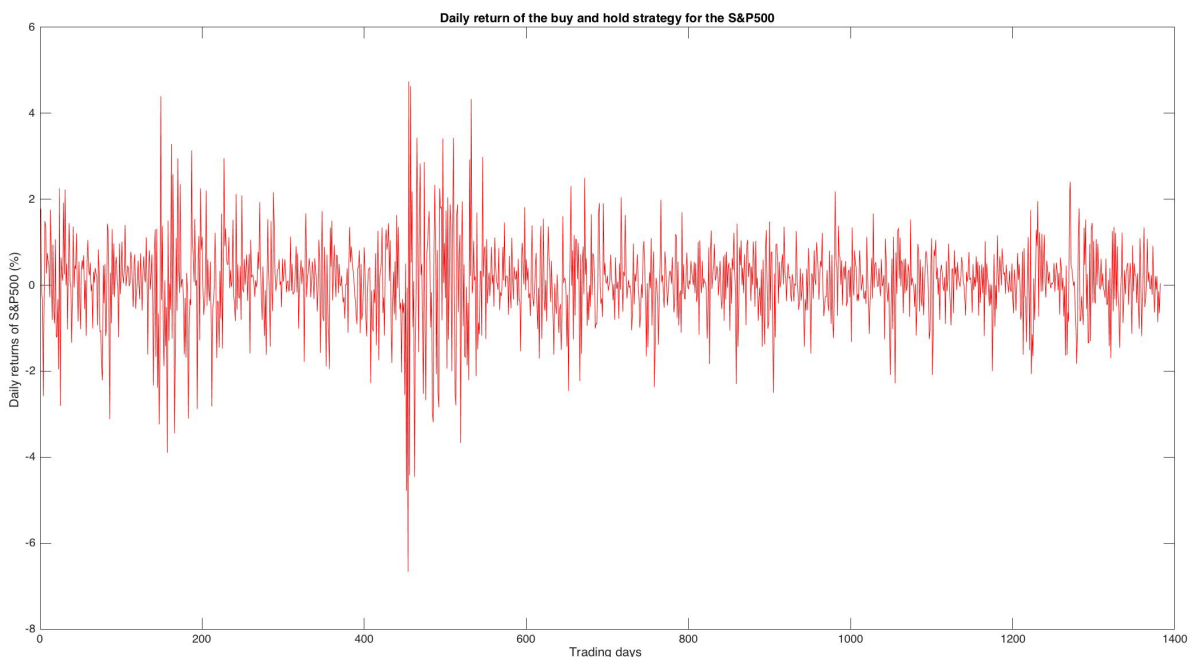
The returns of this strategy are highly positive when transaction costs are not taken into account, and when converted in monthly returns, it yields an average return of 38.52 percent per month. The standard deviation of the daily returns for this strategy is 2.92 percent. On the average there are 167 trades each day, which is fairly lower than the average trades per day of three other strategies. I suppose that this is the main reason why the daily return with transaction costs is somewhat higher than the other three strategies, although still negative.

The most profitable day when considering the MA (50,100) rule is March the 15<sup>th</sup> of 2010 with a return of 6.35 percent. Meanwhile when transaction costs are considered the most profitable day July the 15<sup>th</sup> of 2014 with a return of 1.86 percent. The minimum daily return is -2.11 percent, and it is reached on October the 10<sup>th</sup> of 2014.

### *The S&P500 daily return*

As said earlier, the returns of each strategy will also be considered with the return of the S&P500 index, as one of the most important indices in the market. The daily percentage change of the S&P500 is analyzed for the same time period in which I develop my strategy. The graph below shows the daily returns of this index.

*Fig. 16 The daily returns of S&P500*



*Source: Graph computed by the author of the study*

The highest return of the S&P500 is registered on August the 10<sup>th</sup> of 2011 with a value of 4.74 percent. Meanwhile the minimum daily return realized by the index is -6.66 percent on August the 8<sup>th</sup> of 2011. It is interesting to notice that the minimum and the maximum returns are registered in two consecutive days suggesting a period of high volatility. This market event is connected to the Black Monday of 2011, when on August 8<sup>th</sup>, the United States sovereign debt credit rating was downgraded by the Standard and Poor from AAA to AA+. This was the first time the credit rating of the US debt was downgraded. By the market closing time the Dow Jones Industrial Average lost 634.76 points (-5.55%), one of the largest drop of the index in the history. The NASDAQ Composite Index fall 174.72 points (-6.90%) closing at 2,357.69, the S&P 500 Index shed 79.92 points (-6.66%), the New York Stock Exchange lost 523.02 points (-7.05%).

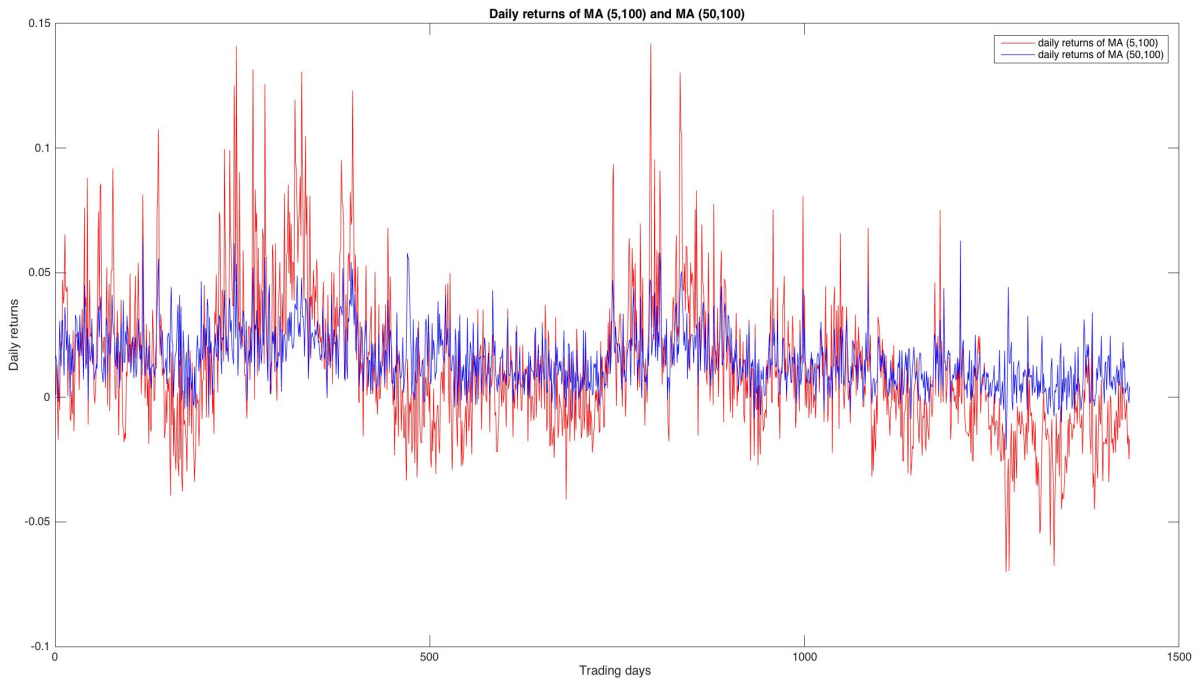
When comparing with the return of the S&P500 on average, the daily returns of each strategy without considering transaction costs are higher, meaning that the strategies developed outperform the index. This fact changes when I consider transaction costs, in this case on average none of the strategies is better than the S&P500 index. In terms of volatility the S&P500 standard deviation is lower than the standard deviations of the strategies I build.

## **5.2 Comparisons among strategies**

Firstly, I compare the two strategies that produce the largest number of trades. The MA (5,100) and the MA (5,150) generate in average 429 and 340 trade per day respectively, and the MA (5,100) has a higher daily return with respect to MA (5,150). This could make us think of a relation between the number of trades and the daily return which will be considered in the next section where I construct the different regression models.

The strategy that performs better with respect to the others is the MA (50,100) with a mean of daily returns of 1.47 percent. This strategy also has one of the lowest standard deviations of 2.92 percent, only 0.1 percent higher than the standard deviation of the MA (5,200) which has the lowest standard deviation. Meanwhile the strategy with the highest volatility is the MA (5,100). The second highest volatile strategy is the MA (5,150), both strategies that generate the highest number of trades. The graph below shows the daily returns of the MA (50,100) and MA (5,100), where it can be noticed the differences in the volatility.

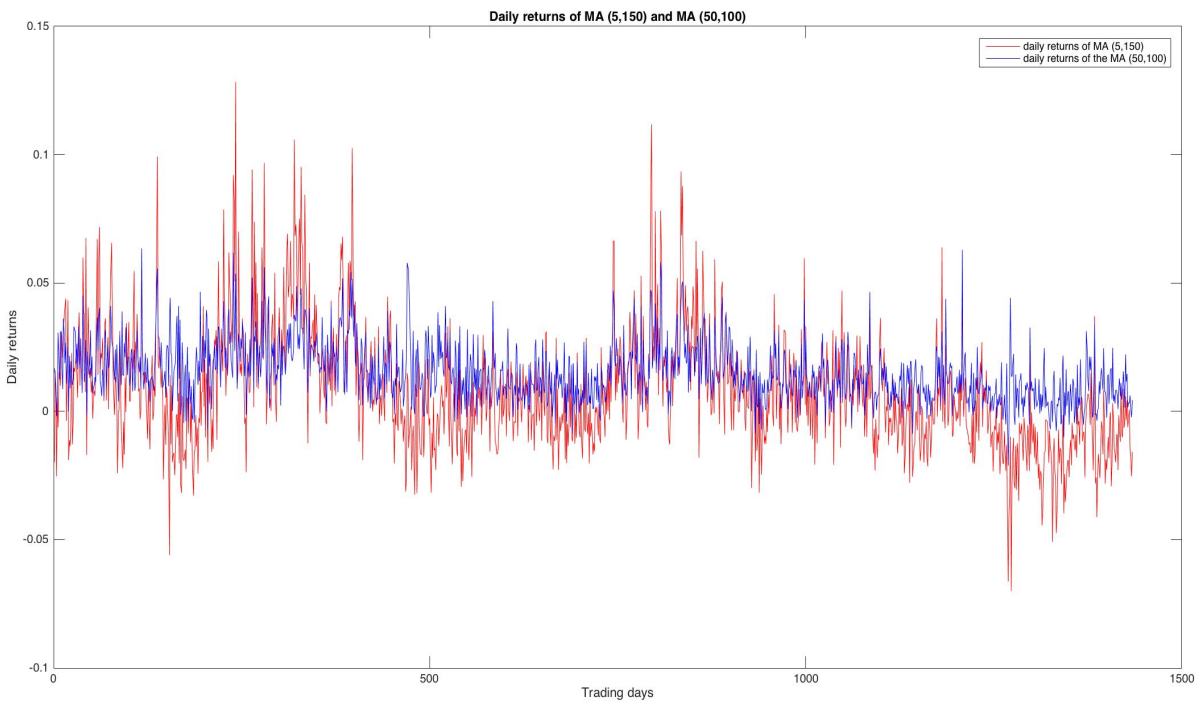
*Fig. 17 The daily returns of MA (5,100) and MA (50,100)*



*Source: Graph computed by the author of the study*

Next the daily returns volatility of the MA (50,100) is compared to the daily return of the MA (5,150). The figure below shows these differences.

*Fig. 18 The daily returns of MA (5,150) and MA (50,100)*

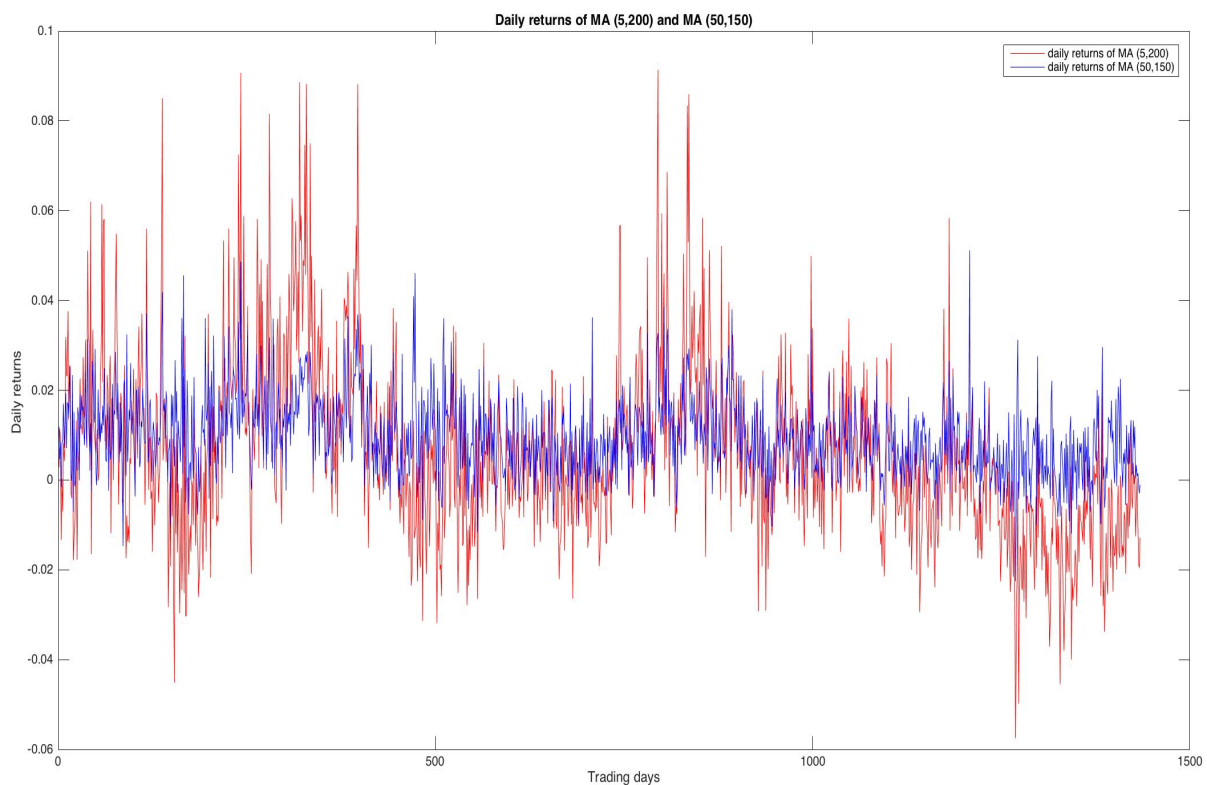


*Source: Graph computed by the author of the study*

In both graphs the blue line represents the daily returns of the MA (50,100), while the red line in the first graph represents the daily returns of the MA (5,100), while in the second graph the returns of MA (5,150). The two graphs are similar and it can be noticed easily the difference on the volatility of the MA (50,100) from the volatility of the other two strategies.

Next I compare the daily returns of the MA (5,200) and MA (50,150), two strategies that generate large differences in number of trades, where the trades produced by the MA (5,200) are almost 3 times the number of trades of MA (50,150). The following pictures shows precisely the difference in daily returns and volatility of these two strategies.

*Fig. 19 The daily returns of MA (5,200) and MA (50,150)*



*Source: Graph computed by the author of the study*

What all these three graphs have in common, is that the strategies that generate less trades also yield lower levels of standard deviations. This fact seems pretty normal and there have been a lot of studies that show positive relation between the volume of transactions and the volatility. Nonetheless in the next section where different regression models are built to assess the relation between the different elements of this study, this relation will also be considered.

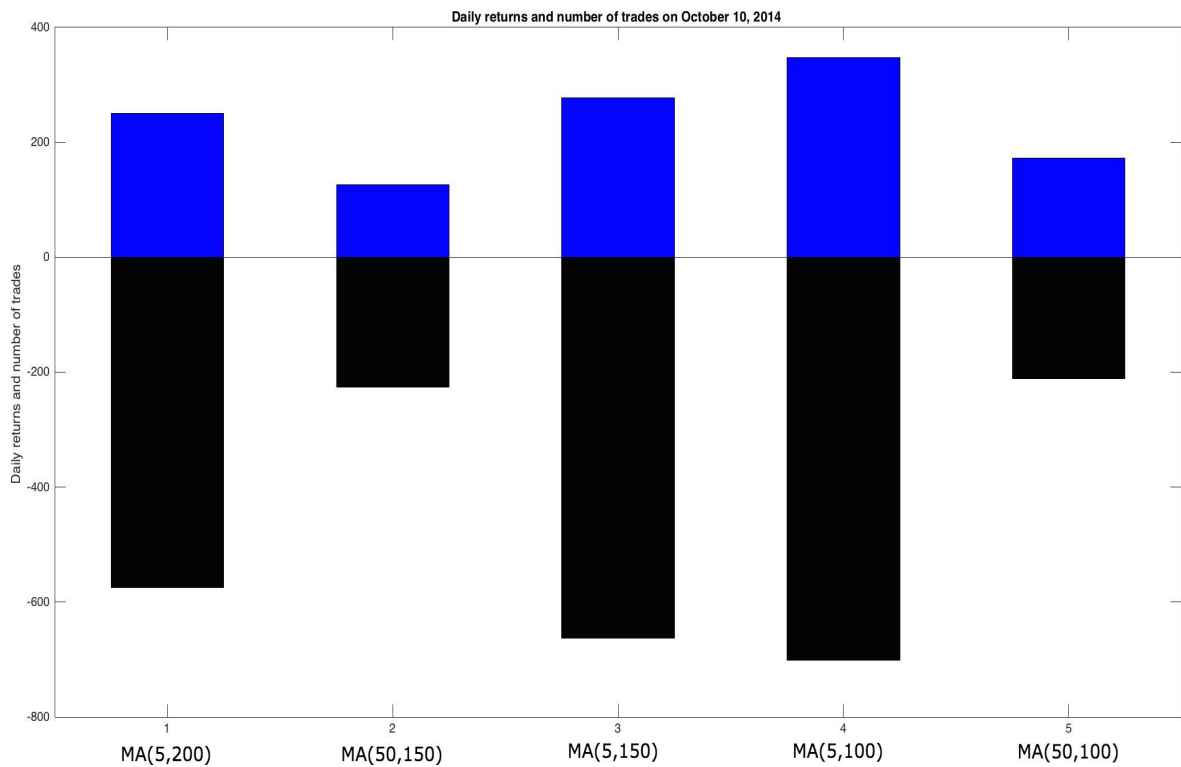
Next I analyze the daily returns and number of trades of all five strategies in specific days of high market volatility. The three days chosen are the October the 10<sup>th</sup> 2014, May 6<sup>th</sup> 2010 and August 8<sup>th</sup> 2011.

*Daily returns and number of trades on October 10<sup>th</sup> 2014*

An interesting thing to notice is that even though the most profitable day differs for each moving average strategy, the day they perform worse is almost the same. For four out of five strategies the worst performing day is October the 10<sup>th</sup> 2014, and for one moving average strategy the worst performing day is October 15<sup>th</sup> 2014, which is still very close to the others. This day is connected to what have been described as a ‘market freak out’ by a CNN Money’s reporter. On this day the Dow index fell by 460 points while then increasing slowly to close the day by a decrease of 173 points. The Nasdaq also fell briefly by 10% of a prior higher, and then re-bouncing back sharply, to close at a similar level of the day before.

The graph below shows the number of trades shown in blue, and the daily return shown in light blue for the strategies on this day. The daily returns are expressed in basis points.

*Fig. 20 The daily returns and number of trades on October 10<sup>th</sup> 2014*



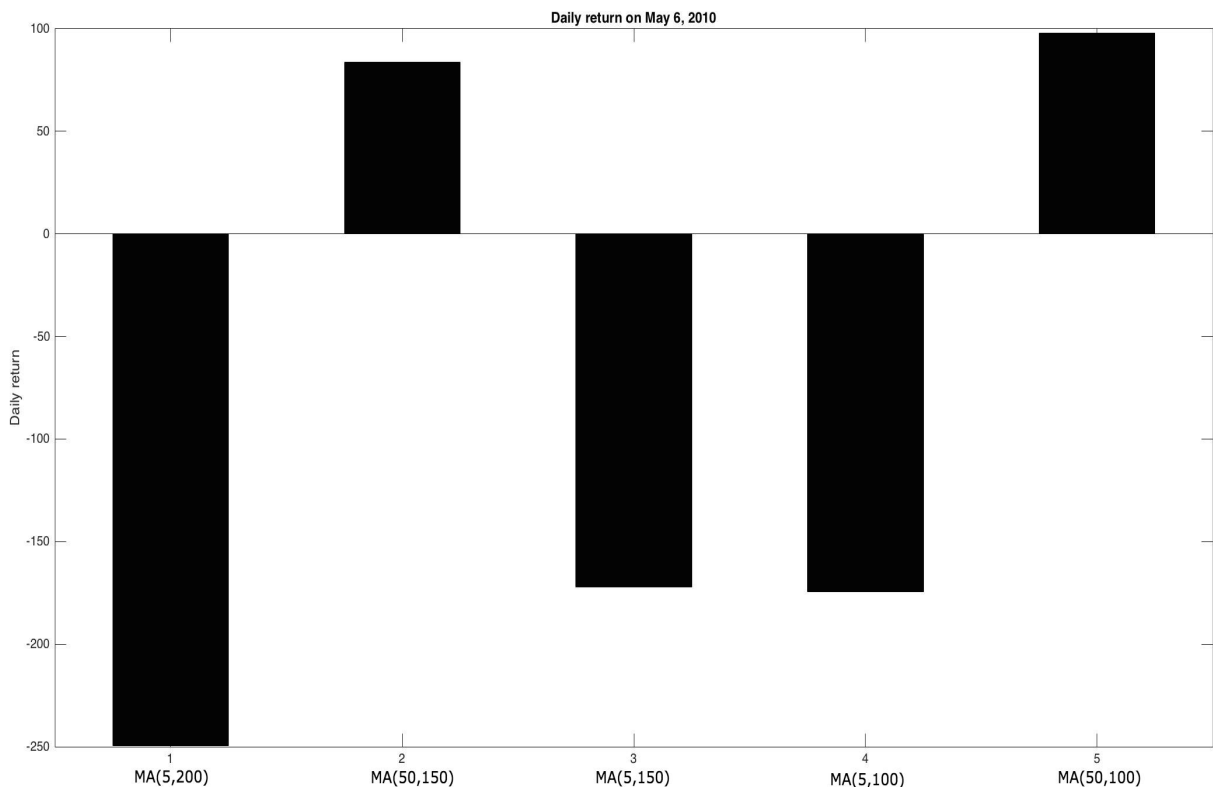
*Source: Graph computed by the author of the study*

*Daily returns and number of trades on May 6<sup>th</sup> 2010*

The May 6<sup>th</sup> 2010, also known as The Flash Crash was a United States trillion-dollar stock market crash, which started at 2:32 and lasted for more or less 36 minutes. Stock indexes, such as the S&P 500, Dow Jones Industrial Average and Nasdaq Composite, collapsed and rebounded very rapidly. The Dow Jones Industrial Average had its biggest intraday point drop (from the opening) up to that point, plunging 998.5 points (about 9%), most within minutes, only to recover a large part of the loss. It was also the second-largest intraday difference between intraday high and intraday low up to that point, at 1,010.14 points. As it is known the prices of stocks, stock index futures, options and exchange-traded fund (ETFs) were volatile, thus trading volume reached high levels. A CFTC 2014 report described it as one of the most turbulent periods in the history of financial markets.

The following pictures shows the returns of each strategy in this day expressed in basis points.

*Fig. 21 The daily returns on May 6<sup>th</sup> 2010*

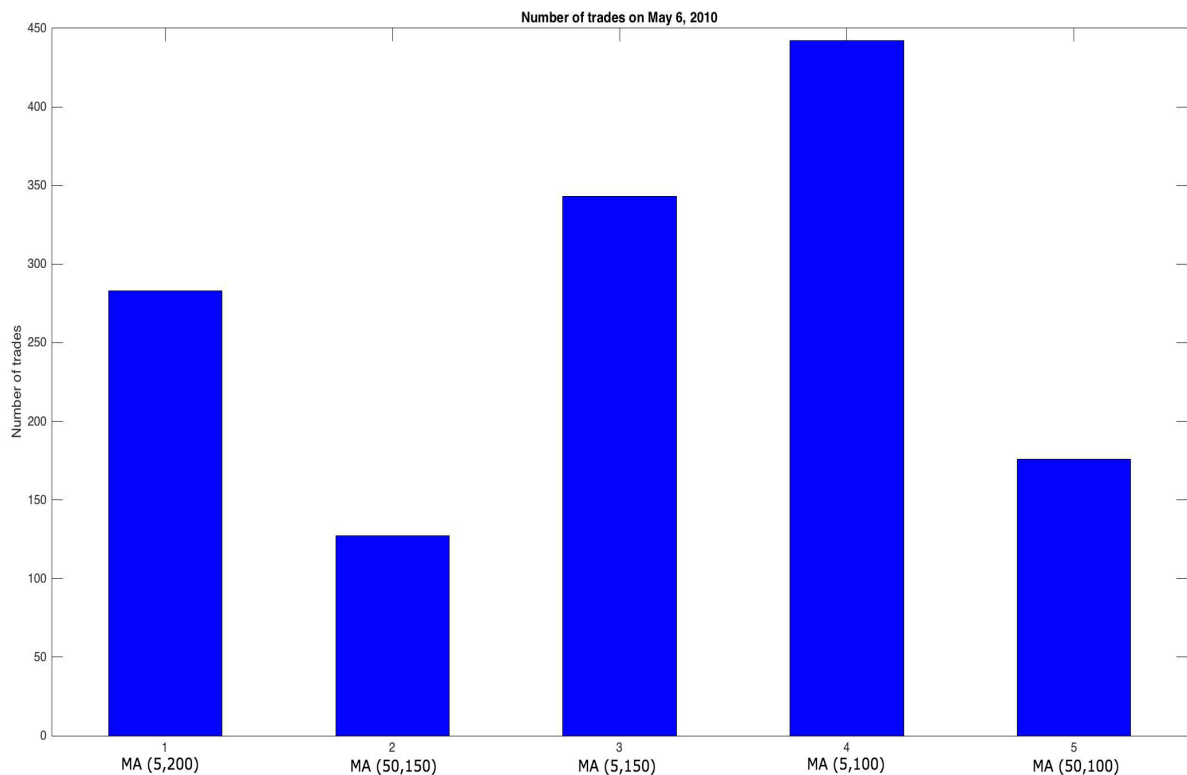


*Source: Graph computed by the author of the study*

While in the previous graph it can be seen that although the high volatility present in the market on this day, two of the strategies, the MA (50,150) and MA (50,100) yield positive returns. Of course I consider the daily returns without the transaction costs, in order to see only the effect of the strategy. Once transaction costs are introduced, all the strategies returns are negative.

In the next figure it is shown the respective number of trades in this day for every strategy and it is attempted to see the relation between the number of trades and the returns.

*Fig. 22 The number of trades on May 6<sup>th</sup> 2010*



*Source: Graph computed by the author of the study*

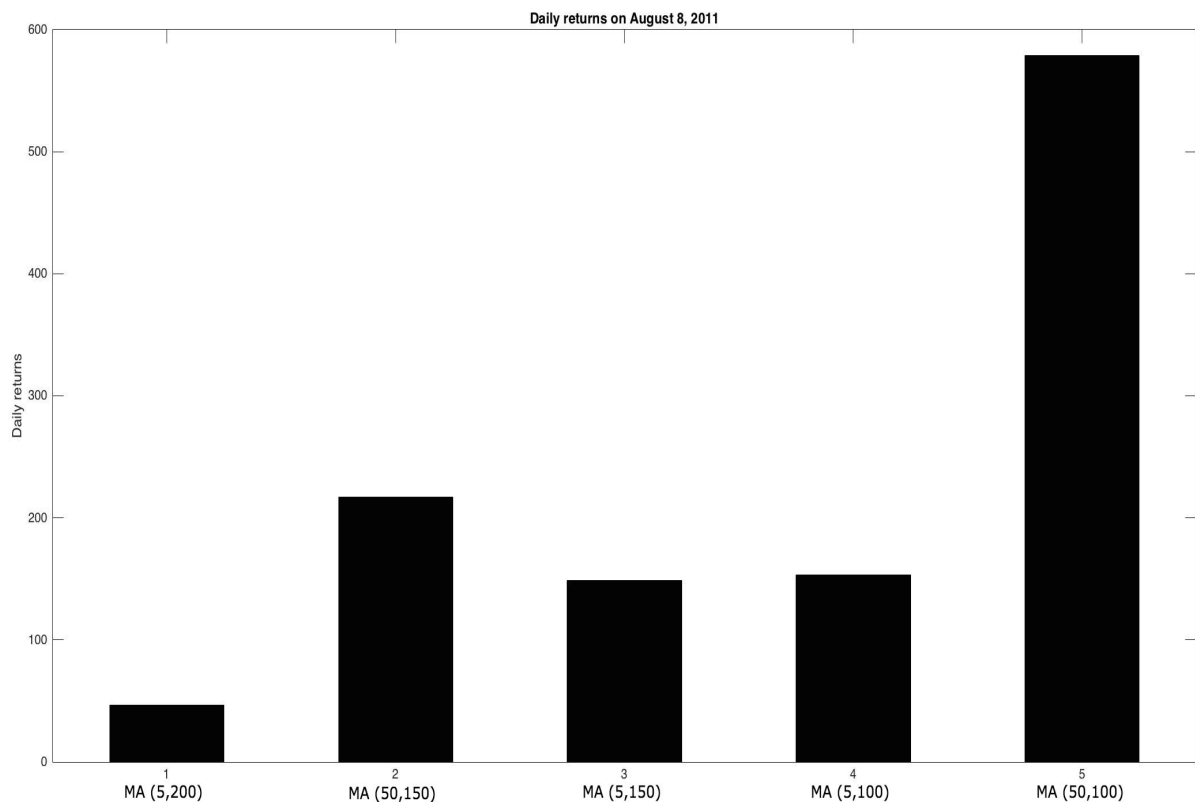
As can be seen by the two figures above, the two strategies that yield positive returns are the ones that generate less trades. This could be explained by the fact that in days of high volatility it is harder to predict the price movement in each moment, so the probability to be on the wrong side of a transaction is higher. The higher number of transactions that are made, the higher also the number of wrong transactions and thus the daily return is negative. This might not be true on rather stable days, with low volatility, in these cases models that generate larger number of transactions could capture small price movements and yield a higher return.

### *Daily returns and number of trades on August 8<sup>th</sup> 2011*

This market event is connected to the Black Monday of 2011, when on August 8<sup>th</sup>, the United States sovereign debt credit rating was downgraded by the Standard and Poor from AAA to AA+. This was the first time the credit rating of the US debt was downgraded. By the market closing time the Dow Jones Industrial Average lost 634.76 points (-5.55%), one of the largest drop of the index in the history. The NASDAQ Composite Index fall 174.72 points (-6.90%) closing at 2,357.69, the S&P 500 Index shed 79.92 points (-6.66%), the New York Stock Exchange lost 523.02 points (-7.05%).

The graph below shows the returns of the different strategies on this day.

*Fig. 23 The daily returns on August 8<sup>th</sup> 2011*



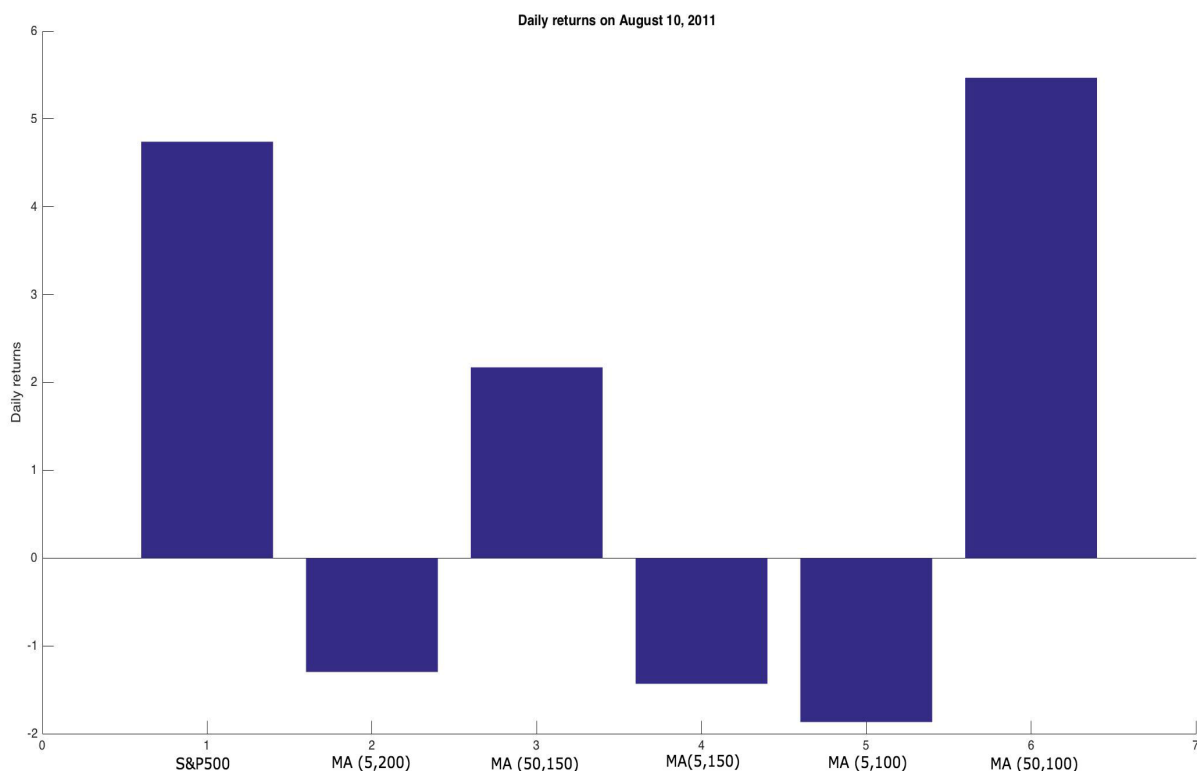
*Source: Graph computed by the author of the study*

As the figure above shows, all the strategies yield positive rates of return on this day, even though the most important market indices experienced large drops. It can be said that the strategies implemented responded well to the market volatility in this case. Although in general the daily returns are negatively correlated to the market volatility, as will be seen in the regression analysis part.

*Comparing the maximum return of the S&P500 with the MA strategies*

After comparing the returns of the strategies on volatile days, I compare the moving averages strategies with the maximum return of the S&P500 index reached in this period. The maximum return was 4.74 percent and was realized on August 10<sup>th</sup> 2011. The following figure shows precisely the returns of the S&P500 and the returns of the strategies in this day.

*Fig. 24 The daily returns on August 10<sup>th</sup> 2011*



*Source: Graph computed by the author of the study*

As can be seen by the above graph, on this day, when the S&P500 reaches its highest level of return, only one of the trading strategies actually performs better than the index. This strategy, the MA (50,100) is the best performing strategy among the others also. Its return on this day is 5.468 percent without considering transaction costs.

While when transaction costs are taken into account the return of this strategy is 1.48 percent. The strategy that performs worse in this day is the MA (5,100), even though this strategy was the best performing one on May 6<sup>th</sup> 2010.

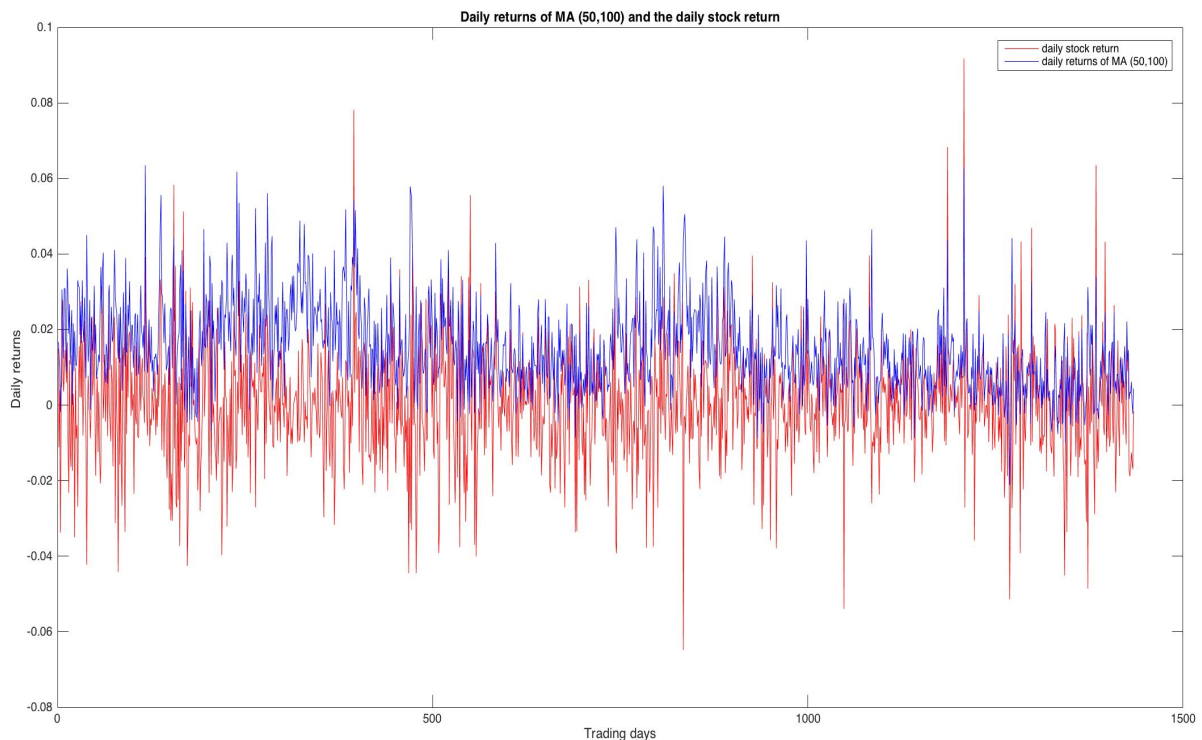
### *The impact of transaction costs*

As seen by the data shown previously transaction costs have a huge impact on the actual daily return of each strategy. In fact, for three of these strategies, the MA (5,200), MA (5,150), MA (5,100) when the transaction costs are included all daily returns become negative. While, for the MA (50,150) and MA (50,100) there are some days that generate positive returns even with transaction costs present. This is of course what it would be expected knowing that these two strategies are the ones that generate less trades, so the effect of the transaction costs is lower. More specifically the MA (50,150) has positive post-transaction costs return in 63 out of 1434 days, which corresponds to the 4.4 percent of days of the total time period. The MA (50,100) in 30 days out of 1434 generates positive returns with transaction costs taken into account, which corresponds to only 2.09 percent of days of the total trading period.

### *Comparing the daily returns of the best performing strategy with the daily return of the stock*

As a last comparison, I confront the daily returns of the MA (50,100) with the daily price movements of the Intel stock which I consider for this study. The graph below shows these two daily returns.

*Fig. 25 The daily returns of MA (50,100) and the daily stock return*



*Source: Graph computed by the author of the study*

### 5.3 Regression analysis

In this section different regressions are built in order to try and estimate the relationship between the variables produced by the strategies. The aim is to investigate the effect of one variable upon another one, or the effect of more than one variable on a specific variable. The different regressions are created using the datasets from the strategies. The variables that are considered from each strategy are: the daily return, the daily standard deviation, the number of trades per day and the realized volatility. Except the variables generated by each strategy, I also consider other market variables, such as the market volatility.

In the first regression the daily return is considered as the dependent variable. Before regressing the daily return to the variables mentioned above, I first regress it to each independent variable separately to see if these variables could explain the daily return. In this way it can be decided which variables to include in the final regression model.

The first variable I regress the daily return on is the Nasdaq market volatility. The dataset of the daily market volatility was downloaded for the same time period on which I build the trading strategy, in this way there are 1434 data of market volatility. The form of the regression is the following:

$$rD = \alpha + \beta \cdot NV + \varepsilon$$

where:

$rD$  – daily return

$NV$  – Nasdaq market volatility

$\varepsilon$  - error

This regression is applied to the dataset of the MA (50,100) strategy. Given that there are also datasets from the other strategies considered, the regression is applied also to the other datasets. If the independent variable is a good estimator of the dependent variable it should yield similar results. Each regression is applied to the different data from the strategies that were developed, allowing us to make comparisons. As said earlier the first dataset I use is the one of the MA (50,100) strategy and the results that are generated are shown in the following table.

Table 2. Daily return on market volatility regression MA (50,100)

	Estimate	SE	tStat	pValue
Intercept	0.011003	0.00059178	18.592	2.7557e-69
NV	0.014443	0.0021207	6.8106	1.4267e-11

Source: Table computed by the author of the study

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.011

R-squared: 0.0375, Adjusted R-Squared 0.0368

F-statistic vs. constant model: 55.7, p-value = 1.43e-13

To interpret these results, I start with the p-value measure of the estimates. The estimates are presented in the second column of the table and refer to the  $\alpha$  and  $\beta$  coefficient. While in the last column there are the p-values of these estimates, and both these values are less than the 0.05 so it can be said that the null hypothesis is rejected. The estimate of the market volatility is significantly different from 0 and it is likely to be a meaningful addition to the model because changes in the predictor's value are related to changes in the response variable.

As regards the Root Mean Squared Error (RMSE), it is an absolute measure of fit. As the square root of a variance, RMSE can be interpreted as the standard deviation of the unexplained variance, and has the useful property of being in the same units as the response variable. Lower values of RMSE indicate better fit.

R-squared has the useful property that its scale is intuitive: it ranges from zero to one, with zero indicating that the proposed model does not improve prediction over the mean model and one indicating perfect prediction. Since the R-squared is relatively small, and the RMSE has high levels one could argue that this model is not very relevant. Although one important thing to notice is that the R-squared is not very relevant measure, when considering the relationship between variables. That is why even though the R-squared measure is very low I still consider the independent variable as an explanatory variable for the daily return.

As regards the F-statistic tests the overall significance, and compares the model with no predictors with the model chose by me. For values as in this case of p-value lower than the significance level of 5 percent, the null hypothesis is rejected and the model provides a better fit than the intercept-only model.

*The daily return regressed on market volatility applied on the returns of MA (5,200)*

Next to see if there are similar results I regress the daily return to the Nasdaq market volatility on the MA (5,200) strategy results. The proceeding is in the same way I did previously, building the same regression model, only that in this case a different dataset is provided. The table below shows the results the regression model yields.

*Table 3. Daily return on market volatility regression MA (5,200)*

	Estimate	SE	tStat	pValue
Intercept	0.0054078	0.00094765	5.7066	1.3989e-08
NV	-0.0050003	0.003396	-1.4724	0.14114

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.0177

R-squared: 0.0118, Adjusted R-Squared 0.0111

F-statistic vs. constant model: 17.2, p-value = 3.65e-05

What is interesting to notice is that the results obtained in this case are partially similar and somewhat different from the results obtained in the previous regression. One important difference is that the p-values of the estimate is actually higher than the significance level, which means the null hypothesis is accepted. The acceptance of the null hypothesis which is that the market volatility has no effect on daily returns does not actually mean that the market volatility has no effect. The correct interpretation would be that there is not strong evidence that the market volatility has an effect.

While in the previous regression the null hypothesis was rejected, the question whether to include the market volatility in the model or not requires for more proof. That is why I apply the regression also to the dataset of two other strategies.

While as regards the RMSE, the R-squared and the F-statistic the results are similar. The R-squared shows a low level, close to 0, but as mentioned before this is not very relevant in this case. The F-statistic on the other hand has a p-value lower than the significance level of five

percent. This means that the null hypothesis is rejected and this model provides a better fit than the intercept-only model.

*The daily return regressed on market volatility applied on the returns of MA (50,150) and MA (5,100)*

Since the two previous regression yield different results I decide to regress the daily return to the Nasdaq market volatility on two other strategies. The strategies chosen are the MA (50,150) and MA (5,100). The proceeding is the same as the previous one, building the same regression model, only that in this case two different datasets are provided. Next are presented the tables with the results that are generated by each of the regressions.

*Table 4. Daily return on market volatility regression MA (50,150)*

	Estimate	SE	tStat	pValue
Intercept	0.0074383	0.00047339	15.713	1.8927e-51
NV	0.0077116	0.0016965	4.5457	5.9367e-06

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.00882

R-squared: 0.0167, Adjusted R-Squared 0.016

F-statistic vs. constant model: 24.3, p-value = 9.4e-07

The results obtained in this case are similar to those of the regression when applied to the MA (50,100). As can be seen the p-value of the estimate is actually lower than the significance level, which means the null hypothesis is rejected. Even in this case it can be said that there is evidence that the market volatility has an effect on the daily returns.

With respect to the other elements, the RMSE, the R-squared and the F-statistic yield similar results also. The R-squared shows a low level, close to 0, but as mentioned before this is not very relevant in this case. The F-statistic on the other hand has a p-value lower than the significance level of five percent. This means that the null hypothesis is rejected and this model provides a better fit than the intercept-only model.

Since there are two cases where the p-value rejects the null hypothesis of the  $\beta$  coefficient being equal to zero, and only one that accepts it I go on and regress the daily returns of MA (5,100) to the market volatility. The regression model is constructed using the data from the strategy and then compare the results with the previous results in order to build up an idea on whether the market volatility should be included as a variable on the final regression model. Below the table contains the results of the regression.

*Table 5. Daily return on market volatility regression MA (5,100)*

	Estimate	SE	tStat	pValue
Intercept	0.010491	0.0013599	7.7148	2.2574e-14
NV	-0.006553	0.0048734	-1.3446	0.17895

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.0253

R-squared: 0.0148, Adjusted R-Squared 0.0142

F-statistic vs. constant model: 21.6, p-value = 3.72e-06

The results of this regression are similar to the one built on the data of the MA (5,200) strategy, but different in terms of p-value of estimator, with respect to the other two regressions. This means that in this case the p-values is higher than the significance level of five percent which means that the null hypothesis is accepted. There is no strong evidence to rely on the effect of the market volatility on the daily returns. Given these somewhat contradictory results I decide to include the market volatility as an independent variable on the final regression model.

#### *Regressing the daily return on the realized volatility*

The second regression considered is the one where I regress the daily return on the realized volatility.

As have been mentioned on the first section of this chapter, I calculate the daily realized volatility as the sum of the square of the returns of every trade during the day. The regression that is built has the following form:

$$rD = \alpha + \beta \cdot RV + \varepsilon$$

where:

$rD$  – daily return

$RV$  – realized volatility

As I did on the first regression, I firstly apply the regression to the data from the best performing strategy, the MA (50,100). In the following table are summarized the results generated and then I comment each of them in order to understand the effect of the realized volatility on the daily returns.

*Table 6. Daily return on realized volatility regression MA (50,100)*

	Estimate	SE	tStat	pValue
Intercept	0.0098786	0.00038769	25.48	2.0467e-118
RV	87.7	4.4287	19.803	2.4748e-77

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.0108

R-squared: 0.216, Adjusted R-Squared 0.215

F-statistic vs. constant model: 394, p-value = 1.44e-77

The results of this regression show definitely a better regression model than the previous one. The p-value of the estimate, which in this case is the  $\beta$  coefficient of the realized volatility, is very close to zero. The fact that this values is close to zero means that the null hypothesis is rejected, meaning that the realized volatility does affect the daily returns.

As regards the Root Mean Squared Error, its value is low with respect to the value of the estimator. The RMSE indicates the absolute fit of the model to the data—how close the observed data points are to the model’s predicted values. Lower values of the RMSE generally indicate better fit, although the RMSE as the R-squared are mostly relevant in regressions used for predictions, rather than regressions that analyze the relation between variables.

Meanwhile the R-squared shows a higher level than the previous regression, a level of 0.215, which is not very close to one, but still as said earlier this is not very relevant in this regression. There are in fact regressions which interest is on the relation of variables and not on the prediction, for which a level of R-squared of 0.1-0.15 is reasonable. That is why it can be said that the R-squared is at an acceptable level since I am only interested in the relation of these variables.

Finally, for F-statistic the null hypothesis is rejected, since the level of its p-value is lower than the significance level of five percent and in fact, the value is very close to zero. As already explained the rejection of this hypothesis means that this model is better than the only-intercept model.

*Regressing the daily returns on the realized volatility of MA (5,200)*

Since the previous regression showed that it is needed to test the model on different datasets if possible, I go on and build again the second regression and this time using the data generated by the strategy MA (5,200). The dependent variable of this regression is the daily return of the strategy, while the independent variable considered is the realized volatility computed with the data of this strategy.

The table below summarizes the values this regression yields, values which will be explained and compared to the previous ones.

*Table 7. Daily return on realized volatility regression MA (5,200)*

	Estimate	SE	tStat	pValue
Intercept	0.0049605	0.00061591	8.0538	1.6738e-15
RV	-17.044	8.3554	-2.0399	0.041544

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.0176

R-squared: 0.0139, Adjusted R-Squared 0.0132

F-statistic vs. constant model: 20.1, p-value = 7.85e-06

As in the previous regression when strategy is switched, meaning the dataset used changes, the results of the regression also change a lot. For example, in this case the  $\beta$  coefficient is negative suggesting a negative correlation between the realized volatility and the daily return. Also, in

this case the p-value of the estimator is as previously lower than the confidence level, in which case I reject the null hypothesis. Its value though is closer to the five percent level, while on the other hand, the p-value generated on the previous regression is almost zero.

With respect to the R-squared there are also differences, in the previous regression I had a higher value on the level of 0.215 which was perfectly reasonable to this type of regression model, while in this case this value is much lower.

Lastly on the F-statistic there are not any huge differences. As in the previous regression the p-value of the F-statistic is almost zero, so the null hypothesis is rejected, meaning that this model and the intercept-only model are equal.

*Regressing the daily returns on the realized volatility of MA (50,150)*

To better assess if the realized volatility should be one of the variables included in the regression which tries to explain the daily return variable, I apply the last regression to the dataset generated to by the MA (50,150) strategy. The daily return is regressed on the realized volatility and the values obtained by this regression are presented in the following table.

*Table 8. Daily return on realized volatility regression MA (50,150)*

	Estimate	SE	tStat	pValue
Intercept	0.0065162	0.00029494	22.093	2.5907e-93
RV	61.967	3.5632	17.391	1.3166e-61

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.0087

R-squared: 0.174, Adjusted R-Squared 0.174

F-statistic vs. constant model: 302, p-value = 1.31e-61

The results provided by this regression are similar to the previous two. Except of the sign of the  $\beta$ , which in this case is positive as is in the MA (50,100) strategy, while in the regression on the data from MA (5,200) this coefficient is negative. When considering the significance of the coefficient, the p-value is very close to zero as in the MA (50,100). Since the p-value is

lower than the significance level of five percent the null hypothesis is rejected, accepting that the realized volatility does have an effect on the daily return.

The Root Mean Squared Error has a very low level which suggests that the model is a good fit.

With respect to the R-squared there are also differences, the previous regression generated a lower value on the level of 0.0139, while in this case I have a R-squared value closer to the one generated in MA (50,100). More precisely the value of R-squared 0.174 which is perfectly reasonable for the model.

Lastly on the F-statistic there are not any huge differences. As in the previous regressions the p-value of the F-statistic is almost zero, so the null hypothesis is rejected meaning that the model and the intercept-only model are not equal.

Given the results of the last three regressions it can be said that the realized volatility helps explain the daily return and will be included in the final model of regression.

#### *Regressing the daily returns on other variables*

The next variables I test on whether should be included or not in the regression model are the number of daily trades and the daily standard deviation of the strategy, that measures the volatility of the trade returns within one day.

I begin by regressing the daily returns on the number of trades using a simple linear regression as I did with the other two variables. The regression is the following:

$$rD = \alpha + \beta \cdot n + \varepsilon$$

where:

$rD$  – daily return

$n$  – number of daily trades

As I did in the previous cases, the first regression that is built, is the one on the dataset from the MA (50,100).

The values obtained by this regression could tell if the number of trades per day could be a good estimator of the daily returns according to the data from this strategy. Then as I did previously the same regression is going to be applied using the data from the other strategies

and I look for differences and similarities among them. In the table below there are the results of the first regression of the daily returns on number of trades.

*Table 9. Daily return on number of trades regression MA (50,100)*

	Estimate	SE	tStat	pValue
Intercept	-0.016587	0.00086622	-19.149	5.9784e-73
n	0.00018934	5.0197e-06	37.72	8.7331e-217

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.00804

R-squared: 0.499, Adjusted R-Squared 0.498

F-statistic vs. constant model: 1.42e+03, p-value = 5.07e-217

As can be seen by the values, the p-value of the coefficient of the number of trades is very close to zero meaning the null hypothesis is rejected, and the number of trades does have an effect on the daily return. The coefficient is positive which means that the returns are higher in days with more trades. This is what would be expected, for the number of trades having a positive effect on daily returns. Since if more trades happen the strategy generates more buy and sell signals capturing price movements and gaining from it. Also the fact that this estimate is positive, implying that the daily returns increase with the number of trades, suggests that the strategy is able to capture predictability in the stock market.

As regards the RMSE and R-squared values, both suggest that the model is a good fit. The RMSE has a very low value which means that in absolute terms the model is a good fit. The R-squared value is almost 0.5 which is pretty good since the model only contains one independent variable. The R-squared is an estimator that usually increases with the addition of more variables to the regression, that is why I am more concerned for its value in the final model, where all the significant variables will be included.

Finally, for the F-statistic the value rejects the null hypothesis, since the level of its p-value is lower than the significance level of five percent and in fact, the value is very close to zero. As already explained the rejection of this hypothesis means that this model is better than the only-intercept model.

*Regressing the daily return on the number of trades for the MA (5,200)*

In order to assess the significance of the number of trades as a variable I apply the regression also on the data from other strategies. The next regression I apply is actually, on the data of the MA (5,200) strategy. The results generated from this regression are summarized in the table below and will be compared to the ones obtained in the previous regression.

*Table 10. Daily return on number of trades regression MA (5,200)*

	Estimate	SE	tStat	pValue
Intercept	-0.048358	0.00099294	-48.702	4.376e-306
n	0.00018954	3.3096e-06	57.271	0

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.0104

R-squared: 0.696, Adjusted R-Squared 0.696

F-statistic vs. constant model: 3.28e+03, p-value = 0

The results of this regression are very similar to the previous one. The coefficient of the number of trades is also positive suggesting a positive correlation of the number of trades and the daily return. The p-value of this estimate is zero, meaning less than the significance level, as in the previous regression, implying that the null hypothesis is rejected and suggesting that the number of trades has an effect on the daily return.

Looking at the values of the RMSE and R-squared there can be noticed similar values. The RMSE value is low, while the R-squared is almost 0.7 which is a more than reasonable level, meaning that overall this model is a very good fit.

The last element considered is the F-statistic, the p-value of which is zero. In this case as in the one before the level of the p-value is lower than the significance level of 5 percent. The null hypothesis is rejected, which implies that this model is better than the only-intercept model.

The fact that both these regressions have similar results suggests that the number of trades is actually a good explanatory variable of the daily return and should be included in the model. Since there are five strategies, before deciding to include this variable I apply this regression to

the data of one more strategy, and see if the results confirm the conclusions drawn by the last two regressions.

*Regressing the daily return on the number of trades for the MA (50,150)*

As mentioned above, I decided to try the regression on the data of one last strategy. The strategy's data on which I apply the regression this time is the MA (50,150). The results obtained are shown on the table below, results which are then described and compared to the results of the previous regressions.

*Table 11. Daily return on number of trades regression MA (50,150)*

	Estimate	SE	tStat	pValue
Intercept	-0.048358	0.00099294	-48.702	4.376e-306
n	0.00018954	3.3096e-06	57.271	0

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.00744

R-squared: 0.296, Adjusted R-Squared 0.295

F-statistic vs. constant model: 602, p-value = 3.37e-111

The results this regression yields are similar to the previous one. The coefficient of the number of trades is positive and its p-values is 0. The level of p-value of course is less than the significance level and also in this case the null hypothesis is rejected, implying that the number of trades has effect on the daily return.

When considering the values of the RMSE and R-squared there can be noticed similar values to the ones in the previous regressions. The RMSE value is low, while the R-squared is almost 0.3 which is a quite reasonable level, meaning that overall this model is a very good fit.

Finally, the last element I consider is the F-statistic, the p-value of which is very close to zero. In this case as in the others before the level of the p-value is lower than the significance level of 5 percent. The null hypothesis is rejected, which implies that this model is better than the only-intercept model.

Since the regression of the daily returns on the number of trades for all three datasets from the different strategies suggest that the number of trades effects the daily return I decide to include it in the model.

*Regression of the daily returns on the daily standard deviation*

The last variable I consider for the regression model is the standard deviation. Since the standard deviation represents the variation of the trade returns within a trading day one would expect it to effect the overall daily return. But, in order to assess if these expectations are correct I regress the daily returns on the standard deviations using the following model of regression:

$$rD = \alpha + \beta \cdot sD + \varepsilon$$

where:

$rD$  – daily return

$sD$  – daily standard deviation

As I did with the previous regressions, I apply this regression to the data generated by the different moving averages strategies. The first data that I use for this regression are the ones produced by the MA (50,100). The results this regression yields are summarized in the table below, and the values are interpreted with respect to the p-values estimated. This regression will also be applied to other two datasets from the other strategies constructed.

*Table 12. Daily return on daily standard deviation regression MA (50,100)*

	Estimate	SE	tStat	pValue
Intercept	0.015907	0.00090528	17.571	9.7195e-63
sD	-2.5634	1.5183	-1.6884	0.091561

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.0112

R-squared: 0.00891, Adjusted R-Squared 0.00822

F-statistic vs. constant model: 12.9, p-value = 0.000344

The coefficient of the standard deviation is negative, which would suggest a negative correlation between the standard deviation and the daily returns, if the p-value was lower than the significance level. In this case though, the p-value is larger than the 5 percent level which means the null hypothesis is accepted, suggesting that there is no strong evidence to support that the standard deviation has an effect on daily returns.

As regards the RMSE and the R-squared, the values produced also imply that the overall model is not a very good fit. The R-squared values are very close to 0, meaning the model does not generate reasonable values to be considered a good model. Even though as mentioned before, the R-squared is not very relevant when one is only interested in the relation between variables, it is more important when looking for the predictive ability of the model.

When looking at the F-statistic though, the p-value it produces is lower than the significance level, rejecting the null hypothesis. What this means is that however the model produced is better than the only-intercept model.

*Regression of the daily returns on the daily standard deviation for MA (5,200)*

The results of the above regression show that there is no strong evidence of the standard deviation having an effect on daily return. Anyway since I also have data from other strategies, I try and run the regression also in another dataset in order to see if there is an effect of the standard deviation. The regression is applied on the data from MA (5,200) strategy. Below the table shows the values generated and I compare them to the previous regression.

*Table 13. Daily return on daily standard deviation regression MA (5,200)*

	Estimate	SE	tStat	pValue
Intercept	0.017772	0.0013374	13.288	4.396e-38
sD	-34.73	3.2144	-10.804	3.2629e-26

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.017

R-squared: 0.0852, Adjusted R-Squared 0.0845

F-statistic vs. constant model: 133, p-value = 1.49e-29

In this case the results are different from the previous ones. The coefficient of the standard deviation is negative as in the previous regression but its p-value is almost zero, meaning the null hypothesis is rejected, and the standard deviation has an effect on the daily return.

As regards the other estimates the results are similar. The RMSE is not very low while the R-squared is mostly close to zero meaning the overall model is not a very good fit. Although as mentioned before, the R-squared is not a very relevant estimate when one wants to assess the relation between variables. That is why at this point, I do not consider R-squared as a necessary estimate.

The measure of F-statistic is also similar, with a p-value generated at a level below the significance level, meaning that the null hypothesis is rejected. The rejection of the null hypothesis means that the model constructed is better than the intercept-only model, suggesting that the daily standard deviation should be included in the final regression.

*Regression of the daily returns on the daily standard deviation for MA (50,150)*

Given that in the previous two regressions the results were contradictory on whether the standard deviation has an effect on the daily return or not, I decide to apply the regression to one more dataset and observe the results generated. On the basis of these regressions I, then decide if to include the standard deviation in the final model of regression. I apply the regression model lastly, on the data from the MA (50,150) strategy. The results obtained are summarized in the table below.

*Table 14. Daily return on daily standard deviation regression MA (50,150)*

	Estimate	SE	tStat	pValue
Intercept	0.010879	0.00069432	15.668	3.4359e-51
sD	-2.5638	1.0144	-2.5274	0.011599

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1432

Root Mean Squared Error: 0.00887

R-squared: 0.00792, Adjusted R-Squared 0.00723

F-statistic vs. constant model: 11.4, p-value = 0.000739

The results of this regression are very similar to the ones of the last regression. The coefficient of the standard deviation is negative, suggesting once again a negative correlation between the two variables. Its p-value is at a level below the significance level, so the null hypothesis is rejected and it can be said that the daily standard deviation has an effect on the daily returns.

As regards the other estimates, they are also similar. Low level of the R-squared, even though as mentioned earlier, the R-squared is not very important when considering only the relation between variables, a higher level is needed when one is interested in the prediction ability of the model. The p-value of the F-statistic has a value lower than the significance level, meaning the hypothesis that this model is better than the intercept-only model is accepted. Given these results I decide to include the standard deviation in the final regression model.

#### *Final regression model*

After assessing the validity of each variable I decided to build the final regression which as a dependent variable will have the daily returns, while as independent variables are included: the market volatility, realized volatility, number of trades per day and the daily standard deviation.

I regress the daily returns to each of these variables individually before deciding to insert them in the model, as shown above. The previous regressions provide evidence to support the relevance of these variables in explaining the daily returns. The final regression has the following form:

$$rD = \alpha + \beta_1 \cdot NV + \beta_2 \cdot RV + \beta_3 \cdot n + \beta_4 \cdot sD + \varepsilon$$

where:

$rD$  – daily return

$NV$  – Nasdaq market volatility

$RV$  – realized volatility

$n$  – number of daily trades

$sD$  – daily standard deviation

$\varepsilon$  - error term

As in the previous regressions with only one independent variable, also in the final regression, I apply the model to the data produced by the different moving average strategies. The aim is to analyze if the model is a good representative model of the relation between the different variables, and try and see the effect that every independent variable has on the daily returns.

Below I will apply the regression to the data from the different strategies in order to see the results generated. The results are then analyzed and compared.

The first data used are the ones from the MA (50,100) strategy. As I did in the previous regression, the first strategy on which the model is applied, is the strategy that performs better. Eventually the regression will be applied also in the data from the other strategy in order to see if the model is a good fit for most of the strategies. The results of the estimates for the first strategy are all summarized in the table below.

*Table 15. Final regression applied to MA (50,100)*

	Estimate	SE	t-statistic	p-value
Intercept	0.0012106	0.0017796	0.68024	0.49646
NV	0.0034274	0.0015859	2.1612	0.030848
RV	229.09	7.6417	29.979	1.3393e-153
n	0.00012908	5.851e-06	22.062	4.5923e-93
sD	-37.739	2.6499	-14.242	3.8924e-43

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1429

Root Mean Squared Error: 0.00759

R-squared: 0.714, Adjusted R-Squared 0.714

F-statistic vs. constant model: 893, p-value = 0

The results of the regression show primarily a good model. The coefficients are all positive except one, suggesting positive correlation of all variables with the daily return with the exception of the standard deviation. The p-values of the coefficient of each variable are lower than the significance level of 5 percent. So, for each of the independent variables the null hypothesis is rejected, affirming that each variable has an effect on the daily return.

With respect to the RMSE, it generates low levels, meaning that in absolute terms the model is a good fit. The R-squared also is at a good level of 0.71 suggesting that the model is rather good in explaining the relation between the variables.

Finally, when looking at the F-statistic it produces a p-value lower than the significance level of five percent. The null hypothesis is rejected, implying that the model is better than the intercept-only model.

These results all suggest that the overall regression model is good in explaining the relation between the daily returns and the independent variables, mentioned above, that were included in the regression.

Next the regression is applied on the data from the other strategies developed and the results obtained are described and compared. The expectation is that the estimates produced by the regression will be similar even when implemented on the other datasets. Although some differences are expected but no huge variations in values.

*Final regression model applied to MA (5,200)*

Next I apply the final regression model, specified earlier, to the data generated by the MA (5,200) moving average strategy. The outcomes produced by this regression are summarized in the table below.

*Table 16. Final regression applied to MA (5,200)*

	Estimate	SE	t-statistic	p-value
Intercept	-0.046353	0.0022307	-20.779	5.1914e-84
NV	-0.0089417	0.0021439	-4.1708	3.2173e-05
RV	-24.74	11.774	-2.1013	0.03579
n	0.00019202	4.0423e-06	47.503	2.7141e-296
sD	1.2076	4.9372	0.24459	0.80681

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1429

Root Mean Squared Error: 0.0104

R-squared: 0.702, Adjusted R-Squared 0.702

F-statistic vs. constant model: 843, p-value = 0

The results again show an overall good model. Differently from the previous regression though, the coefficient of the market volatility and realized volatility suggest negative correlation to the daily returns, while the standard deviation is positively correlated. The p-values of all the estimates are lower than the significance level meaning that these variables do have an effect on the daily returns.

When looking at the RMSE and R-squared the results are very similar to the ones obtained earlier, with a low level of the RMSE and a R-squared of 0.7 which means that overall the model is a reasonable one when considering the relation among variables.

Lastly, when considering the F-statistic the values it produces are almost the same as the ones in the previous regression. The p-value of the F-statistic is zero, a value for which the null hypothesis is rejected and I accept that the model is better than the intercept-only model.

Subsequently, I continue by applying the final regression to the data from another strategy, more precisely the MA (50,150) strategy.

*Final regression model applied to MA (50,150)*

As mentioned above, I apply the final regression developed on the data from the MA (50,150) strategy. The results that this regression yields are shown in the table below, and will be compared to the results of the last two regressions.

*Table 17. Final regression applied to MA (50,150)*

	Estimate	SE	t-statistic	p-value
Intercept	0.0047345	0.0015326	3.0892	0.0020456
NV	0.001772	0.0014911	1.1884	0.23487
RV	192.74	6.4915	29.691	2.6953e-151
n	0.00011422	8.4321e-06	13.546	2.0328e-39
sD	-27.28	1.8756	-14.545	8.4648e-45

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1429

Root Mean Squared Error: 0.00722

R-squared: 0.612, Adjusted R-Squared 0.611

F-statistic vs. constant model: 563, p-value = 9.02e-292

The results of this regression are more similar to the ones from the regression on the data of the MA (50,100). The coefficients of all variables except one are positive, suggesting positive effect, while the standard deviation shows negative effect on the daily returns. One important difference is that in this regression the p-value of the market volatility, different from the other regressions, is larger than the significance level. This means that the null hypothesis cannot be rejected and that there is no strong evidence on the effect the market volatility has on daily returns.

As regards the RMSE and R-squared the results are very similar to the ones obtained earlier, with a low level of the RMSE and a R-squared of 0.6 which means that overall the model is a reasonable one when considering the relation among variables.

Finally, when looking at the F-statistic the values it produces are almost the same as the ones in the two previous regressions. The p-value of the F-statistic is very close to zero, a value for which the null hypothesis is rejected, which implies that the model is better than the intercept-only model.

*Final regression model applied to MA (5,100)*

At this point, I decide to regress the daily returns on the independent variables using the data from the MA (5,100) strategy. As in the regressions above the results obtained are described in absolute terms but they also compared to the previous regression results. The outcomes of this regression are presented in the table below.

*Table 18. Final regression applied to MA (5,100)*

	Estimate	SE	t-statistic	p-value
Intercept	-0.066821	0.0028831	-23.177	3.813e-101
NV	-0.011369	0.0025899	-4.3898	1.2178e-05
RV	-1.6044	12.724	-0.1261	0.89967
n	0.00020288	3.452e-06	58.773	0
sD	-15.377	7.1338	-2.1555	0.03129

*Source: Table computed by the author of the study*

Number of observations: 1434, Error degrees of freedom: 1429

Root Mean Squared Error: 0.0125

R-squared: 0.795, Adjusted R-Squared 0.794

F-statistic vs. constant model:  $1.38e+03$ , p-value = 0

The results are somewhat similar to the ones in the previous regressions with some differences. In this model all the coefficients of the variables, except one are negative, suggesting they have a negative effect on the daily return. The only variable whose coefficient is positive is the number of trades. The difference from the other regressions is that in this model the p-value of the realized volatility estimate is higher than the significance level, meaning there is no strong evidence to support the effect of the realized volatility on the daily returns. Although in the other regressions the p-value was at a level below, rejecting the null hypothesis.

As regards the RMSE and the R-squared the results are also similar. The RMSE is low, which is the criteria for having a model that is a good fit. The R-squared is at a reasonable level of almost 0.8, which suggests that the model is significantly good.

At last the F-statistic, as in all the regressions has a p-value at a level below the significance level, meaning the null hypothesis is rejected and the model is better than the intercept-only model.

#### *Summary of regression results*

After considering all the regressions above the following conclusions are achieved:

- 1) The overall regression model chosen to explain the effect the independent variables have on the daily returns is fairly good, and generally accepted.
- 2) The Nasdaq market volatility in most cases has a negative effect on the daily returns as one would expect, since situations of high volatility lead mostly to lower returns.
- 3) The realized volatility on the other hand has a positive effect on the daily returns. Although in two of the regression the coefficient is negative, in one of them the p-value it generates does not reject the null hypothesis and it is not considered.
- 4) The coefficient of the number of trades is positive in all the regressions, suggesting a positive effect on the daily returns. This is what one would expect, since the higher number of trades in a day would translate into a higher daily return.
- 5) Finally, the coefficient of the standard deviation is negative in all regression except one, but in the one that isn't the p-value is such that the null hypothesis cannot be rejected. So, as expected it can be said that the standard deviation has a negative effect on the daily return, which is normal given that the standard deviation represents the volatility of the returns within a day.



## 6. Conclusions

In this study I focus on building a trading strategy based on the technical analysis, more specifically, moving averages. Researchers have been long interested in understanding if the technical analysis could actually be used on predicting price movements, and on whether the stock market is efficient or not. Many studies have been conducted to check the profitability of these technical rules in different markets. The results are contradictory since some of these studies support the profitability of the technical analysis, while others are in favor of the Efficient Market Hypothesis, and sustain that any profitability from technical analysis is due to data snooping bias.

The efficient market hypothesis developed by Fama (1970) argues that the prices reflect all the available information and hence it would not be possible to make profits by using only information of past price data. Different studies have shown actually that the profitability of the technical analysis has declined over time. The reason assumed behind this is that with markets becoming more efficient technical trading rules lost their profitability.

Another theory I consider is the Adaptive Market Hypothesis developed by Lo (2004). According to this theory, differently from the efficient market hypothesis approach, prices reflect as much information as possible giving a combination of market participants and market conditions. Also, this theory admits there are arbitrage opportunities in the market in different times, and once they are exploited, they disappear. According to Lo (2004), contrary to the classical approach of efficient market hypothesis in which arbitrage opportunities are competed away, eventually eliminating the profitability of the strategy designed to exploit the arbitrage, the adaptive market hypothesis implies that such strategies may decline for a time, and then return to profitability when environmental conditions become more conducive to such trades.

As I said, there are many studies that show a declining in profitability of the technical trading rules. This however could be due to the fact that most of these studies use daily data to build their strategy. Of course though, in today markets, where it is traded with a very high frequency, it would be hard to try and exploit any price predictability in daily data. One of the benefits of this study is precisely this, I implement moving average trading strategies using high frequency data. In order to adapt to current market conditions, in this study I use price data of 1-second intervals, and I do so to check if these technical rules could be profitable in a high frequency environment.

The results produced from the different moving averages strategies I build suggest that there are actually some arbitrage opportunities to be exploited through intra-day trading. In fact, the

daily returns yielded are mostly positive, although when considering the transaction costs, the returns are almost all negative. This is due to two factors that will be described below.

The first factor is the large number of daily trades these strategies generate. There are approximately 300 trades per day, where each trade consists of a buy and a sell transaction. One could imagine that with these numbers the large costs of transactions that have to be covered, the small returns on each trade are not higher than the transaction costs faced.

The second factor, which is connected to the first one also, is that in many trades generated, yield a return of 0. This is explained by the fact that for some trades the buy and sell transaction happens within seconds, while the price level remains the same, causing the difference to result zero. Though these zero returns are not concerning when transaction costs are not considered, but when they are accounted for, these type of trades yield negative returns.

What I can draw up from these two factors is precisely that the presence of transaction costs drives away any profit which can be generated by the trading strategies. The returns generated by each trade in average are not high enough to cover the transaction costs.

In order to understand the relation between the variables the strategy generates I build a regression model, where as the dependent variable I use the daily return, which is regressed on the number of trades, the realized volatility, the market volatility and the daily standard deviation of the returns. From the individual regressions and the final regression, the hypothesis that each of the independent variables have an effect on the daily returns is accepted. In most cases the results of these regressions suggest a negative effect of the market volatility and the standard deviation, meanwhile a positive effect of the number of daily trades and the realized volatility on the daily returns. For all the coefficients of the final regression the null hypothesis is rejected, implying that all the coefficients are significantly different from zero.

The market on which I apply the trading strategy, is a mature and efficient market, that is why all profits opportunities that might have been present have been exploited, and it can only generate positive returns without transaction costs. This does not mean that the technical analysis does not have value. I believe it can be profitable under other market conditions. One possible extension of this study would be in fact to apply these strategies on high frequency data from other markets and see the results they would yield.

Another element to consider is that I base the trading strategy only on one type of stock. It would be interesting as a further extension of this study the construction of a trading strategy using moving averages, applied to high frequency data to more than one type of share. This

strategy could include buying and selling different shares during the day, using the signals generated by the moving averages crossovers.

Finally, in this study I only test the profitability of the moving average rules, while there are other instruments of the technical analysis that can be used to build trading strategies, even a combination of different instruments could yield better performing strategy.

Overall, even though the trading strategies based on moving averages rules do not yield positive returns when transaction costs are considered, I do believe that there are certain conditions for which the technical analysis has value. Therefore, I think that the technical analysis should be taken into account by investors and traders.



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## 8. Tables and Figures

Figure 1: Filter rules graph .....	6
Figure 2: A simple moving average crossover .....	7
Figure 3: Bollinger bands .....	8
Figure 4: Bollinger bands channels .....	9
Figure 5: MACD .....	11
Figure 6: RSI example .....	12
Figure 7: Daily price changes of the sock .....	45
Figure 8: The MA (5,200) .....	48
Figure 9: The MA (50,100) .....	49
Figure 10: Total number of trades .....	53
Figure 11: The daily returns of MA (5,200) .....	56
Figure 12: The daily returns of MA (50,150) .....	57
Figure 13: The daily returns of MA (5,150) .....	58
Figure 14: The daily returns of MA (5,100) .....	59
Figure 15: The daily returns of MA (5,100) .....	60
Figure 16: The daily returns of S&P500 .....	61
Figure 17: The daily returns of MA (5,100) and MA (50,100) .....	63
Figure 18: The daily returns of MA (5,150) and MA (50,100) .....	63
Figure 19: The daily returns of MA (5,200) and MA (50,150) .....	64
Figure 20: The daily returns and number of trades on October 10 <sup>th</sup> 2014 .....	65
Figure 21: The daily returns on May 6 <sup>th</sup> 2010 .....	66
Figure 22: The number of trades on May 6 <sup>th</sup> 2010 .....	67
Figure 23: The daily returns on August 8 <sup>th</sup> 2011 .....	68
Figure 24: The daily returns on August 10 <sup>th</sup> 2011 .....	69
Figure 25: The daily returns of MA (50,100) and the daily stock return .....	70

Table 1: Summary of results .....	55
Table 2: Daily return on market volatility regression MA (50,100) .....	72
Table 3: Daily return on market volatility regression MA (5,200) .....	73
Table 4: Daily return on market volatility regression MA (50,150) .....	74
Table 5: Daily return on market volatility regression MA (5,100) .....	75
Table 6: Daily return on realized volatility regression MA (50,100) .....	76
Table 7: Daily return on realized volatility regression MA (5,200) .....	77
Table 8: Daily return on realized volatility regression MA (50,150) .....	78
Table 9: Daily return on number of trades regression MA (50,100) .....	80
Table 10: Daily return on number of trades regression MA (5,200) .....	81
Table 11: Daily return on number of trades regression MA (50,150) .....	82
Table 12: Daily return on daily standard deviation regression MA (50,100) .....	83
Table 13: Daily return on daily standard deviation regression MA (5,200) .....	84
Table 14: Daily return on daily standard deviation regression MA (50,150) .....	85
Table 15: Final regression applied to MA (50,100) .....	87
Table 16: Final regression applied to MA (5,200) .....	88
Table 17: Final regression applied to MA (50,150) .....	89
Table 18: Final regression applied to MA (5,100) .....	90

## 9. Appendix

### Matlab Code

```
%load data set
fileID=fopen('INTC.txt');

c = 0;
while ~feof(fileID)
    c = c+1;
    C=textscan(fileID,'%s %s %f %f %f %f %d',1e6,'Delimiter',' ');
    data(c,1) = {C};
    disp(c)
end
fclose(fileID);

%save raw data
save raw.mat;

load raw.mat;

%convert cell objects to vectors
for i=1:18
    C=data{i,1};
    Datestr(i,1)=C(1,1);
    Timestr(i,1)=C(1,2);
    Openp(i,1)=C(1,3);
    Highp(i,1)=C(1,4);
    Lowp(i,1)=C(1,5);
    Closep(i,1)=C(1,6);
    j=(i-1)*1e6+1:length(C{1,1})+(i-1)*1e6;
    D(j,1)=Datestr{i,1};
    T(j,1)=Timestr{i,1};
    Open(j,1)=Openp{i,1};
    High(j,1)=Highp{i,1};
    Low(j,1)=Lowp{i,1};
    Close(j,1)=Closep{i,1};
    disp(i)
end

%create matrix Data containig all the data
formatIN1='mm/dd/yyyy HH:MM:SS';
formatIN2='HH:MM:SS';
DateVector = datevec(D,formatIN1);
timevec= datevec(T,formatIN2);
Data(:,1:3)=DateVector(:,1:3);
Data(:,4:6)=timevec(:,4:6);
Data(:,7)=Open(:,1);
Data(:,8)=High(:,1);
Data(:,9)=Low(:,1);
Data(:,10)=Close(:,1);

% logical vector for rows to delete
deleterow = false(size(Data, 1), 1);

% loop over all lines
% delete data before 9.30 and after 16.00
for n = 1:size(Data, 1)
    if Data(n,4)<9
        deleterow(n) = true;
    elseif Data(n,4)==9 && Data(n,5)<30
        deleterow(n)=true;
    end
end
```

```

elseif Data(n,4)==16 && Data(n,5)>0
    deleterow(n)=true;
elseif Data(n,4)==16 && Data(n,5)==0 && Data(n,6)>0
    deleterow(n)=true;
elseif Data(n,4)>16
    deleterow(n)=true;
end
end

% delete rows
Data(deleterow, :) = [];
save data.mat Data

load data.mat;
%calculating a vector with the average of the 4 prices
for n=1:size(Data,1);
    Avg(n,1)=mean(Data(n,7:10));
end

%constructing the moving averages
SMA=movingmean(Avg,50);
LMA=movingmean(Avg,100);

%creating the vector with the buy and sell signals
pos=zeros(size(SMA));
for i=1:size(SMA)
    if SMA(i)>LMA(i)
        pos(i)=1;
    elseif LMA(i)>SMA(i)
        pos(i)=-1;
    end
end;
%closing open positions at the end of the day
for i=2:size(Avg)
    if Data(i,4)==16 && pos(i-1)==1
        pos(i-1)=-1;
        pos(i)=-1;
    end
end;

%trading strategy, no short-selling constraint
buy=zeros(size(Avg));
sell=zeros(size(Avg));
dt=zeros(size(Data(:,1:6)));
T=zeros(size(Avg));

for i=2:size(Avg);
    if pos(i)==pos(i-1)
        T(i)=1;
    end;
end;

h=find(T==0);
p_b=1000000*0.8;
nr_shares=0;

for i=2:(size(h)-1);
    if pos(h(i))==1
        nr_shares=p_b./Data(h(i)+1,9);
        p_b=0;
        buy(h(i))=nr_shares*Data(h(i)+1,9);
    elseif pos(h(i))==-1
        p_b=nr_shares*Data(h(i)+1,8);
        sell(h(i))=nr_shares*Data(h(i)+1,8);
    end
end

```

```

        nr_shares=0;
        dt(h(i),1:6)=Data(h(i),1:6);
    end
end;

%creating the strategy matrix with all the transactions
strg=zeros(1,10);

for i=1:size(dt);
    if dt(i,1)>0
        strg(end+1,1:6)=dt(i,1:6);
    end
end
a=2;
for i=1:size(sell);
    if sell(i)>0
        strg(a,7)=sell(i);
        a=a+1;
    end
end

a=2;
for i=1:size(buy);
    if buy(i)>0
        strg(a,8)=buy(i);
        a=a+1;
    end
end

for i=1:size(strg);
    strg(i,9)=strg(i,7)-strg(i,8);
end

for i=1:size(strg);
    strg(i,10)=(strg(i,7)*(1-0.0001))-(strg(i,8)*(1+0.0001));
end

strg(1,:)=[];

save strg.mat strg

%converting to daily data
load strg.mat;

for i=1:size(strg,1);
    r1(i,1)=strg(i,9)/strg(i,8);
end

for i=1:size(r1);
    r1(i)=1+r1(i);
end

for i=1:size(strg,1)
    rT1(i,1)=strg(i,10)/strg(i,8);
end
for i=1:size(rT1);
    rT1(i)=rT1(i)+1;
end

pD=[];
dD=[];
ind=[];

```

```

% find the first end of the day
d1=strg(1,1:6);
for j=2:size(strg,1);
    if d1(1,3)==strg(j,3);
    else
        pD=strg(j-1,7:10);
        dD=strg(j-1,1:6);
        ind=j-1;
        break;
    end;
end;
d1=dD;

% loop to build data
for i=j:size(strg,1);
    if d1(1,3)==strg(i,3);
    else
        pD=[pD; strg(i-1,7:10)];
        dD=[dD; strg(i-1,1:6)];
        d1=strg(i,1:6);
        ind=[ind; i-1];
    end;
end;
ind(1)=1;

%computing daily returns
rD=zeros(size(pD(:,1)));
for j=1:size(ind)-1;
    rD(j)=prod(r1(ind(j):ind(j+1)));
end
for i=1:size(rD);
    rD(i)=rD(i)-1;
end

%computing daily standard deviation
for i=1:size(r1);
    r1(i)=r1(i)-1;
end

sD=zeros(size(pD(:,1)));
for j=1:size(ind)-1;
    sD(j)=std(r1(ind(j):ind(j+1)));
end

%computing daily returns with transaction costs
rTD=zeros(size(pD(:,1)));
for j=1:size(ind)-1;
    rTD(j)=prod(rT1(ind(j):ind(j+1)));
end
for i=1:size(rTD);
    rTD(i)=rTD(i)-1;
end

%number of trades per day
for i=1:size(ind)-1;
    n(i,1)=ind(i+1,1)-ind(i,1)+1;
end

save day.mat rD rTD sD n dD;

```

```

%computing the realized volatility
load strg.mat;

for i=1:size(strg,1);
    r1(i,1)=strg(i,9)/strg(i,8);
end
for i=1:size(r1)
    r1(i,1)=r1(i,1)^2;
end

pD=[];
dD=[];
ind=[];

% find the first end of the day
d1=strg(1,1:6);
for j=2:size(strg,1);
    if d1(1,3)==strg(j,3);
    else
        pD=strg(j-1,7:10);
        dD=strg(j-1,1:6);
        ind=j-1;
        break;
    end;
end;
d1=dD;

% loop to build data
for i=j:size(strg,1);
    if d1(1,3)==strg(i,3);
    else
        pD=[pD; strg(i-1,7:10)];
        dD=[dD; strg(i-1,1:6)];
        d1=strg(i,1:6);
        ind=[ind; i-1];
    end;
end;
ind(1)=1;

%computing daily realized volatility
rV=zeros(size(pD(:,1)));
for j=1:size(ind)-1;
    rV(j)=sum(r1(ind(j):ind(j+1)));
end
rV(1435)=[];

save rvol.mat rV;

%computing the regression model
load ('day.mat');
load ('VolNdaq');
load rvol.mat;
Var=zeros(1434,4);

for i=1:size(Var);
    Var(i,1)=VolNdaq(i);
    Var(i,2)=rV(i);
    Var(i,3)=n(i);
    Var(i,4)=sD(i);
end
mdl=fitlm(Var,rD,'linear','RobustOpts','on')

```