Technical Trading, Data-Snooping and the Impact of Speed.

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In this paper we examine the profitability of 48,548 different technical trading rules. We will apply all the rules to the 63 trading days from April 1st 2009 to June 30th 2009 for the following 6 securities: MU, SPY, MMM, DELL, IBM and Microsoft. We will test these securities on 5 different intervals; 12, 30, 45, 60 and 300 seconds. We will then correct the results for data-snooping bias using White's reality check (White(1999)). For the seemingly best working interval length we will vary starting times and evaluate possible differences.

1. Introduction

Technical trading is about forecasting future prices by studying past market data, like price and volume. The main tool of a technical trader is the stock chart. Using the stock chart, a trader will try to find patterns and make strategies. The strategies will tell him at what point he should enter the market and make transactions. Nowadays, with recent electronic developments, there are far more possibilities for technical traders than before.

Before electronics were used to connect buyers and sellers, trading only happened on floor markets. On floor markets, all buyers and sellers were represented by a relatively small number of brokers. Nowadays almost all trades are made electronically. It is now possible for traders to take actions in a matter of seconds instead of minutes. Because of the increased speed of the trading markets, trading is more various than before.

A lot of research has already been done when it comes to technical trading. Sullivan, Timmermann and White (1999) describe and test the five most basic and most commonly used trading rules on the equity market over the period 1897-1986. With these 5 basic rules they constructed over 7000 strategies, using different parameters. In their research they found that a number of strategies made profit. However, a lot of these strategies have made profit just because of luck, since they tested over 7000 strategies. This is called the data-snooping bias, after adjusting for the data-snooping bias they found that none of the profitable strategies were significant.

These strategies were tested again by Marshall, Cahan and Cahan(2008). They used intraday time horizons of 5 minutes, and included the same 7000 as Sullivan et al (1999). Hsu and Kuan (2005) extended this research by adding 7 different rules, as well as the counterparts of all strategies and different ways to combine strategies. For both Marshall et al.(2008) and Sullivan et al. (1999) the conclusions remained the same; after accounting for data-snooping bias, no strategy remained profitable.

Hasbrouck and Saar (2010) did research on trading-activity. They found that, on average, there is a lot more activity in the beginning of a second than at the end of a second. This means trading a few milliseconds earlier or later might produce different results.

In this research, we will reconsider most of the strategies that Hsu and Kuan used in their article. However, we will test these strategies on new data, starting on April 1, 2009 until June 30, 2009, for a total of six different securities. This gives a total of 63 trading days per security. We will split this up in two sub samples: The first 40 days which is our in-sample period and the other 23 days which is our out of sample period. Also the intervals will differ from past research, instead of the 5 minute or even daily intervals which are used in former papers, we will test for 12, 30, 45, 60 and 300 second intervals. By using these smaller intervals we want to exploit the electronic developments from the past 20 years. We will test a total of 11 rules, and with these 11 rules we construct 24,274 different strategies. We double the amount of strategies by also using the contrarian rules. These contrarian rules give exactly the opposite signal as the original rules. This means that with these contrarian rules, we have a total of 48,548 strategies. Afterwards, we test these strategies while accounting for data-snooping bias. Furthermore we will test if different starting periods, 2,15,30,45 and 58 seconds later than the original starting point, will lead to different returns and a more profitable strategy.

In this paper we will start off with an introduction to market microstructure. In Section 3 we will discuss the data, which we will be using for this research. The structure of the order book can be found in section 3.1. In section 3.2 we discuss the data properties and in section 3.3 the data will be analyzed. The different methods and strategies can be found in Section 4. The results will be discussed in section 5. First we will examine the results of the in-sample returns, followed by the out-of-sample results in section 5.2. In section 5.3 we correct our results for data-snooping bias and in section 5.4 we discuss whether results differ when our strategies start at different starting periods. Conclusions can be found in section 6.

2. Market microstructure

Market microstructure studies trading behavior in financial markets. This includes not only how different markets operate, but also the factors influencing trading behavior: transaction costs, prices, quote and volume. In this chapter we will first discuss two market types: the floor market and the limit order market. After that we will discuss some basic properties of trading. Finally we will discuss some special trading actions, which traders can decide to take.

In a floor market, all buyers and sellers are represented by a relatively small number of brokers, who try to find matching buyers and sellers and make the deal. Brokers cannot trade for themselves, because in that case they could pursue self-interest. Floor trading looks chaotic, but there are very clear rules. Hand signals reveal exactly the type of order and deceptive actions to find a seller willing to sell at a lower price than the current bid are not allowed. However, due to electronic developments, the floor markets are nowadays used less.

The main reason is the speed: trading over the internet is faster and is therefore more attractive to most traders. In 2011, only two major stock exchanges still had floor trading activity, namely the New York Stock Exchange and the Frankfurt Stock Exchange[1].

A limit order market is one of the most common mechanisms to accomplish a trade nowadays. These markets all have a limit order book that stores all the current open orders that traders place if they want to buy or sell an amount of securities. If these orders are executed, they will be removed from the order book. As everything goes electronically, these type of markets do not need a trading floor or any brokers. Traders can check the limit order book to place an order on the internet, rather than going to the floor of the stock exchange itself. An example of such a limit order market is the NASDAQ.

There are some basic properties regarding to trading for the different market mechanisms. Most of these are concerning the price. If traders think the stock will rise in the next period, they place an order to buy an amount of stocks against a certain price, also called going long or taking a long position. The price for which you can buy this stock will be higher than the price for which you can sell it. These buying and selling prices are called the ask price and the bid price respectively. The difference between the lowest ask price and the highest bid price is called the bid-ask spread. The current price, which can be seen on stock quotes, will always be between the bid and ask price.

As a lot of orders are placed every day, the bid-ask spread will be only a couple of cents for the largest securities. If, for example, someone places an order with a bid price that is equal to a ask price, a trade can be made. Orders do not have to be exact opposites to be matched. For example, if the order book contains the order: Sell 500 at $20.05. Then another order arrives: Buy 100 at $20.07, there is a partial match. If this is case, the price of the first order will be used, and in this example 100 securities are traded at the price of $20.05. The collections of all the orders that have not been fulfilled are saved in the limit order book. Of course, this book changes all the time with every new order and the possibly following trade.

If more orders are executed at the same time there are several rules which need to be complied. Firstly there is price priority. Orders with a better price will be executed before orders with a worse price. Secondly, there is time-priority: If two orders match in price, the one which arrived first will be executed first.

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1 Information is adapted from
http://blogs.wsj.com/marketbeat/2011/02/09/deutsche-boerse-nyse-so-long-nyse-trading-floor/

A trader can extend the orders he places with special actions. He can, for instance, decide to set the order to be executed 'at the market' or buy or sell it immediately at the best available price. If the order quantity the trader wants to trade is bigger than the quantity available at the best price, an order will 'walk the book'. In some cases, traders want to buy or sell securities at progressively worse prices until the whole order is executed. In some markets this is not allowed, as it can lead to a chain reaction. In these markets, an order will execute at most for the quantity of the best price. The remainder will be added to the book as an order at the same price.

Markets also often permit qualifications on the order. The time-in-force (TIF) tells you how long the order will be active. If the trader wants to cancel earlier, this is still possible. If a trader wants to execute immediately or not at all, this is called an immediate-or-cancel (IOC) order. These actions will never reach the limit order book. Also, all-or-nothing (AON) orders will be executed as a whole, or not at all.

A trader willing to trade large amounts of securities may not want everybody to know this. Therefore some markets allow hidden and/or reserve orders. If an order cannot be executed, it will be added to the book, but hidden for everybody except for new incoming orders of traders who may then be pleasantly surprised. Reserve orders are only partially hidden. An amount will be displayed, and if executed, be refreshed from the reserve quantity until the order is totally executed.

The data in a limit order book is very accurate and detailed, however there are limitations. Because of the enormous amount of orders, computing is made far from easy. And because of precise specifications of the orders, modeling is difficult as well.

3. Data

In this research, we use the data of five different stocks and one exchange-traded fund (ETF), over the period of April 1, 2009, till June 30, 2009. As the stock exchange markets are closed during the weekend and holidays, the data consists of 63 trading days. We will use the first 40 trading days in this research to test our analysis. The last 23 days will be used for an out-of-sample test. The stocks that are considered are Mircon Technology, 3M Company, International Business Machines Corporation, DELL Inc and Microsoft Corporation. The ETF we analyze is the S&P 500 index, also referred to as SPY.

The regular market hours of the NASDAQ stock exchange range from 9.30 am to 4.00 pm. Further, there are pre-market trading hours from 4.00 am until 9.30 am, and after-market hours from 4.00 pm until 8.00 pm. In these hours traders are still capable of placing buy and sell orders to fully utilize the influences that may occur outside of the regular trading hours. Chris Concannon, former executive Vice President in the transactions Service Group of the NASDAQ quoted "Many companies report earnings either before the market opens or after the market closes. The intrinsic value of a stock is constantly moving whether the market is open or not, and people want to access the market when the intrinsic value is changing"[2]. Due to these pre-market and after-market hours this is made possible. However, trading between these market hours will give more risks. These market hours will not be analyzed during this research.

We will first look at the structure of the limit order books. This can be found in section 3.1. Furthermore, we look at the properties of the limit order books and we will discuss them in more detail in section 3.2. Finally we will analyze some characteristics of the data in section 3.3 including the moments of taking actions.

3.1 Structure of the order book

The NASDAQ exchange market produces millions of messages every day. These messages consist of incoming orders and system notifications. With all these messages, the order book can be constructed. However, for the limit order book, you only need the order messages, so the first thing that has to be done, to work with the data, is selecting only those messages that contain an action of a trader.

Before we are able to do this, we need to have more information about the different messages. Every message starts with two letters. The first letter gives information about what the message represents. There are a total of five different categories which can represent this first letter: system event messages; stock related messages; add order; modify order messages and trade messages. Every category contains one or more different letters which represent the second letter. A clear overview of these letters can be found in the appendix, in Table A.1. For the construction of the limit order book, we only need the last three categories; the add order, the modify order and the trade messages.

The second letter displays the action that is taken in the aforementioned categories. In this way there are a whole lot of possible combinations. A full analysis of these different letters can be found in the NASDAQ Totalview ITCH specification. As we only need the order messages to construct the limit order book, we excluded the system messages and stock related messages in our research.

After the two letters follow more specific details about the order message. These details include the time in seconds and nanoseconds at which the message is placed. Note that the seconds are provided in the number of seconds since midnight. At the start of the trading hours at 9.30 am, the

[2] The time of the trading hours as well as the quote of Chris Concannon are adapted from http://www.nasdaq.com/newscontent/20090216/understanding-pre-market-and-after-hours-stock-trading.aspx

seconds are already at 34,200 and count further from this number. Finally, the day ends at 57,600 seconds, at 4.00 pm.

The message further contains the amount of securities that the trader would like to buy or sell and the price for which the trader wants to trade his securities.

With this information, we can construct the limit order book. This book records the number of current buy order messages and sell order messages, along with the amount of shares involved in trading or selling against a certain price. When a bid price of an order matches an ask price, a line will be added in the order book to declare that a trade is made, and the corresponding buy and sell orders will be deleted from the limit order book.

The limit books in this research keep track of the total amount of current buy and sell orders. However, it only saves the best five buy orders and best 5 sell orders, with the amount of securities and the price.

3.2 Data Properties

Table 3.1 provides the total number of messages that influence the limit order book for every security. The messages are displayed for every category. In the columns can be found how often that specific letter appears for the given stock in the 63 days, measured in percentages. The last row shows the total number of observations for each of the securities over the period of 63 days.

This total number of messages is quite different for each security. For SPY, we observe over 310 million actions in 63 days, whereas this is a lot less for the five stocks. Also, the row with the replaced messages (shown by the U in the Table) shows a higher percentage compared to all other stocks. A possible reason for this is that people can use this ETF for hedging purposes. Hedging means that a trader owns a security, which brings a certain risk. This trader wants to minimize this by buying another security to try and make his portfolio risk neutral. An ETF is a common hedge fund.

Category	Action	DELL	MU	IBM	MMM	Microsoft	SPY
Added message	A	43.71%	43.07%	46.93%	45.47%	43.59%	38.71%
	F	1.09%	0.38%	0.95%	0.72%	1.40%	0.07%
	Total	**44.80%**	**43.44%**	**47.88%**	**46.19%**	**44.99%**	**38.78%**
Execution message	E	6.39%	5.35%	4.03%	2.66%	6.89%	5.31%
	C	0.23%	0.52%	0.17%	0.16%	0.22%	0.24%
	Total	**6.62%**	**5.86%**	**4.20%**	**2.82%**	**7.10%**	**5.55%**
Trading message	X	0.32%	0.58%	0.77%	0.62%	0.57%	1.75%
	D	39.86%	39.32%	44.43%	44.06%	39.73%	34.77%
	U	7.93%	10.33%	2.00%	5.82%	7.18%	19.02%
	P	0.47%	0.47%	0.72%	0.48%	0.43%	0.14%
	Total	**48.58%**	**50.70%**	**47.92%**	**50.98%**	**47.91%**	**55.68%**
Total messages		28,256,600	13,019,369	21,129,545	15,078,760	52,960,603	310,336,256

Table 3.1. The percentages of different messages in the order books, evaluated for every security. The first column shows the category of the message, whereas the second category indicates the more specific action. In the last row, the total sum of all messages is displayed.

Another point of interest is the high percentages of added and deleted orders, compared to a relatively small amount of orders that were actually executed. One possible way to explain this is by the bid-ask spread. In the last section, we already explained that the difference between the bid and the ask price will usually be only a couple of cents due to the large amount of buy and sell orders that are open at the same time. If then, for example, a trader owns a share of MMM and he wants to sell it, he adds a sell order. If the price of MMM lowers, it might be attractive for the trader to delete his order and add a new order with a lower selling price, because then he will probably sell his stock earlier.

3.3 Analyzing the data

Hasbrouck and Saar (2010) found that on average, there is a lot more activity in the beginning of a second than at the end of a second. Also every first minute of every hour seemed to be the most active minute. Assuming that this is indeed the case, there are maybe possibilities to get higher returns by taking unusual intervals or starting periods. As

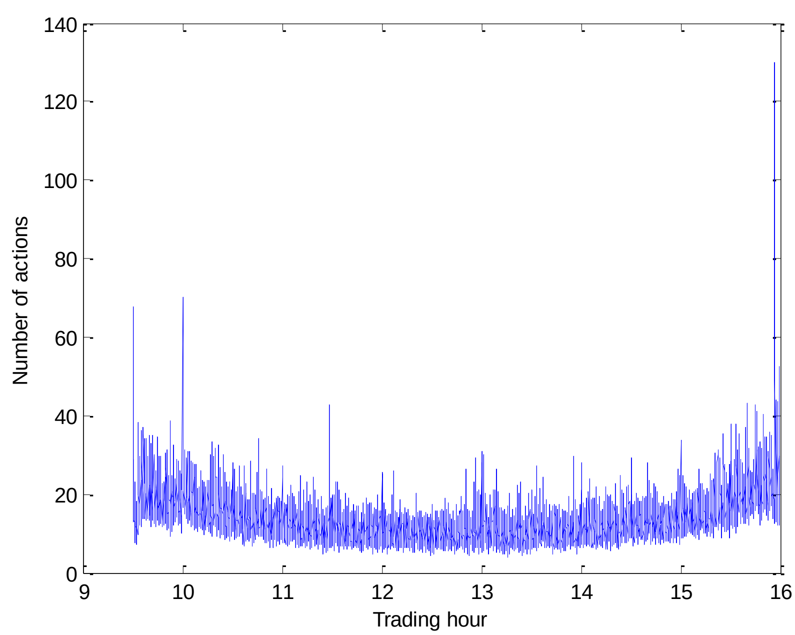

Figure 3.2. Graph of the number of actions throughout the day. The day starts at 9.30 and 16.00. These are averages over all 63 days for the IBM stock.

the ordinary intervals of one or five minutes all take the data of the last second, which always is on the last second of a minute, you might ignore the findings in those first seconds.

To investigate whether similar patterns are present in our own data, we have taken the average activity per second over the 63 days of the security . We will discuss the results of the IBM stock in more detail. In Figure 3.2 the amount of actions that are made can be seen in the graph. The graph displays a couple of peaks. The first peak is at the start of the day, when a lot of traders place their bid and ask prices. The second peak is at 10 am. Another peak is at the end of the day, when orders that are still placed are deleted. Due to the increasing activity at the start and at the end of the days, the graph shows a U-pattern.

Figure 3.3 investigates the actions made in every second of a minute. This is an average over the complete sample period of 63 days. The Figure contains 4 graphs. In (a) we can see the average of the complete sample; in (b) the average of only the first 20 minutes; (c) contains the averages of the last 20 minutes; and finally (d) shows the number of actions over the whole sample without the first and last 20 minutes. The first second in (a) shows most activity compared to all other seconds. However, we just mentioned that the opening time of the market is the most active period. This might influence the first second, in the sense that the first minute of every day heightens the average too much. However, the graph in (b) shows that the first second does not seem to contain the most activity. On the contrary, there are a lot of seconds that show more actions.

Part (c) does show the results of a lot of activity for the first seconds, compared to relatively low activity at other seconds. Also the last few seconds seem to contain more actions that are made by traders. We can therefore say that the last 20 minutes influence the high activity in the first second.

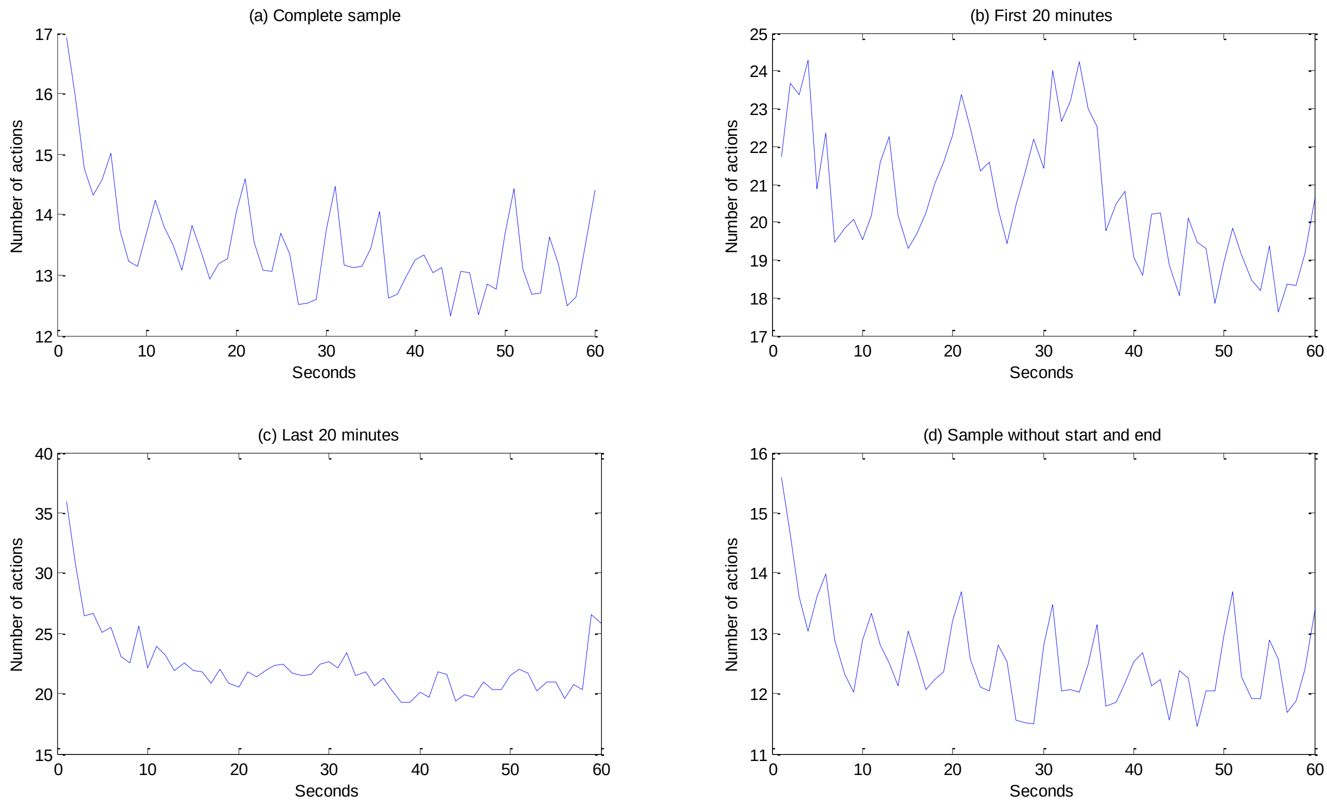

Figure 3.3. Average number of actions for all seconds every minute. These seconds are an average over the whole sample. Figure (a) contains data of the complete trading days. Figure (b) only contains the averages of every second over the first 20 minutes of every day. (c) is the average over the last 20 minutes. Finally, (d) contains the whole sample except the first and last 20 minutes.

But the large number of actions does not seem to come only from these last 20 minutes. Also in part (d), the first minute is the noisiest second. So we can conclude that we have found the same results as Hasbrouck and Saar: the first second is very valuable for testing for the moment of taking actions, as this second shows the most activity.

The same test can be executed for every minute of the day. Figure A.2 in the appendix gives the activity over a complete day. The values are averages computed over the total sample of 63 days. Compared to the amount of seconds in Figure 3.2, the start and end of the trading day are even more active.

Figure 3.4 shows the average activity in every minute. This average is computed over all hours and all days in the total sample. The first minute again shows the highest top. The other peaks are at the 6^{th}, 11^{th}, 16^{th} and 31^{st} minute. The last 20 minutes of every hour are calmer. Traders are more active in the minute after every five minutes from the start of the hour. Also in this aspect our findings are equal to those of Hasbrouck and Saar (2010): the first minute of every hour is the most active minute compared to the rest.

The last investigation contains the differences between the days of the week. As a lot of news might occur in the weekends, the Mondays may be more volatile because a lot of traders may want to make profit out of this news. The Fridays may contain more actions because everyone wants to finish the trades or may want to delete the orders that will not be executed before the weekend starts.

When we investigate these results, we find that the Mondays are always more calm than all other days. However, the difference was not large. Also there was no day that contained by far the most messages.

Similar investigations have been done for the stocks of MU, MMM and DELL. The four graphs for the comparison of every second of MU can be found in Figure A.3 in the appendix. The results for this security are about the same as IBM. The first second shows the most number of actions.

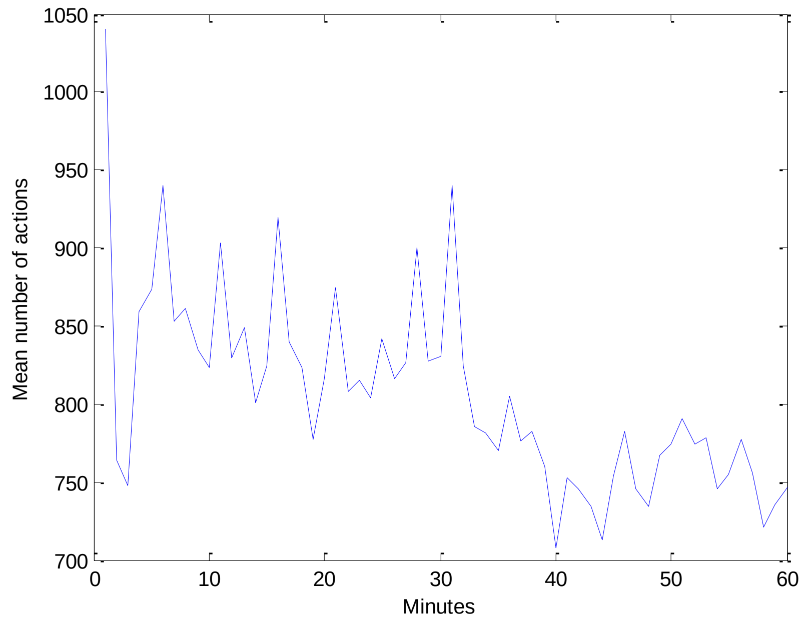

Figure 3.4. Average number of actions for every minute of the hour. Averages are computed for all hours in the 63 trading days.

Figure A.4 in the appendix contains the average amount of actions for every minute over the whole sample for MU. Here we see, in contrast of the findings for IBM, that the first minute is not the most active minute. It is around the same level as the 6th and the 11th minute. The 31st minute shows more activity.

The four graphs for MMM can be found in Figure 3.5**.** Here we see in (a) that the first second is the most important one in the complete sample. However, on average, this is only one action more than a couple of other peaks around the 6th, 21st and 51st second. In the first 20 minutes, again shown by graph (b), we see that the 31st second now has the highest peak. Graph (c) again shows the same conclusion as the other two securities: the first second is by far the noisiest second. And finally, for the average number of actions in the sample without the first and last 20 minutes, the first second is also the most active second. The other seconds are showing a lot of tops and bottoms, but none comes close to the first second.

The average amount of activity during every minute for MMM can be found in Figure 3.6 in the appendix. Just like the case for MU, the 31st minute seems to be the most valuable. But now the 16th minute shows a large amount of actions as well. The first minute follows, but is again not the highest peak in the graph.

In Figure A.5 of the appendix can be concluded that the DELL security leads to the same conclusions as the other three securities: The first second is the most active second. However, in figure (b), between seconds 30 and 40 there is a peak that exceeds the first seconds, sometimes even by 10 actions. But the last 20 minutes correct this, as the first second now has almost 20 actions more compared to the next peak at 17 seconds.

In Figure A.6 in the appendix, where the average activity of every minute of the DELL security can be seen, it is again clear to see that the first and the 31st minute are the most active minutes.

Based on these findings, it might be a good idea to change the starting values of the intervals. For example, if we start two seconds after the opening of the trading market and we will investigate the interval of 60 seconds, the end of every interval will be at the 2nd second of every minute. The activity of the first second will be clearer this way. The same holds for the minute based intervals. If we start at two minutes after the opening, the peaks in, for example, Figure 3.4 will be given more attention, as well as the 31st minute.

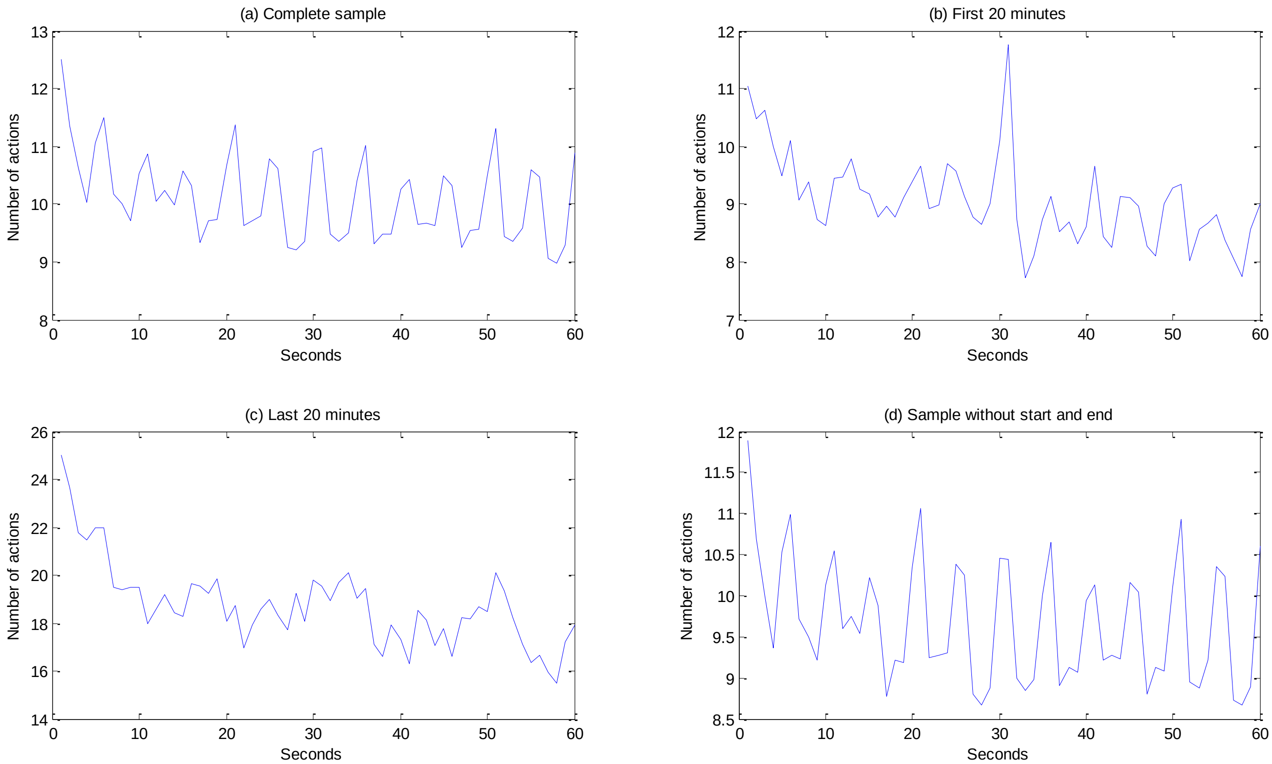

Figure 3.5. Average number of actions for all seconds every minute for MMM. These seconds are an average over the whole sample. Figure (a) contains data of the complete trading days. Figure (b) contains the averages of every second over the first 20 minutes of every day. (c) is the average over the last 20 minutes. Finally, (d) contains the whole sample except the first and last 20 minutes.

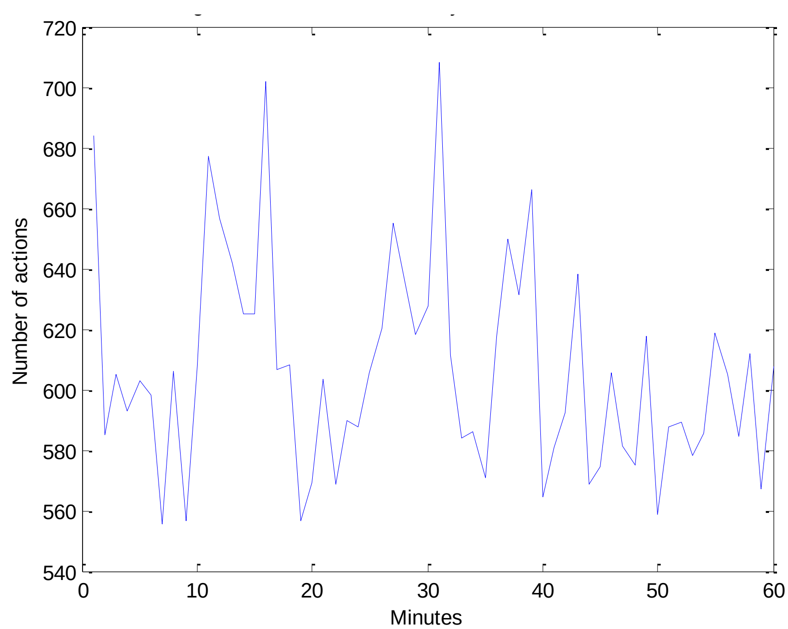

Figure 3.6. Average number of actions for every minute of the hour for MMM. Averages are computed for all hours in the 63 trading days.

4. Methods

Now we will introduce the methods we used to investigate whether we can find profitable strategies for the given order books. We will test this for five different intervals, namely 12, 30, 45, 60 and 300 seconds. We have added the 300 seconds interval, which equals 5 minutes, to see whether we can find significant positive results, unlike former results of Sullivan et al. (1999), Hsu and Kuan (2005) and Marshall et al. (2008).

In this research, we make a few assumptions regarding the trading of securities. The first assumption is that we can only hold one security at a time. When the portfolio contains a security due to a buy signal, all other buy signals from our trading rule will be ignored until the security is sold. The second assumption is that the trade will be completed immediately. For example, if a sell signal is given, the security will be sold directly. The transaction will take no amount of time. The last assumption is that the transaction costs are equal to zero. In reality, traders have to pay a fee to trade, and this should be subtracted from the returns found in this research.

Most of the rules in this research are based on those from the paper of Hsu and Kuan (2005). However, we will test for a smaller amount of parameters, and the values of those parameters will differ as well. Hsu and Kuan defined three categories of rules: The simple rules, the contrarian rules and finally the complex rules. We will use 11 different rules of the simple rules, and also investigate their counterparts.

In this paper, we will redistribute the used rules in two other categories. The first category is called the basic rules, and contains six of the most standard rules and their contrarian rules. The second category is the Extremum rules. These rules include the other five rules.

In section 4.1, we will discuss the properties of the basic rules, followed by the Extremum rules in section 4.2. The description of the data-snooping tests and checks for significance will follow in section 4.3.

4.1 The basic rules

The basic rules are standard in the sense that only one small change in the price or volume of the security is needed to receive a signal. Four of the strategies were also tested by Sullivan et al. (1999), and Hsu and Kuan (2005) added the other two rules.

These rules are sensitive to the values of the parameters, as the rules do not depend on anything else. The values of the parameters will change when and what kind of signal will be given. A small change might lead to results that are a lot different from previous found results.

Together, all basic rules contain a total of 7,568 trading strategies. When we add the contrarian rules, the total comes down to 15,136 strategies. Appendix B shows how this total of strategies is split between the different rules.

The filter rules are the first and most standard rules, and this is the strategy that many starting traders use. In these strategies, actions will depend on a certain threshold value, measured in percentage. If the price of a security grows more than this percentage compared to the period before, the security should be bought. If the price of a security declines more than the threshold, the security should be sold. Hence, these rules use only one parameter.

The moving average rule focuses on the price trend of a particular security. If the current price of the security is above its moving average of the last several periods, buy this security. If the current price is lower, sell it or go short. Included parameters are a threshold value, which determines the percentage change compared to the moving window, before actions will be taken, and the size of the moving window.

The Support and Resistance[3] rules are less known. Here, it is assumed that the price of a security cannot get higher than a certain value, the so called resistance line, or cannot fall beneath a certain price, which is called the level of support. The idea of the support and resistance rules is to buy the security if the price of a security is close to the level of support. When the price reaches the level of resistance, sell the stock.

Momentum Strategies in Price uses the data of the past period. If the price of the security has fallen in this period, it will, according to this strategy, more likely fall in the next period as well. The main idea of these momentum strategies is to buy the security if prices have risen in the past few periods, and sell or go short if the prices have fallen. The two parameters involved are: Threshold value and a time horizon.

Momentum Strategies in volume use the same methods and parameters as the momentum strategies in price, but now they depend on the trade volume of the security. If the price increases in a certain time horizon, the total traded securities should be added to the trading volume of that day. If the price decreases, one should subtract the traded volume. Percentages can now be computed by dividing the current traded volume of the day by the previous traded volume. If the volume has risen with a certain threshold, one should buy the security and hold it for the same period as the time the volume has grown, and vice versa.

On-Balance Volume Averages are quite the same compared to the moving average rules. However, in this case the focus is on the market volume of the time horizon instead of the price of the security. If the market volume exceeds the average market volume of the last period, the stock should be bought. If the volume is less, the stock should be sold. As in the case of the moving average, a threshold is used to decide when actions will be made, and a variable moving window.

4.2 The Extremum rules

The Extremum rules contain five sets of strategies, and another five for the contrarian rules.
The rules need to spot a pattern in order to give a signal. This pattern differs for every rule, but all do include tops and bottoms. Afterwards it is easy to see, but it is important to act quickly after a top. We used multiple methods to recognize tops. However, some of them took a lot of time, and that is why we added just a few of these strategies using this time expensive methods for peak recognition.

One way to recognize a top is by using a moving average or a moving median. If the average price is increasing for a period, and then decreasing for the next period, the method defines this as a peak.
The opposite holds for a minimum. Another way to recognize extremes is to use local regression.
The methods used in this paper are LOWESS and LOESS and their robust versions for outliers.

These techniques use two kinds of parameters: The window in which the extremes will be located and another parameter that tells the percentage of points used within the neighborhood of the point we're evaluating for the local regression: The so called span. This gives a total of 46 different optimizations. The parameter values for the different rules can again be found in appendix B. The total amount of strategies, along with the contrarian rules, equals 33,412.

The first set of rules is called the Head and shoulder rules. In this method, the price of a security first reaches a local top (the left shoulder), followed by a local minimum. Afterwards, the price reaches

[3] More information about the support and resistance can be found at http://www.investopedia.com/articles/technical/061801.asp

its global maximum of this period. This is again followed by a minimum that is around the previous minimum. And finally, another local maximum can be seen (the right shoulder). If such a pattern arises, the prices of a security are likely to decrease, and one should sell the security or go short. If, on the other hand, the pattern is upside down and the head and shoulders are minima, the security should be bought. The rule uses only one extra parameter, and different top recognitions.
This parameter tells what the maximum change between the two bottoms may be as percentage.

The pattern of Triangle rules can be found in a period with three decreasing tops with in between two bottoms at approximately the same level. If this is the case, the security should be sold. If an opposite pattern can be seen (three increasing bottoms with tops at the same level in between) the security should be bought. To define whether two tops or two bottoms bottoms are at the same level, we can use a maximum change. If the difference would exceed the change, we would define the identified maxima or minima as not on the same level.
Figure 4.1 shows the idea behind the Triangle rules.

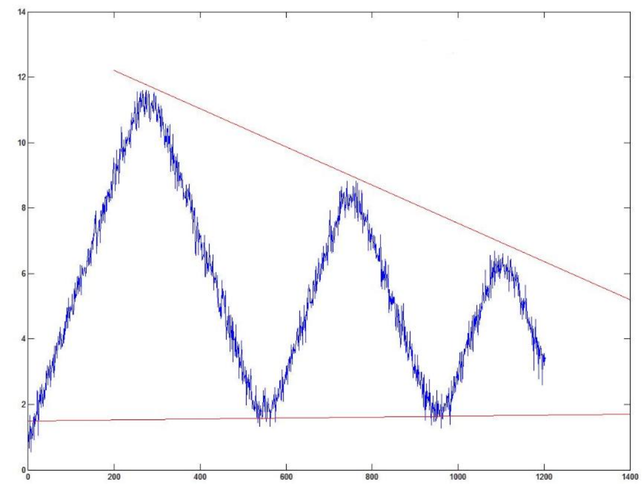

Figure 4.1. Example of the Triangle rule. The three tops should decrease, while the bottoms are around the same level.

Rectangle rules are quite similar to the triangle rules, except that now the tops and bottoms are around the same horizontal line. When the three tops can be spotted and are around the same level, and in between there are two bottoms around the same value, the security should be sold. On the other hand, if the changes in the price contain two tops and three bottoms, the security should be bought. This set of rules only use one parameter, which indicates the maximum percentage change in both the tops and bottoms that is allowed.

The double tops and bottoms can also be called the ‘shortened triangle’. It contains a pattern of two tops and one bottom (for the double bottoms case two bottoms and one top). The second top will be lower than the first one. Just like in the case of the triangle rules, the security should be sold when the two decreasing tops have been spotted and in between one bottom.

Broadening tops and bottoms are quite similar to a reversed triangle. There are again three tops and two bottoms, but now the tops increase and the minima also decrease, so it looks like a reversed triangle. Again, we buy the security when the last peak or bottom of the pattern has been identified.

4.3 The Bootstrap method

Combining the total amount of strategies of the basic rules and the Extremum rules, we get 48,548 strategies. However, during the testing of all these strategies, data-snooping, or sometimes called data mining, may occur. This is because there are so many strategies being generated, there will be always at least one strategy that will look profitable, but the results will most likely be based on luck.
White (2000) presented an example about a newsletter scam. In this example, a large number of people are selected, which are given a free newspaper. If they want to get another free paper next week, they have to forecast correctly what the stock exchange will do in the upcoming week. They can choose between a rise in the price of a security, or a decline. If they are correct, they will receive the

newspaper. After a couple of months, there will still be a couple of people, or even a large group, that will receive this newspaper, just based on the luck they have had. This effect is called data-snooping.

The same thing might happen during the testing of all the strategies we generate. Because we use little differences in the parameters every time, the most profitable strategy may be based on a lucky guess of those strategies. To avoid this, White (2000) presented a reality check. In his paper it is proven that this White Reality Check gives asymptotically correct p-values while accounting for the data-snooping bias. For proofs concerning this test statistic we refer to this paper.

The White reality check consists of two parts. The first part concerns the execution of the stationary bootstrap. We will mainly follow the ideas of Politis and Romano (1994) by exercising this test. The second part is calculating of the test statistic and the corresponding p-values. Sullivan et al (1999) showed in their article that the stationary bootstrap can be used for calculating this p-value.

4.3.1 The Bootstrap:

Defining variables:

R_{it}= time series of returns for a certain strategy ' i '.
$i = 1,2,3, \ldots\ldots l$ $\qquad$ $t = 1,2,3, \ldots\ldots n$

Where 'l' is defined as the number of strategies tested and 'n' as the number of returns in each of these time series. Now we will create a new time series still containing properties of the original time series with the stationary bootstrap (Politis & Romano (1994)).

$R^*_{it} = Newly\ created\ timeseries$ of returns for a certain strategy ' i'

Let's take R^*_{1t} for example: The first element of this vector is a randomly chosen return from the original series R_{1t} . Now for the second element we take the following element of the original series with probability 'q' or take a randomly selected return with probability '1-q'. Do this recursively until you have attained a time series with the same amount of elements as the original time series.

The value of q can be chosen by your best judgment. Sullivan et al (1999) found that there was little sensitivity to the choice of 'q'. Therefore, we will use the same value of 0.1.

For each strategy we create B = 300 bootstrapped series.

4.3.2 The acquiring of the p-value

With the B new time series using the Bootstrap we can calculate B new performance measures for each strategy by calculating the total return of the newly created time series. Sullivan et al (1999) set B = 500. We set B=300 because of computational burden.

Now to acquire the test statistics we define:

$P_{ik}^{*} = \ Performance\ of\ strategy\ \ i\ for\ series\ k\ of\ the\ bootstrapped\ data$
$i = 1,2,3, \ldots, l\ \ and\ k = 1,2,3, \ldots, B$

$P_i = Performance\ of\ strategy\ i\ for\ the\ original\ data$
$i = 1,2,3, \ldots, l$

$$T = \max_{i=1,2,3\ldots,l} \{\sqrt{m}\, P_i\}$$

$$T_k^{*} = \max_{i=1,2,3,\ldots,l} \{\sqrt{m}\,(P_{ik}^{*} - P_i)\} \qquad k = 1,2,3, \ldots .. B$$

$We\ have\ 40\ days\ where\ we\ trade\ between\ 09{:}30\ and\ 16{:}00$
$divided\ in\ intervals\ of\ (12;\ 30;\ 60; 300)\ seconds.$
$This\ gives\ the\ following\ values\ \ for\ m\ given\ \ wich\ interval\ you\ are\ testing\ for$:

$$m = \|78000 \quad 31200 \quad 20800 \quad 15600 \quad 3120\|$$

Now we compare T to the percentiles of T_k^{*} to get our p-value. We sort the values of T_k^{*} and find the number p where holds that $T_{(p)}^{*} < T < T_{(p+1)}^{*}$.
$p - value = 1 - p/B$

To increase the accuracy of this p-value you can fit a model with interpolation or a kernel.
We did re-simulation by first estimating the density function of T_k^{*} with a kernel and then simulating 10000 values from this estimated distribution to obtain a second p-value and we calculated a third by approximating the surface under the probability density function to the right of T with adaptive recursive Simpson's rule for approximating integrals.

5. Results

As discussed before, we test the performance of trading strategies for five different intervals. The in-sample performance of the trading rules is provided in section 5.1. The details of all settings of the parameters used can be found in appendix B.

The performance of the best strategies for every interval and security will be tested for the out-of-sample data. This gives a better view whether these strategies do not only perform well for the in-sample data, but also show positive results on other data. These results will be shown in section 5.2. The White Reality Check to test for significant profits will follow in section 5.3. In the last section, we will show the differences in the returns when we use a lagging starting point, rather than the opening time of 9.30 am.

All the results in this chapter will be discussed in more detail in chapter 6.

5.1 Discussion of the in-sample returns

All the strategies were tested on the in-sample data of 40 trading days. Table 5.1 contains the strategies that work best for every interval and for every security. These results are based on the three assumptions that we made in chapter 4.

At first the name of the rule is mentioned, followed by the return it made over the total period of 40 days. Where a ‘C’ can be found after the name of the rule, this indicates that the maximum return has been provided by the contrarian rule. The values of the parameters of any of these strategies can be found in the appendix, in Table A.7. The maximum returns for every rule can also be found in the appendix, in Tables A.8 through A.31. These tables show the maximum return that has been made by the specific rule, for any given interval and security.

Security	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	Double Tops and Bottoms C, 34.6%	Double Tops and Bottoms C, 30.0%	Double Tops and Bottoms C, 45.8%	Double Tops and Bottoms C, 62.0%	Momentum Strategies in Price C, 50.8%
MMM	Double Tops and Bottoms C, 13.9%	Double Tops and Bottoms C, 18.7%	Double Tops and Bottoms C, 18.0%	Double Tops and Bottoms, 15.7%	Momentum Strategies in Price C, 10.3%
IBM	Double Tops and Bottoms C, 14.0%	Triangle C, 12.2%	Triangle C, 9.7%	Triangle C, 13.0%	Moving Average C, 12.5%
DELL	Double Tops and Bottoms, 36.6%	Double Tops and Bottoms C, 37.9%	Double Tops and Bottoms, 32.9%	Head and Shoulders, 29.7%	Double Tops and Bottoms, 16.4%
MSFT	Head and Shoulders, 20.8%	Rectangle C, 16.5%	Rectangle, 12.4%	Triangle, 11.7%	Momentum Strategies in Price C, 13.5%
SPY	Head and Shoulders C, 28.6%	Triangle C, 22.4%	Double Tops and Bottoms, 18.2%	Head and Shoulders C, 20.0%	On Balance Volume Average C, 18.7%

Table 5.1. The maximum returns for every combination of interval and security, tested on the in-sample data. First the name of the rule is given, followed by the return. A 'C' behind the name of the rule defines the counterpart of the rule. The value of the parameters can be found in the appendix, in table A.7.

The returns found in this Table contain the returns over 40 days. All securities seem to have at least one positive return over 10%, except for the IBM security with an interval of 45 seconds. MU shows some of the highest results, up to 62%. In chapter 2 we have seen that MU was the security that contained the least messages that influenced the order book. This indicates that, on average, it has the least buy and sell orders compared to the other securities. An extra buy or sell order might influence the price of the security more quickly, which can lead to a more volatile price. The strategies are able to find more signals, and so more trades can be accomplished. When using a profitable strategy, the return might rise even more for this small security, compared to others.

Comparing these different intervals, we see that the 300 seconds interval never contains the highest return for a security. On the contrary, most of the highest returns can be found in the smaller intervals, and so seem to perform best.

If we look at the different strategies that work best, we come to the conclusion that the contrarian double tops and bottoms rules are working well. The normal strategy of double tops and bottoms also contains 5 returns that are among the best returns.

The division between the two categories leads to the conclusion that the more complex Extremum rules work better. This might be due to the fact that the basic rules only depend on a single basic action before a signal is given. As these signals occur more often than the patterns that are needed in the Extremum rules, the basic rules give more buy and sell signals. Every time such a signal is given, the traders pay the ask price, or get the bid price. The return a trader gets with the strategy also needs to make up the difference between these two prices, but this may not always be the case. As this occurs more often due to the amount of actions a trader makes, more positive returns are needed compared to the Extremum rules to make up these 'costs'. The basic rules seem only to perform better at the 300 seconds interval, when fewer actions can be taken. However we should not forget that the Extremum rules make up for about 67% of the total amount of strategies tested.

The contrarian Momentum Strategies in Price has the highest returns over all basic rules. In Table 5.2, the highest returns for every security and every interval can be found for this set of strategies. For every combination of securities and intervals, a positive return can be found. The highest returns are obtained in the last interval of 300 seconds.

Momentum Strategies in Price C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	5.6%	16.2%	14.9%	14.9%	50.8%
MMM	2.8%	3.0%	2.2%	0.6%	10.3%
IBM	1.2%	2.7%	3.1%	3.1%	7.1%
DELL	3.6%	7.6%	7.7%	7.4%	10.3%
MSFT	2.3%	2.9%	2.0%	2.2%	13.5%
SPY	2.0%	1.6%	1.0%	6.9%	10.3%

Table 5.2. Maximum in-sample returns for the contrarian Momentum Strategies in Price for every combination of the security and the interval.

The best set of rules of the Extremum rules is the contrarian Double Tops and Bottoms. We have already seen that this strategy gave most of the highest returns in Table 5.1. In Table 5.3, the returns for every combination of the security and the interval can be found. Here we see that the smallest maximum return is equal to 4.7%. MU seems to work best, and the interval with the highest returns is 30 seconds. The 300 second interval seems to perform least. A reason for this is that in the smaller intervals, more patterns can be spotted, as there are more observations. More patterns mean more actions, and with a profitable strategy, this means more profit.

Double Tops and Bottoms C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	34.6%	30.0%	45.8%	62.0%	25.9%
MMM	13.9%	18.7%	18.0%	15.6%	7.2%
IBM	14.0%	10.6%	9.4%	9.0%	4.7%
DELL	28.9%	37.9%	26.2%	28.7%	13.1%
MSFT	6.3%	14.5%	11.2%	9.1%	8.9%
SPY	18.0%	14.2%	13.3%	12.0%	7.5%

Table 5.3. Maximum in-sample returns for the contrarian Double Tops and Bottoms for every combination of the security and the interval.

Similar tables for all other rules can be found in Tables A.8 to A.29 in appendix A. Here we can see that there are also rules that do not seem to work at all. For example, the Support and Resistance rules do not produce a single positive return. For the 12 seconds interval, the best strategy even loses over 90% of the invested amount of money. Also the contrarian rules contain only one positive return of 0.6%. Also the On Balance Volume Average shows only a few positive returns, which can all be found in the last interval again. One of these results however, is a return of 18.7% which can also be found in Table 5.1 above. We will test in a later section if this return was really positive or a coincidence.

The Momentum Strategies in Volume, along with its counterpart, show negative returns for the smaller intervals, but contain large positive returns in the larger intervals. This strategy seems to work better for larger intervals like 60 or 300 seconds.

We have seen in this section that there is a large difference between the basic rules and the Extremum rules. Where the basic rules prefer to have larger intervals, the Extremum rules perform better at smaller intervals. Due to the patterns that have to be spotted, the amount of actions in the second category is smaller than the first category, which does not seem to make up the losses due to the bid-ask spread.

MU was the best performing security. However, this might be due to the large volatility in the price, like we discussed earlier this section. Also DELL showed returns that were above the 35%. Together, MMM and IBM showed the lowest maximum returns for most of the strategies.

5.2 Out-of-sample results

The 30 best strategies found in section 5.1 will be further analyzed here. It has been shown that these strategies work for the in-sample data. The out-of-sample data will test if these strategies also work for data that has not been taken into account when deciding what the highest returns will be. The out-of-sample data contained 23 trading days. The former results of the strategies we are testing are based on a 40 day period, so the results of the out-of-sample data should have a tendency to be lower. However, when the returns are positive for our out-of-sample as well, this would lead to the suspicion that these strategies do not only work for those 40 days, but will work in general.

The results can be found in Table 5.2. The names of the rules are displayed again as well, followed by the returns of the out-of-sample results.

Table 5.2. The same strategies as in Table 5.1 are used to test the performance on the out-of-sample data of 23

Security	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	Double Tops and Bottoms C, -1.2%	Double Tops and Bottoms C, -13.2%	Double Tops and Bottoms C, -15.7%	Double Tops and Bottoms C, -6.6%	Momentum Strategies in Price C, -3.1%
MMM	Double Tops and Bottoms C, 0.9%	Double Tops and Bottoms C, 1.9%	Double Tops and Bottoms C, 0.5%	Double Tops and Bottoms, 3.8%	Momentum Strategies in Price C, 1.2%
IBM	Double Tops and Bottoms C, 0.4%	Triangle C, 5.2%	Triangle C, -6.6%	Triangle C, -3.7%	Moving Average C, -0.2%
DELL	Double Tops and Bottoms, 11.9%	Double Tops and Bottoms C, -5.1%	Double Tops and Bottoms, 2.9%	Head and Shoulders, 3.1%	Double Tops and Bottoms, 4.6%
MSFT	Head and Shoulders, -3.5%	Rectangle C, -3.7%	Rectangle, 4.2%	Triangle, -5.4%	Momentum Strategies in Price C, 5.2%
SPY	Head and Shoulders C, -2.3%	Triangle C, -1.7%	Double Tops and Bottoms, 2.7%	Head and Shoulders, 3.1%	On Balance Volume Average C, 0.3%

days. A 'C' behind the name of the rule defines the contrarian rule. The value of the parameters of these strategies can be found in the appendix, in Table A.7.

We can immediately see that MMM shows some good results. All returns are positive and they are quite high for a period of 23 days. 0.5% might not look that much, but this still equals about 8.2% on a yearly basis. Apart from MMM, there is no other security that has realized a positive return for every interval in this 23-day period. The only one that comes close is DELL, with 5 positive returns.

In the former section, MU had the highest returns of all securities. However, if you look in the table now, none of the returns is positive anymore. It even shows negative results of -13.2% and -15.7%. The 12 seconds interval seems to works best for MU, but still shows a negative result of -1.2%.

DELL, on the other hand, shows a high result of 11.9% at the 12 seconds interval. The contrarian Double Tops and Bottoms rule still seems to work at this point. Except for the 30 seconds interval, DELL shows interesting positive returns. Hence, the best strategies of section 5.1 still work for DELL.

Maybe we can find a good result if we do not look at the table as a whole, but at the strategies one by one. Because of the MU stock resulting in all negative returns, the double tops and bottoms contrarian strategy does not seem to perform that well anymore. However, this strategy produces some small positives for MMM. The normal Double Tops and Bottoms strategy does show only positive results, and these returns are all above the 2.5%. It seems like this is a strategy that might work well, regardless of the stock and the interval. This strategy is also the strategy with the highest return over the 23 days.

Apart from the Double Tops and Bottoms, there does not seem to be another very good performing strategy. The contrarian Momentum Strategies in Price do show two positive returns as well and one of those is even higher than 5%. However, it does not seem to perform well for MU.

We can also have a look at the Table by interval. The 12 second interval has 3 negatives and 3 positives. But the positives average 4.4% and the negatives 2.3%. The overall maximum can be found in this interval with 11.9%.

The 30 second interval performed badly. It contains four negative results, with the biggest loss being 13.2%. The 45 second interval seems to work a little better. Four positive values can be found, although one of the two negatives is also the overall worst return. A negative 15.7% is realized for MU. And in absolute value, the other negative return is also bigger than all four of the positive returns. So, although four of the 6 values are positive, this looks better than it is, two values are negatives and quite big. This results in an average for the 45 second interval of exactly a negative 2% return.

The 60 second interval results in 3 positives and 3 negatives. The absolute values are all between 3.1 and 6.6, which indicate that these strategies will either give a large reward, or will lose a lot of the invested amount of money. The average return is also negative over the whole interval.

The 300 second interval has realized 4 profits. There is one return of -0.2%. Although this is a loss, it is very small. The other loss is 3.1%. There are two profits bigger than 3.1%. The average return for the 300 second interval is 1.3%.

Overall, this means that that the 300 second interval resulted in the highest average return. There was only one other interval with a positive average return. This was the 12 second interval. This means that both the smallest and the biggest interval were the only ones realizing positive average returns for our out-of-sample data, using the strategies that performed best in our 40 in-sample days.

5.3 Testing for data-snooping

In paragraph 4.2 we discussed testing the result for data-snooping bias. In the next group of tables are the results of these tests for significance. These results give information about, whether the profit of our best strategy was thanks to luck or because of an effective strategy. In the table 5.3 are the p-values of the ordinary White Reality check, from which you can see that none of our strategies significantly outperformed the benchmark of no return at all.

Security	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	1.0000	1.0000	0.8267	0.2467	0.3667
MMM	1.0000	0.9667	0.9933	1.0000	1.0000
IBM	1.0000	1.0000	1.0000	1.0000	1.0000
DELL	0.6533	0.4100	0.660	0.790	1.0000
MSFT	0.9867	1.0000	1.0000	1.0000	1.0000
SPY	0.1900	0.7700	0.9967	0.9067	0.5033

Table 5.3. The p-values obtained by comparing the best results that are found in section 5.1 and the random results that are generated by the bootstrap method. The p-values are computed by means of the standard White Reality Check.

White (2000) proposed fitting a model to the calculated test statistic to increase the accuracy of the approximated p-value. We estimated the probability density function of the test statistic using a Gaussian kernel. We then approximated the integral to get a more accurate estimate of our p-value. These p-values can be found in table 5.4.

Security	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	0.9983	0.9997	0.8016	0.2599	0.3658
MMM	0.9999	0.9563	0.9793	0.9989	1.0000
IBM	0.9993	1.0000	1.00000	1.0000	0.9923
DELL	0.6428	0.4284	0.6574	0.7858	0.9994
MSFT	0.9714	0.9997	1.0000	1.0000	0.9996
SPY	0.1969	0.7587	0.9908	0.9003	0.5621

Table 5.4. The p-values obtained by comparing the best results that are found in section 5.1 and the random results that are generated by the bootstrap method. The p-values are computed by means of quad function in MATLAB.

The other option we tried was re-simulating data from the probability density function of our test statistic by simulating 10000 values from the inverse empirical cumulative distribution function. This gave the result that can be found in table 5.5.

Security	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	0.9977	0.9997	0.8056	0.2620	0.3674
MMM	0.9999	0.9570	0.9797	0.9993	1.000
IBM	0.9992	1.000	1.000	1.000	0.9926
DELL	0.6442	0.4290	0.6590	0.7909	0.9994
MSFT	0.9734	0.9999	1.0000	1.0000	0.9996
SPY	0.2045	0.7592	0.9901	0.9031	0.5682

Table 5.5. The p-values obtained by comparing the best results that are found in section 5.1 and the random results that are generated by the bootstrap method. The p-values are computed by re-simulation from the empirical cumulative distribution function.

Finally in table 5.6, we show the “naïve p-values”. The naïve p-value is similar to the White Reality Check, however now we do not take into account all 48000+ models. Instead we only use the best model. Therefore, this p-value does not take the data-snooping bias into account.

Security	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	0.0033	0.000	0.0000	0.0000	0.0000
MMM	0.0033	0.0000	0.0000	0.0000	0.0000
IBM	0.0000	0.0033	0.0033	0.0000	0.0000
DELL	0.0000	0.0000	0.0000	0.0000	0.0033
MSFT	0.0000	0.0000	0.0000	0.0000	0.0033
SPY	0 .0000	0.0000	0.0000	0.0000	0.0000

Table 5.6. The p-values obtained by comparing the best results that are found in section 5.1 and the random results that are generated by the bootstrap method. The p-values are computed by means of the naïve p-value computations.

The White Reality Check and variations shows that there are no strategies that significantly outperformed our benchmark of zero return. However comparing the table 5.3, 5.4 and 5.5 with table

5.6 shows the size of de data-snooping bias. Since the naive p-values conclude that there are definitely strategies that significantly outperform the benchmark. This gives insight of the extend of the data-snooping problem.

5.4 The investigation for unusual intervals

In section 3.3 we have shown that the average activity over the complete sample is the highest in the first second. Also, the 1st and 31st minute contain the most actions on average. It may lead to other, more profitable results if we shift the starting value of our trading day.

In this section we will look at five different starting values. The market starts at 9.30 am, and we will start 2, 15, 30, 45 and finally 58 seconds after this opening. We will only be analyzing the 300 seconds interval now, as this interval showed to be the best choice for the basic rules. The Tops-and-Bottoms rules also still gained positive returns, although the 30 seconds interval would be a better choice for these sets of rules. However, we did not choose the short interval because of the great losses some of the basic rules gave.

Table 5.7 provides the returns that are simulated using the 40 days in-sample period. The second column shows the maximum results we gained by using the regular 300 seconds interval. These results are discussed in section 5.1. The other columns contain the returns, which are generated by the same strategies and parameters to compare the results. The returns that differ most compared to the regular starting period can be found at SPY, where the On Balance Volume Average first was the best strategy. Three out of the five returns are very negative. The two other results still are positive, but a lot lower compared to the regular starting period.

The contrarian Momentum Strategies in Price seem to produce very well results for MU and Microsoft, as well as for the MMM security at the 58 seconds lagged starting time. So this strategy, along with the specific parameters, seems to perform even better. The other two strategies, the contrarian Moving Average and the Double Tops and Bottoms, are performing less than the regular starting time.

Security and strategy	Regular starting period	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU, Momentum Strategies in Price C	50.8%	52.3%	49.1%	51.1%	50.3%	40.4%
MMM, Momentum Strategies in Price C	10.3%	8.5%	8.1%	8.0%	8.4%	13.2%
IBM, Moving Average C	12.5%	11.2%	11.9%	11.2%	9.2%	9.3%
DELL, Double Tops and Bottoms	16.4%	13.3%	8.9%	5.5%	9.5%	8.6%
MSFT, Momentum Strategies in Price C	13.5%	10.9%	13.3%	14.9%	14.6%	14.7%
SPY, On Balance Volume Average C	18.7%	1.8%	-8.9%	4.3%	-10.6%	-14.9%

Table 5.7. The maximum strategies of the 300 seconds interval of section 5.1 are compared to the same strategies, but now with a number of seconds lag. This means the strategies starting working a number of seconds later than the opening of the market.

Due to the mixed results that we have found in the former table, there might be some maximums that are higher than the results in Table 5.7. Table 5.8 contains the maximum strategies for every combination of securities and lagging periods. These maximums are computed over the in-sample data of 40 days. The table contains some differences compared to the maximums we have just seen, indicating that other strategies are working better for the lagged periods. One difference for example is the change of the strategies for SPY. Where the On Balance Volume Average was the best strategy for the 300 seconds interval on a regular opening time, this strategy has disappeared from table 5.7. The contrarian Triangle rules seem to perform best for SPY now.

The strategies that worked best for the contrarian Momentum Strategies in Price are still the best strategies for MU and Microsoft. However, the results are a bit higher due to some changes in the values of the parameters. The contrarian Momentum Strategies in Volume have overtaken the maximum return for MMM. The maximum return for this security is now 14.7%.

The maximum return for every security found in table 5.8 is exceeding the maximum return for the regular starting period in five out of six times. Only IBM performs worse at every lagging period. Where the maximum strategy for the regular starting period equaled 12.5%, the maximum strategy now is equal to 11.9%. Apart from this result, the lagging starting times seem to work well for the other securities. This also accounts for MU. The former maximum return of 50.8% is exceeded by another 3.9%.

When we compare the lagging periods, the 45 seconds lag contains most of the maximum returns. It can therefore be said that this lagging time seems to work best for the in-sample days.

Security	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	Momentum Strategies in Price C, 52.3%	Momentum Strategies in Price C, 49.7%	Momentum Strategies in Price C, 53.5%	Momentum Strategies in Price C, 54.7%	Momentum Strategies in Price C, 44.5%
MMM	Momentum Strategies in Price C, 9.3%	Momentum Strategies in Price C, 11.9%	Momentum Strategies in Price C, 10.1%	Momentum Strategies in Volume C, 11.0%	Momentum Strategies in Volume C, 14.7%
IBM	Momentum Strategies in Price C, 11.6%	Moving Average C, 11.9%	Moving Average C, 11.3%	Momentum Strategies in Price C, 10.1%	Triangle C, 10.2%
DELL	Double Tops and Bottoms C, 19.5%	Double Tops and Bottoms C, 18.3%	Double Tops and Bottoms C, 15.1%	Rectangle, 20.7%	Double Tops and Bottoms, 17.7%
MSFT	Momentum Strategies in Price C, 12.8%	Momentum Strategies in Price C, 14.3%	Momentum Strategies in Price C, 15.2%	Momentum Strategies in Price C, 14.6%	Momentum Strategies in Price C, 15.3%
SPY	Triangle C, 15.3%	Momentum Strategies in Price C, 12.7%	Triangle C, 13.2%	Triangle C, 21.8%	Momentum Strategies in Volume C, 16.7%

Table 5.7. The maximum performing strategy for every combination of security and lagging period. The name of the rule that performed best is given, followed by the returns. A 'C' indicates the contrarian version of that rule. The values of the parameters that are used for these strategies can be found in the appendix, in Table A.30.

The strategies with the highest returns in the in-sample period – which were shown in Table 5.7 – are tested again for the 23 out-of-sample days. The results of these tests can be found in Table 5.8. The high returns of MU in the in-sample period do not seem to produce well. On the contrary, the lagged opening times all give very negative results. We saw a similar result in sections 5.1 en 5.2. The 300 seconds interval for MU showed a 50.8% return, also for the contrarian Momentum Strategies in Price. But the out-of-sample data showed a loss of 3.1%. The same thing happened here, only now the results are even more negative.

The security of IBM also performs rather badly, as all returns are negative or they are not taking action. DELL and MSFT are working better. All six returns are positive for MSFT, and only one negative return of 0.2% is obtained for DELL. The highest return can also be found by DELL, which equals 5.4% profit at a lag of 2 seconds. This value exceeds the maximum return that is tested for the regular starting periods.

The returns for MMM are also positive, except for one value of -0.1%. This shows that also this security works well for the tested strategies. The last security, SPY, shows some mixed results. It achieves a return of 2.8% at the 30 seconds lagged starting period. However, it loses about the same percentage at the 2 seconds lag, while using the same strategy.

Security	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	Momentum Strategies in Price C, -8.3%	Momentum Strategies in Price C, -10.8%	Momentum Strategies in Price C, -11.0%	Momentum Strategies in Price C, -14.5%	Momentum Strategies in Price C, -9.2%
MMM	Momentum Strategies in Price C, 1.2%	Momentum Strategies in Price C, -0.1%	Momentum Strategies in Price C, 0.4%	Momentum Strategies in Volume C, 1.4%	Momentum Strategies in Volume C, 1.4%
IBM	Momentum Strategies in Price C, 0.0%	Moving Average C, -0.4%	Moving Average C, -0.3%	Momentum Strategies in Price C, 0.0%	Triangle C, -1.0%
DELL	Double Tops and Bottoms C, 5.4%	Double Tops and Bottoms C, 2.4%	Double Tops and Bottoms C, 2.5%	Rectangle, 3.5%	Double Tops and Bottoms, -0.2%
MSFT	Momentum Strategies in Price C, 4.2%	Momentum Strategies in Price C, 4.0%	Momentum Strategies in Price C, 1.7%	Momentum Strategies in Price C, 2.4%	Momentum Strategies in Price C, 6.1%
SPY	Triangle C, -2.6%	Momentum Strategies in Price C, -0.8%	Triangle C, 2.8%	Triangle C, 0.7%	Momentum Strategies in Volume C, -0.5%

Table 5.9. Returns for the out-of-sample data of 23 days. The strategies used in this table were the best performing strategies for the in-sample test. These strategies can also be found in Table 5.7. For the values of the parameters we refer to Table A.30 in the appendix.

6. Conclusions

In this research, we have used technical trading in order to find strategies that give a positive return. We have used the limit order books for five different securities, namely Mircon Technology, 3M Company, International Business Machines Corporation, DELL Inc and Microsoft Corporation. We have limit order books from every trading day between April 1, 2009 and June 30, 2009.

Analyzing this data, we have found that the first second of every minute is the most common second to place an order. This agrees with findings by Hasbrouck and Saar (2010). After analyzing the data, we generated over 48000 strategies and executed these over a sample period of 40 days. With these results we checked whether we found strategies that significantly outperformed our benchmark of zero return. However, regular test are not valid for testing whether we have found a strategy that outperforms the benchmark. Since executing 48000 strategies is accompanied with the issue that you are bound to find a strategy that seems to be significantly outperforming the benchmark just because of luck.The White Reality Check was used for this reason, which gives asymptotically correct p-values while accounting for this so called data-snooping bias. We improved accuracy of these p-values by fitting a model to the acquired test statistic for the White Reality Check. To get an insight in the size of the data-snooping bias we also calculated a 'naïve p-value' , which only uses the model with the highest return and therefor does not take into account the data-snooping bias. We concluded that none of the generated strategies outperformed our benchmark and that the extend of our data-snooping bias was quite large. We left out 23 days from our sample for testing the best performing strategies. This is an extra test in case significantly outperforming strategies were found. However, since the White Reality Check already concluded no profitable strategies were found the out-of-sample test was not neccesary.

A lot of things about our research can be improved. First of all it is up for debate whether 300 resamples are enough for an accurate p-value. Especially, because a lot of strategies only traded a few times. This on its turn has an impact on the bootstrap, because there are a lot of irrelevant elements for that strategy, since we did not trade in that period. However, we were unable to do any more resamples, because of the long computing time. (Approximately 120 hours for 300 resamples). It is also doubtfull whether it was valid to use the White Reality Check, since a lot of badly performing strategies might have an impact on the test according to White(2000). However it is hard to estimate what impact these issues have on this test.

Our research can also be extended by comparing it to the market return of the same period instead of taking zero return as a benchmark. It is also possible to test even smaller intervals or testing these strategies for other stocks. So there are a lot of options for extensions and improvements.

7. References

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Appendix

A. Extra Figures

Category	Letter	Explanation
System Event Messages	S	System event message.
Stock Related Messages	R	Stock directory message.
	H	Stock trading action message.
	L	Market Participant Position Message.
Add Order Messages	A	Order add message.
	F	Order add with MPID Attribution message.
Modify Order Messages	E	Order executed message.
	C	Order executed message (executed at different price from initial display).
Trade Messages	P	Trade Message
	X	Order cancel message (partial cancellation).
	D	Order delete message.
	U	Order replace message.
	Q	Cross trade message.
	B	Broken trade message. A trade is broken when an exchange cancels the trade or part of it.

Table A.1. Explains the different letters in the first column of the orders. Letters and explanation adapted from the NASDAQ ITCH, version 4.1.

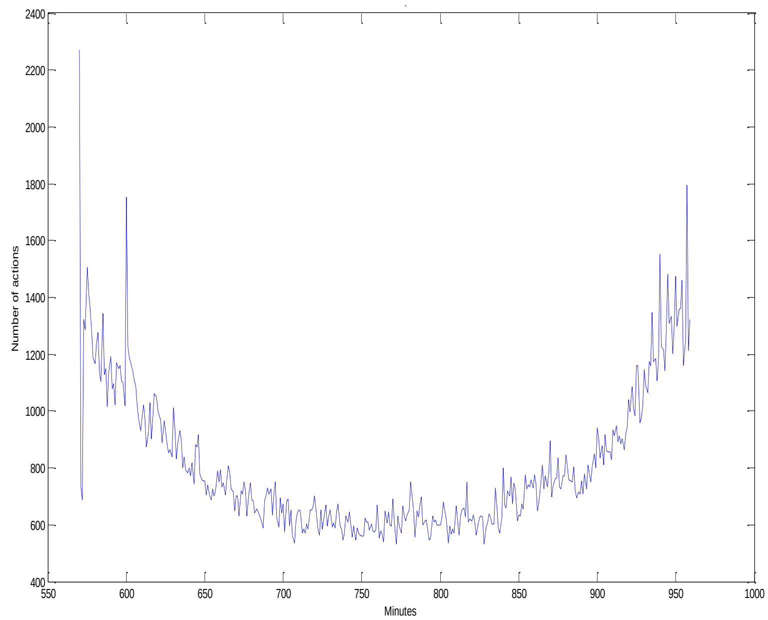

Figure A.2. Graph of the average activity in every second for the IBM stock. The averages are computed over all 63 days. This shows that most traders are taking action at the start or the end of every trading day.

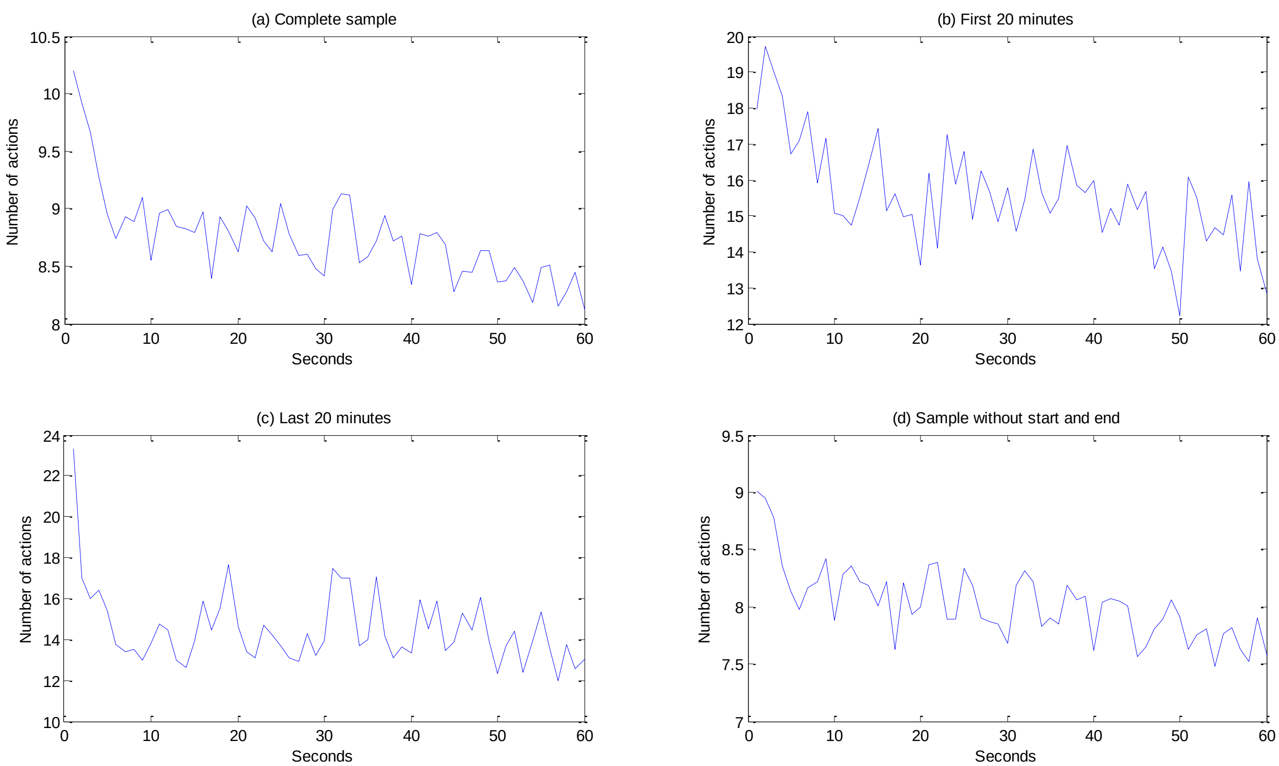

Figure A.3. Average number of actions for all seconds every minute for MU. These seconds are an average over the whole sample. Figure (a) contains data of the complete trading days. Figure (b) contains the averages of every second over the first 20 minutes of every day. (c) is the average over the last 20 minutes. Finally, (d) contains the whole sample except the first and last 20 minutes.

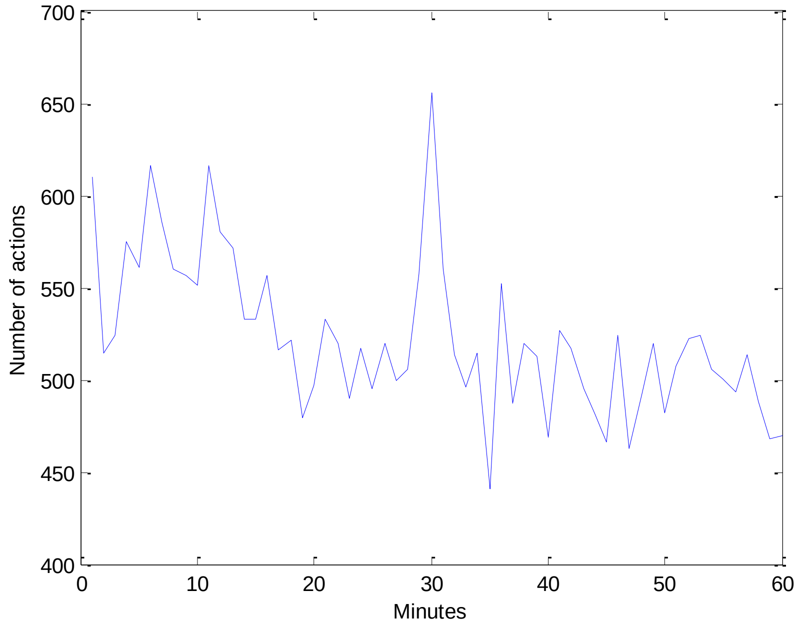

Figure A.4. Average number of actions for every minute of the hour for MU. Averages are computed for all hours in the 63 trading days.

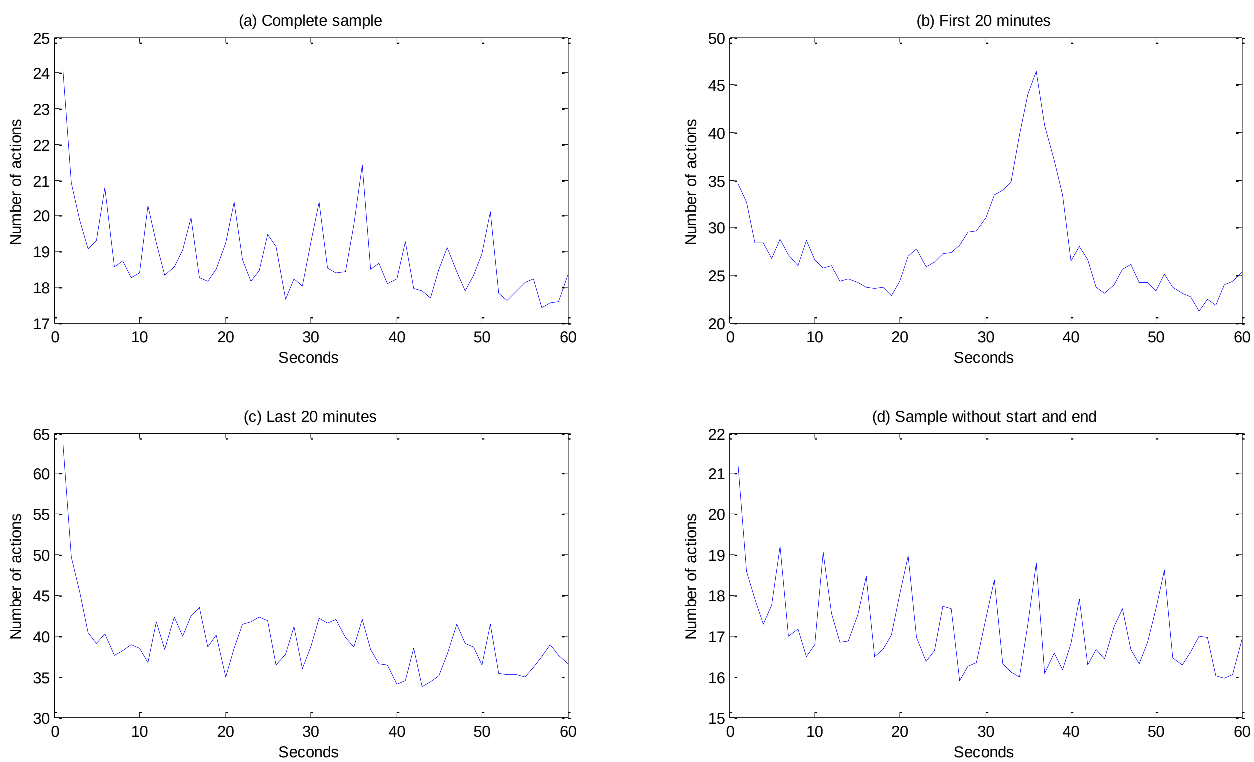

Figure A.5. Average number of actions for all seconds every minute for MMM. These seconds are an average over the whole sample. Figure (a) contains data of the complete trading days. Figure (b) contains the averages of every second over the first 20 minutes of every day. (c) is the average over the last 20 minutes. Finally, (d) contains the whole sample except the first and last 20 minutes.

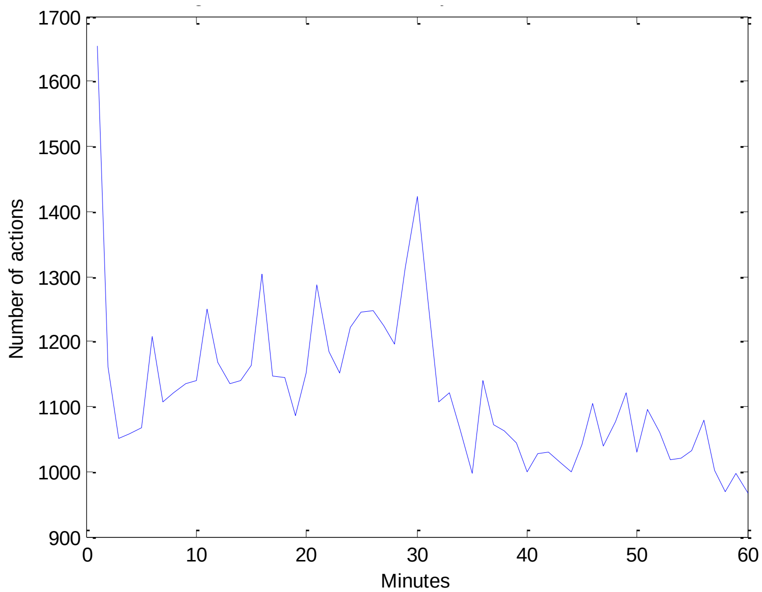

Figure A.6. Average number of actions for every minute of the hour for DELL. Averages are computed for all hours in the 63 trading days.

Security	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	Double Tops and Bottoms C, Moving Average (17) Percent low: 2.0% Percent high: 0.5%	Double Tops and Bottoms C, Moving Average (7) Percent low: 2.0% Percent high: 1.5%	Double Tops and Bottoms C, Moving Average (9) Percent low: 2.0% Percent high: 1.5%	Double Tops and Bottoms C, Moving Average (3) Percent low: 2.0% Percent high: 1.5%	Momentum Strategies in Price C, Horizon: 20, Threshold: 0.63%
MMM	Double Tops and Bottoms C, Moving Average (22) Percent low: 2.0% Percent high: 0.5%	Double Tops and Bottoms C, Moving Average (9) Percent low: 4.0% Percent high: 0.5%	Double Tops and Bottoms C, Moving Average (3) Percent low: 2.0% Percent high: 0.5%	Double Tops and Bottoms, Moving Average (4) Percent low: 0.0% Percent high: 0.5%	Momentum Strategies in Price C, Horizon: 18, Threshold: 0%
IBM	Double Tops and Bottoms C, Moving Average (15) Percent low: 2.0% Percent high: 0.5%	Triangle C, Moving Average (24) Percent low: 2.0% Percent high: 0.0%	Triangle C, Moving Average (21) Percent low: 2.0% Percent high: 0.0%	Triangle C, Moving Average (14) Percent low: 2.0% Percent high: 0.0%	Moving Average C, Horizon: 32 Threshold: 0.07%
DELL	Double Tops and Bottoms, Moving Average (3) Percent low: 0.0% Percent high: 0.5%	Double Tops and Bottoms C, Moving Average (11) Percent low: 2.0% Percent high: 0.0%	Double Tops and Bottoms, Moving Average (4) Percent low: 0.0% Percent high: 0.5%	Head and Shoulders, Moving Average (10) Percentage: 1.1%	Double Tops and Bottoms, Moving Average (11) Percent low: 0.0% Percent high: 0.5%
MSFT	Head and Shoulders, Moving Average (5) Percentage: 0.1%	Rectangle C, Moving Average (21) Percentage: 0.1%	Rectangle, Moving Median (3) Percentage: 0.1%	Triangle, Moving Average (3) Percent low: 2.0% Percent high: 0.0%	Momentum Strategies in Price C, Horizon: 22, Threshold: 0.47%
SPY	Head and Shoulders C, Moving Average (9) Percentage: 1.1%	Triangle C, Moving Average (11) Percent low: 2.0% Percent high: 0.0%	Double Tops and Bottoms, Moving Average (6) Percent low: 0.0% Percent high: 0.5%	Head and Shoulders, Moving Average (12) Percentage: 1.1%	On Balance Volume Average C, Horizon: 20, Threshold: 2.75%

Table A.7. The values of the parameters for the best working strategies. The returns that are found with these parameters can be found in section 5.1. The Extremum rules first contain the method to detect the peaks, followed by the window that is used in brackets.

Filter Rules	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	-0.3%	-2.6%	2.0%	1.0%	-0.6%
MMM	-0.7%	-0.1%	-0.3%	0.1%	0.6%
IBM	-0.4%	0.8%	0.2%	-1.0%	1.4%
DELL	-0.2%	-0.5%	-0.7%	0.8%	1.0%
MSFT	-0.4%	-0.2%	0.2%	0.0%	-0.7%
SPY	-0.1%	-0.1%	0.1%	0.1%	3.2%

Table A.8. Maximum in-sample returns for every stock and interval for Filter Rules.

Filter Rules C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	2.4%	2.1%	-1.8%	-1.0%	2.9%
MMM	0.4%	-0.4%	-0.6%	-0.4%	-0.1%
IBM	0.1%	-0.1%	0.5%	1.1%	0.4%
DELL	0.3%	1.0%	0.8%	0.8%	1.2%
MSFT	1.2%	0.2%	1.6%	0.8%	4.1%
SPY	0.1%	0.3%	0.9%	1.7%	-0.2%

Table A.9. Maximum in-sample returns for every stock and interval for Filter Rules C.

Moving Average	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	3.6%	4.4%	0.9%	1.2%	2.1%
MMM	0.4%	1.4%	2.5%	3.9%	5.7%
IBM	-0.1%	-0.1%	0.1%	-0.2%	0.9%
DELL	0.1%	0.1%	0.4%	1.3%	1.9%
MSFT	0.7%	0.9%	1.6%	1.0%	1.0%
SPY	-0.1%	-0.1%	0.6%	0.9%	4.0%

Table A.10. Maximum in-sample returns for every stock and interval for Moving Average.

Moving Average C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	2.0%	0.5%	2.3%	3.1%	3.1%
MMM	-0.1%	0.3%	0.6%	0.3%	5.6%
IBM	0.7%	1.4%	1.4%	1.8%	12.5%
DELL	1.5%	1.9%	1.5%	2.7%	4.0%
MSFT	0.6%	1.5%	1.6%	0.8%	1.7%
SPY	1.1%	1.5%	1.5%	0.7%	8.9%

Table A.11. Maximum in-sample returns for every stock and interval for Moving Average C.

Support and Resistance	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	-99.9%	-99.0%	-96.2%	-92.8%	-39.4%
MMM	-97.5%	-76.9%	-64.6%	-44.1%	-8.7%
IBM	-95.9%	-73.8%	-59.0%	-51.2%	-14.5%
DELL	-99.2%	-87.8%	-73.6%	-65.6%	-16.1%
MSFT	-93.5%	-69.6%	-56.0%	-46.1%	-16.9%
SPY	-57.6%	-32.4%	-29.0%	-21.3%	-6.1%

Table A.12. Maximum in-sample returns for every stock and interval for Support and Resistance.

Support and Resistance C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	-99.9%	-99.5%	-97.9%	-94.3%	-34.8%
MMM	-97.6%	-76.5%	-59.9%	-49.2%	-9.2%
IBM	-95.7%	-66.5%	-49.7%	-37.7%	0.0%
DELL	-99.5%	-92.7%	-84.6%	-75.6%	-19.6%
MSFT	-96.8%	-78.1%	-63.3%	-52.9%	-4.2%
SPY	-65.8%	-33.4%	-17.9%	-14.8%	0.6%

Table A.13. Maximum in-sample returns for every stock and interval for Support and Resistance C.

Momentum Strategies in Price	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	5.2%	1.7%	1.9%	1.7%	3.2%
MMM	-0.1%	2.6%	3.5%	4.5%	4.9%
IBM	0.6%	0.9%	1.5%	4.2%	2.8%
DELL	1.2%	2.7%	4.1%	8.5%	12.8%
MSFT	1.9%	4.1%	5.5%	4.5%	4.9%
SPY	0.7%	2.4%	6.9%	5.5%	4.6%

Table A.14. Maximum in-sample returns for every stock and interval for Momentum Strategies in Price.

Momentum Strategies in Price C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	5.6%	16.2%	14.9%	14.9%	50.8%
MMM	2.8%	3.0%	2.2%	0.6%	10.3%
IBM	1.2%	2.7%	3.1%	3.1%	7.1%
DELL	3.6%	7.6%	7.7%	7.4%	10.3%
MSFT	2.3%	2.9%	2.0%	2.2%	13.5%
SPY	2.0%	1.6%	1.0%	6.9%	10.3%

Table A.15. Maximum in-sample returns for every stock and interval for Momentum Strategies in Price C.

Momentum Strategies in Volume	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	-93.6%	-76.8%	-62.2%	-31.6%	-18.8%
MMM	-53.3%	-24.0%	-6.3%	5.9%	7.4%
IBM	-56.5%	-21.2%	-0.3%	3.3%	12.0%
DELL	-82.2%	-50.2%	-37.2%	-24.9%	3.6%
MSFT	-70.3%	-27.8%	-18.9%	-8.0%	3.8%
SPY	-8.2%	-7.7%	4.0%	2.6%	1.9%

Table A.16. Maximum in-sample returns for every stock and interval for Momentum Strategies in Volume.

Momentum Strategies in Volume C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	-94.4%	-85.1%	-72.2%	-62.4%	32.0%
MMM	-54.8%	-32.3%	-26.2%	-20.0%	1.4%
IBM	-50.6%	-14.2%	-12.3%	-6.5%	3.4%
DELL	-85.9%	-55.3%	-40.9%	-31.0%	7.0%
MSFT	-67.8%	-29.9%	-19.2%	-11.6%	2.7%
SPY	-17.6%	8.6%	3.8%	13.6%	9.3%

Table A.17. Maximum in-sample returns for every stock and interval for Momentum Strategies in Volume C.

On Balance Volume Average	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	-97.6%	-90.8%	-88.2%	-80.8%	-57.2%
MMM	-82.9%	-63.4%	-49.5%	31.0%	-5.4%
IBM	-82.5%	-59.8%	-52.2%	-48.1%	-4.9%
DELL	-88.6%	-65.9%	-48.7%	-28.1%	-2.9%
MSFT	-71.0%	-41.2%	-29.1%	-23.3%	7.7%
SPY	-37.3%	-19.1%	-4.2%	-16.8%	-10.0%

Table A.18. Maximum in-sample returns for every stock and interval for On Balance Volume Average.

On Balance Volume Average C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	-95.9%	-87.9%	-83.5%	-77.8%	-50.6%
MMM	-77.6%	-57.0%	-51.1%	-49.1%	-5.3%
IBM	-77.8%	-54.3%	-43.5%	-30.2%	-11.7%
DELL	-76.4%	-68.0%	-62.7%	-64.5%	-16.8%
MSFT	-66.8%	-53.0%	-43.6%	-36.7%	-7.7%
SPY	-37.5%	-17.2%	-17.7%	1.2%	18.7%

Table A.19. Maximum in-sample returns for every stock and interval for On Balance Volume Average C.

Head and Shoulders	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	13.3%	9.5%	32.0%	16.8%	6.6%
MMM	1.6%	4.5%	4.0%	3.9%	2.6%
IBM	4.4%	3.9%	2.6%	2.0%	3.0%
DELL	30.6%	15.3%	10.1%	29.7%	5.5%
MSFT	20.8%	7.7%	9.8%	7.8%	7.9%
SPY	7.6%	14.9%	7.8%	7.6%	4.2%

Table A.20. Maximum in-sample returns for every stock and interval for Head and Shoulders.

Head and Shoulder C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	18.5%	22.6%	16.7%	17.0%	9.0%
MMM	4.2%	5.0%	9.6%	8.4%	2.3%
IBM	2.9%	6.6%	4.2%	6.2%	6.6%
DELL	12.8%	18.9%	13.7%	13.2%	6.8%
MSFT	19.0%	8.6%	13.8%	9.1%	6.9%
SPY	28.6%	9.9%	18.0%	20.0%	5.5%

Table A.21. Maximum in-sample returns for every stock and interval for Head and Shoulders C.

Triangle	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	16.6%	15.1%	13.6%	7.6%	7.4%
MMM	6.9%	5.5%	4.7%	5.6%	3.2%
IBM	3.1%	1.9%	6.0%	2.8%	4.0%
DELL	12.0%	13.2%	19.6%	10.4%	5.6%
MSFT	15.1%	8.3%	6.9%	11.7%	4.1%
SPY	12.2%	9.5%	7.9%	2.9%	4.7%

Table A.22. Maximum in-sample returns for every stock and interval for Triangle.

Triangle C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	25.2%	14.3%	22.7%	25.9%	10.4%
MMM	9.7%	15.8%	10.7%	8.8%	4.6%
IBM	7.8%	12.2%	9.7%	13.0%	4.6%
DELL	16.4%	36.1%	11.9%	16.2%	7.7%
MSFT	15.1%	13.3%	11.9%	9.3%	6.8%
SPY	15.6%	22.4%	15.9%	19.9%	8.7%

Table A.23. Maximum in-sample returns for every stock and interval for Triangle C.

Rectangle	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	19.2%	17.3%	27.9%	16.2%	17.6%
MMM	5.1%	10.8%	17.2%	8.9%	3.8%
IBM	7.0%	4.5%	9.2%	12.6%	8.5%
DELL	35.5%	25.3%	24.1%	29.1%	10.0%
MSFT	8.0%	6.1%	12.4%	4.4%	5.3%
SPY	17.6%	7.3%	12.8%	16.7%	6.3%

Table A.24. Maximum in-sample returns for every stock and interval for Rectangle.

Rectangle C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	2.3%	7.8%	7.0%	1.3%	1.7%
MMM	4.3%	3.7%	3.1%	3.1%	3.4%
IBM	2.2%	4.5%	2.8%	4.8%	2.9%
DELL	0.4%	4.6%	13.2%	10.4%	1.9%
MSFT	6.1%	16.5%	4.7%	11.2%	2.0%
SPY	11.2%	15.7%	11.3%	5.8%	6.2%

Table A.25. Maximum in-sample returns for every stock and interval for Rectangle C.

Double Tops and Bottoms	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	12.9%	6.4%	15.8%	12.7%	9.2%
MMM	12.1%	16.3%	15.4%	15.7%	4.3%
IBM	13.6%	10.0%	8.1%	10.2%	4.6%
DELL	36.6%	34.5%	32.9%	23.9%	16.4%
MSFT	9.9%	4.9%	5.5%	8.4%	7.2%
SPY	17.1%	15.1%	18.2%	17.9%	6.4%

Table A.26. Maximum in-sample returns for every stock and interval for Double Tops and Bottoms.

Double Tops and Bottoms C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	34.6%	30.0%	45.8%	62.0%	25.9%
MMM	13.9%	18.7%	18.0%	15.6%	7.2%
IBM	14.0%	10.6%	9.4%	9.0%	4.7%
DELL	28.9%	37.9%	26.2%	28.7%	13.1%
MSFT	6.3%	14.5%	11.2%	9.1%	8.9%
SPY	18.0%	14.2%	13.3%	12.0%	7.5%

Table A.27. Maximum in-sample returns for every stock and interval for Double Tops and Bottoms C.

Broadening Tops and Bottoms	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	10.4%	7.2%	8.4%	3.6%	1.2%
MMM	2.0%	2.0%	1.3%	2.0%	0.0%
IBM	0.0%	0.0%	0.0%	0.0%	0.0%
DELL	3.0%	2.7%	1.6%	1.0%	1.0%
MSFT	-0.5%	1.5%	1.5%	0.0%	0.0%
SPY	0.0%	0.0%	0.0%	0.0%	0.0%

Table A.28. Maximum in-sample returns for every stock and interval for Broadening Tops and Bottoms.

Broadening Tops and Bottoms C	12 seconds	30 seconds	45 seconds	60 seconds	300 seconds
MU	3.5%	1.8%	2.6%	1.7%	2.8%
MMM	0.1%	3.5%	3.4%	0.8%	0.0%
IBM	0.0%	0.0%	0.0%	0.0%	0.0%
DELL	7.4%	1.2%	5.5%	5.5%	0.2%
MSFT	2.4%	0.7%	0.7%	0.0%	0.0%
SPY	0.0%	0.0%	0.0%	0.0%	0.0%

Table A.29. Maximum in-sample returns for every stock and interval for Broadening Tops and Bottoms C.

Security	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	Momentum Strategies in Price C, Horizon: 20 Threshold: 0.63%	Momentum Strategies in Price C, Horizon: 20 Threshold: 0.49%	Momentum Strategies in Price C, Horizon: 20 Threshold: 0.49%	Momentum Strategies in Price C, Horizon: 20 Threshold: 0.49%	Momentum Strategies in Price C, Horizon: 20 Threshold: 0.28%
MMM	Momentum Strategies in Price C, Horizon: 20 Threshold: 0.28%	Momentum Strategies in Price C, Horizon: 16 Threshold: 0.56%	Momentum Strategies in Price C, Horizon: 16 Threshold: 0.63%	Momentum Strategies in Volume C, Horizon: 12 Threshold: 26.80%	Momentum Strategies in Volume C, Horizon: 12 Threshold: 27.20%
IBM	Momentum Strategies in Price C, Horizon: 22 Threshold: 0.56%	Moving Average C, Horizon: 32 Threshold: 0.07%	Moving Average C, Horizon: 29 Threshold: 0.00%	Momentum Strategies in Price C, Horizon: 22 Threshold: 0.49%	Triangle C, Moving Average (3) Percent low: 2.0% Percent high: 0.0%
DELL	Double Tops and Bottoms C, Moving Average (5) Percent low: 2.0% Percent high: 0.0%	Double Tops and Bottoms C, Moving Average (5) Percent low: 2.0% Percent high: 0.0%	Double Tops and Bottoms C, Moving Average (5) Percent low: 2.0% Percent high: 0.0%	Rectangle, Moving Average (7) Percentage: 0.1%	Double Tops and Bottoms, Moving Average (19) Percent low: 0.0% Percent high: 0.5%
MSFT	Momentum Strategies in Price C, Horizon: 22 Threshold: 0.56%	Momentum Strategies in Price C, Horizon: 22 Threshold: 0.56%	Momentum Strategies in Price C, Horizon: 22 Threshold: 0.49%	Momentum Strategies in Price C, Horizon: 22 Threshold: 0.42%	Momentum Strategies in Price C, Horizon: 16 Threshold: 0.14%
SPY	Triangle C, Moving Average (3) Percent low: 2.0% Percent high: 0.0%	Momentum Strategies in Price C, Horizon: 8 Threshold: 0.56%	Triangle C, Moving Average (3) Percent low: 2.0% Percent high: 0.0%	Triangle C, Moving Average (3) Percent low: 2.0% Percent high: 0.0%	Momentum Strategies in Volume C, Horizon: 12 Threshold: 3.2%

Table A.30. The values of the parameters for the best working strategies, for every lagging starting period and security. The returns that are found with these parameters are mentioned in section 5.4. The Extremum rules first contain the method to detect the peaks, followed by the window that is used between brackets.

Filter Rules	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	-1.1%	0.0%	0.0%	0.0%	0.7%
MMM	0.9%	0.8%	1.6%	1.2%	3.2%
IBM	0.5%	0.6%	0.7%	0.3%	0.7%
DELL	1.1%	1.1%	1.5%	1.1%	1.6%
MSFT	0.0%	0.2%	0.5%	1.6%	0.9%
SPY	2.4%	3.3%	1.2%	1.2%	1.0%

Table A.31. Maximum in-sample returns for every stock and lagged starting time for Filter Rules.

Filter Rules C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	4.6%	4.5%	5.9%	5.1%	5.5%
MMM	0.4%	0.0%	0.0%	0.0%	0.0%
IBM	0.3%	0.0%	0.0%	0.3%	0.0%
DELL	0.5%	0.0%	3.6%	1.2%	2.2%
MSFT	4.3%	1.5%	1.6%	0.7%	1.0%
SPY	0.0%	0.0%	1.3%	0.1%	1.2%

Table A.32. Maximum in-sample returns for every stock and lagged starting time for Filter Rules C.

Moving Average	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	3.1%	2.0%	2.5%	2.3%	5.0%
MMM	5.9%	6.6%	6.5%	5.6%	6.4%
IBM	0.9%	1.2%	0.8%	0.8%	1.0%
DELL	2.1%	1.6%	1.1%	2.5%	2.8%
MSFT	1.1%	1.3%	1.7%	1.8%	2.4%
SPY	3.1%	3.8%	3.9%	3.5%	3.2%

Table A.33. Maximum in-sample returns for every stock and lagged starting time for Moving Average.

Moving Average C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	2.7%	3.2%	2.9%	2.3%	3.9%
MMM	7.7%	4.2%	5.1%	3.8%	2.5%
IBM	11.5%	11.9%	11.3%	9.7%	9.6%
DELL	4.3%	5.2%	3.9%	2.1%	2.2%
MSFT	1.9%	1.7%	1.9%	2.1%	1.9%
SPY	12.2%	10.6%	11.2%	9.0%	9.8%

Table A.34. Maximum in-sample returns for every stock and lagged starting time for Moving Average C.

Support and Resistance	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	-40.3%	-40.3%	-33.8%	-34.4%	-36.1%
MMM	-8.9%	-8.7%	-6.6%	-6.5%	-7.9%
IBM	-12.3%	-10.7%	-11.4%	-13.9%	-13.4%
DELL	-14.7%	-15.9%	-15.3%	-15.5%	-14.4%
MSFT	-15.2%	-13.0%	-12.2%	-9.1%	-12.3%
SPY	-8.0%	-8.3%	-6.3%	-6.5%	-9.4%

Table A.35. Maximum in-sample returns for every stock and lagged starting time for Support and Resistance.

Support and Resistance C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	-34.3%	-36.4%	-40.0%	-42.1%	-41.0%
MMM	-9.7%	-9.8%	-11.7%	-12.5%	-10.9%
IBM	-3.8%	-4.5%	-3.4%	-0.8%	-1.3%
DELL	-20.0%	-20.3%	-20.4%	-20.3%	-20.3%
MSFT	-5.2%	-7.2%	-8.2%	-10.6%	-7.7%
SPY	3.5%	4.8%	4.0%	3.2%	5.0%

Table A.36. Maximum in-sample returns for every stock and lagged starting time for Support and Resistance C.

Momentum Strategies in Price	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	2.0%	1.4%	2.7%	2.6%	1.5%
MMM	4.0%	5.5%	4.3%	3.3%	4.0%
IBM	2.9%	1.9%	1.9%	1.9%	1.8%
DELL	11.8%	10.0%	10.3%	8.4%	12.1%
MSFT	3.4%	5.0%	3.7%	3.9%	4.1%
SPY	4.9%	3.8%	5.5%	3.0%	2.8%

Table A.37. Maximum in-sample returns for every stock and lagged starting time for Momentum Strategies in Price.

Momentum Strategies in Price C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	52.3%	49.7%	53.5%	54.7%	44.5%
MMM	9.3%	11.9%	10.1%	10.6%	13.2%
IBM	11.6%	11.2%	10.4%	10.1%	9.9%
DELL	10.4%	11.6%	10.5%	11.2%	11.4%
MSFT	12.8%	14.3%	15.2%	14.6%	15.3%
SPY	10.7%	12.7%	9.6%	9.5%	11.0%

Table A.38. Maximum in-sample returns for every stock and lagged starting time for Momentum Strategies in Price C.

Momentum Strategies in Volume	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	-16.6%	-17.8%	-16.6%	-13.8%	-6.8%
MMM	3.8%	3.8%	4.2%	4.7%	10.9%
IBM	10.4%	8.3%	8.9%	8.9%	9.8%
DELL	-1.0%	4.6%	5.4%	2.8%	12.8%
MSFT	5.8%	10.1%	13.0%	10.8%	6.7%
SPY	3.3%	2.9%	6.1%	3.6%	9.1%

Table A.39. Maximum in-sample returns for every stock and lagged starting time for Momentum Strategies in Volume.

Momentum Strategies in Volume C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	31.2%	23.0%	20.3%	23.9%	26.2%
MMM	3.7%	7.4%	8.1%	11.0%	14.7%
IBM	1.3%	4.4%	6.9%	8.2%	8.7%
DELL	14.9%	7.0%	9.5%	11.8%	12.5%
MSFT	4.3%	8.3%	7.5%	7.5%	12.7%
SPY	9.4%	9.8%	11.1%	14.4%	16.7%

Table A.40. Maximum in-sample returns for every stock and lagged starting time for Momentum Strategies in Volume C.

On Balance Volume Average	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	-29.2%	-19.2%	-13.3%	-35.4%	-24.1%
MMM	-3.1%	-2.0%	-10.6%	2.7%	-4.5%
IBM	-0.6%	-10.3%	-4.7%	-2.0%	-1.3%
DELL	-15.4%	2.7%	4.5%	3.6%	10.4%
MSFT	2.9%	7.1%	0.2%	4.4%	4.4%
SPY	-2.1%	9.4%	0.0%	7.4%	11.5%

Table A.41. Maximum in-sample returns for every stock and lagged starting time for On Balance Volume Average.

On Balance Volume Average C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	-21.8%	-22.4%	-27.4%	-1.3%	-19.8%
MMM	-5.7%	-6.8%	0.3%	-11.4%	-2.1%
IBM	-5.7%	0.9%	4.5%	-11.3%	-6.1%
DELL	-0.9%	-16.2%	-11.0%	-10.7%	-17.0%
MSFT	-5.4%	-13.3%	-1.2%	2.9%	-10.2%
SPY	10.1%	-0.8%	9.8%	-1.9%	4.0%

Table A.42. Maximum in-sample returns for every stock and lagged starting time for On Balance Volume Average C.

Head and Shoulders	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	5.6%	5.5%	3.8%	12.3%	6.8%
MMM	4.7%	3.2%	4.8%	6,.3%	5.2%
IBM	4.2%	3.0%	4.0%	5.1%	3.3%
DELL	8.1%	7.0%	9.9%	9.5%	7.4%
MSFT	11.8%	6.8%	6.4%	9.4%	5.6%
SPY	6.1%	2.9%	7.3%	5.0%	6.2%

Table A.43. Maximum in-sample returns for every stock and lagged starting time for On Balance Volume Average.

Head and Shoulder C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	8.0%	10.7%	11.0%	8.2%	9.6%
MMM	5.5%	5.1%	7.2%	5.5%	7.0%
IBM	6.9%	9.3%	10.3%	6.6%	5.3%
DELL	6.8%	8.8%	6.7%	7.6%	6.4%
MSFT	7.1%	6.4%	5.0%	5.6%	5.8%
SPY	8.5%	10.7%	9.2%	7.8%	8.8%

Table A.44. Maximum in-sample returns for every stock and lagged starting time for On Balance Volume Average C.

Triangle	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	6.9%	2.7%	4.2%	4.0%	6.0%
MMM	3.7%	8.4%	5.7%	5.0%	5.4%
IBM	4.1%	4.2%	3.9%	6.7%	5.1%
DELL	4.1%	6.4%	6.8%	7.0%	12.5%
MSFT	6.0%	8.3%	5.3%	2.5%	4.0%
SPY	3.9%	3.9%	6.0%	5.8%	5.0%

Table A.45. Maximum in-sample returns for every stock and lagged starting time for Triangle.

Triangle C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	11.7%	13.7%	12.8%	15.2%	17.8%
MMM	5.4%	4.3%	3.4%	5.5%	4.7%
IBM	7.5%	6.6%	5.4%	6.1%	10.2%
DELL	9.0%	15.9%	8.0%	12.1%	11.2%
MSFT	5.2%	4.6%	6.8%	7.9%	10.5%
SPY	15.3%	6.4%	13.2%	21.8%	10.5%

Table A.46. Maximum in-sample returns for every stock and lagged starting time for Triangle C.

Rectangle	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	25.8%	22.9%	14.6%	12.0%	14.0%
MMM	7.1%	6.6%	4.5%	9.1%	11.1%
IBM	8.4%	8.6%	6.8%	8.6%	3.7%
DELL	9.7%	16.4%	14.8%	20.7%	13.7%
MSFT	7.5%	6.0%	8.0%	4.5%	5.0%
SPY	6.5%	4.7%	5.4%	6.1%	5.4%

Table A.47. Maximum in-sample returns for every stock and lagged starting time for Rectangle.

Rectangle C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	5.4%	6.8%	5.6%	3.6%	3.3%
MMM	6.8%	4.4%	2.9%	3.9%	5.6%
IBM	2.4%	2.0%	3.9%	5.8%	7.1%
DELL	5.1%	4.5%	8.4%	5.7%	10.1%
MSFT	4.5%	4.7%	5.9%	6.8%	7.9%
SPY	5.2%	5.8%	6.3%	4.8%	2.9%

Table A.48. Maximum in-sample returns for every stock and lagged starting time for Rectangle C.

Double Tops and Bottoms	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	12.3%	6.8%	6.7%	8.8%	10.5%
MMM	7.5%	5.2%	5.1%	5.1%	4.7%
IBM	4.3%	4.5%	4.8%	4.4%	3.6%
DELL	15.3%	10.6%	13.7%	14.8%	17.7%
MSFT	5.9%	5.0%	8.3%	4.5%	4.4%
SPY	4.9%	4.5%	4.6%	4.9%	7.2%

Table A.49. Maximum in-sample returns for every stock and lagged starting time for Double Tops and Bottoms.

Double Tops and Bottoms C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	25.9%	29.6%	23.6%	19.3%	25.7%
MMM	9.2%	7.3%	8.8%	8.0%	6.7%
IBM	7.8%	6.5%	7.3%	7.4%	6.9%
DELL	19.5%	18.3%	15.1%	13.9%	15.6%
MSFT	9.0%	7.4%	6.8%	8.6%	8.8%
SPY	5.5%	5.3%	6.3%	7.9%	8.9%

Table A.50. Maximum in-sample returns for every stock and lagged starting time for Double Tops and Bottoms C.

Broadening Tops and Bottoms	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	0.6%	0.8%	3.9%	2.2%	1.6%
MMM	0.0%	0.0%	0.0%	0.6%	0.6%
IBM	0.0%	0.0%	0.0%	0.0%	1.3%
DELL	1.0%	0.0%	1.3%	0.9%	0.7%
MSFT	0.6%	0.6%	0.4%	0.2%	0.5%
SPY	0.0%	0.0%	0.0%	0.0%	0.0%

Table A.51. Maximum in-sample returns for every stock and lagged starting time for Broadening Tops and Bottoms.

Broadening Tops and Bottoms C	2 seconds lag	15 seconds lag	30 seconds lag	45 seconds lag	58 seconds lag
MU	2.4%	3.2%	3.2%	2.2%	2.9%
MMM	1.1%	1.0%	0.0%	0.0%	0.0%
IBM	0.0%	0.0%	0.0%	0.0%	0.0%
DELL	1.3%	1.3%	1.3%	1.3%	1.3%
MSFT	0.0%	0.0%	0.0%	2.1%	2.2%
SPY	0.0%	0.1%	0.0%	0.0%	0.0%

Table A.52. Maximum in-sample returns for every stock and lagged starting time for Broadening Tops and Bottoms C.

Appendix B. The different parameters

In this appendix, the values of the different parameters are explained for each of the rules used in the research. The contrarian rules use the same number of strategies as the simple rules explained in this appendix.

B.1 The filter rules

For the filter rules, we only used one parameter. These parameters defines the percentage the price of a security needs to rise or drop, before actions will be taken. This parameter can adapt 250 different values, starting at a value of 0.01%. This percentage rises with 0.02% every step, until it reaches a 5% change in the price of a security.

Since this is the only parameter of this strategy rule, the filter rules in this research have 250 different strategies for every interval.

B.2 The moving average rules

The moving average rules use two different parameters. The first parameter is the window of the moving average. As we need enough values to compute a reliable average, we start with a window of 5 periods. In the case of intervals of 12 seconds, this will mean that there will be computed an average over the last minute. The window will then be increased with steps of three periods, until it reaches a window of 35 intervals.

The second parameter is a threshold, which defines the minimum percentage of change in the price of the security. This variable can adapt 101 different values, starting at no threshold at all. This means that we will always will take action when the current price differs from the average price of the window. The threshold value will rise with 0.07% every step, until it reaches 7%. The higher this value will be, the more risk averse this rule will be.

As the window can take on 11 different values and the threshold 101, the moving average rules in this research include 1.111 different strategies.

B.3 The support and resistance rules

First of all, the support and resistance need a time period in which it has to find a support and resistance level. This time horizon can take on the values 2; 4; 6; 8; 10; 12; 14; 16; 18; 20; 22; and 24, and thus includes 12 different values.

Second, we will use the same threshold we used in the moving average rules. As these contained 111 different strategies, the support and resistance rules are using a total of 1.332 different strategies.

B.4 The momentum strategies of price

The momentum strategies take on the same time horizon as the support and resistance rules, and also have the same threshold parameter. As these two parameters are the only variables of these set of rules, the total number of strategies is 1.332.

B.5The momentum strategies of volume

The momentum strategies of volume use, again, the same time horizon as before. However, we now use a different volume threshold, with a minimum rise and a minimum loss of volume compared to the period before. As the amount that has been traded is very volatile, the minimum gain in volume can take on values until 80%, where the maximum loss that will be tested in this research will be 40%. These volume thresholds will give us 101 different values, so the total number of values will be 1,332.

B.6 The On-Balance Moving Average rules

These rules also use the moving window that was introduced earlier. This variable included 11 different values. As an added feature, these rules use two parameters to define volume thresholds differences compared to the average of the window horizon. One parameter measures the minimum rise in the exchanged volume, the other measures the minimum loss before one should go short. Together, these values can take on 201 different values, with a maximum of a 10% change for both of the parameters.

Together, these parameters can generate up to 2,211 different strategies.

B.7 Head and shoulder rules

These set of rules only use one parameter. This parameter defines the difference of the bottoms. This value is measured in percentages. Together with their counter strategies we generate 552 strategies

B.8 Triangle rules

These rules use two parameters. One of them defines the minimum negative difference in percentage between the peaks. The other defines the maximum absolute difference between the bottoms.
These strategies and their counterparts form another 16192 strategies

B.9 Rectangle rules

These rules use one parameter, which defines the maximum absolute difference as percentage between the two peaks and the same for the two bottoms. This gives us another 552 different strategies.

B.10 Double tops and bottoms

Use the same two parameters as the Triangle rules. So this gives another 16192 strategies

B.11 Broadening tops and bottoms

These strategies use one parameter, which restricts the minimum of the sum of the absolute differences as a percentage of the peaks and bottoms. So the absolute difference between the bottoms plus that of the peaks .This gives a total of 644 strategies

Note: B.7 to B.8 all use peak detection, which on its own uses a few parameters. However these were not taken into account with the description of these strategies.

Appendix C. Peak Detection

In this article we discussed the “Extremum Rules” which required peak detection for their effectiveness. Since the recognition for peaks can be thought of as easy for the human eye, however, writing an algorithm for the recognition of peaks by a computer is not that easy. In this article we used several methods to recognize extrema, namely the Moving Average, the Lowess curve and the Loess curve. All of them have robust versions for effectiveness while dealing with outliers.

All of these techniques are strongly related, but can provide quite different results. The moving average was used for most of the strategies since it is not as computationally expensive as the local regression types (Lowess & Loess). All of the techniques described above have robust versions of them: Moving Median, RLowess, RLoess. The moving average and median are widely known and used and don’t need any explanation. The local regression however will be briefly discussed. Lowess is a local regression method which tries to fit a weighted linear least squares regression with a first degree polynomial through our two dimensional data. The points used for this regression are defined by a span. Next, these points are given weights according to the tricube function, which gives higher weights to the points in the neighborhood of the point we are evaluating. RLowess does exactly the same, but gives zero weight to points outside six mean absolute deviations. Loess and RLoess also follow the same idea, but use a second degree polynomial. These local regression methods give seemingly nice result but have the big disadvantage that they are computationally very expensive and tend to overfit the data. For those reasons only a few strategies were executed while using these techniques for peak detection.

After one of these methods was used to smooth the data we defined a peak if there was one moment where the smoothed price increased followed by an instantaneous decrease. Changing the parameters of the peak detection can make it more or less sensitive.

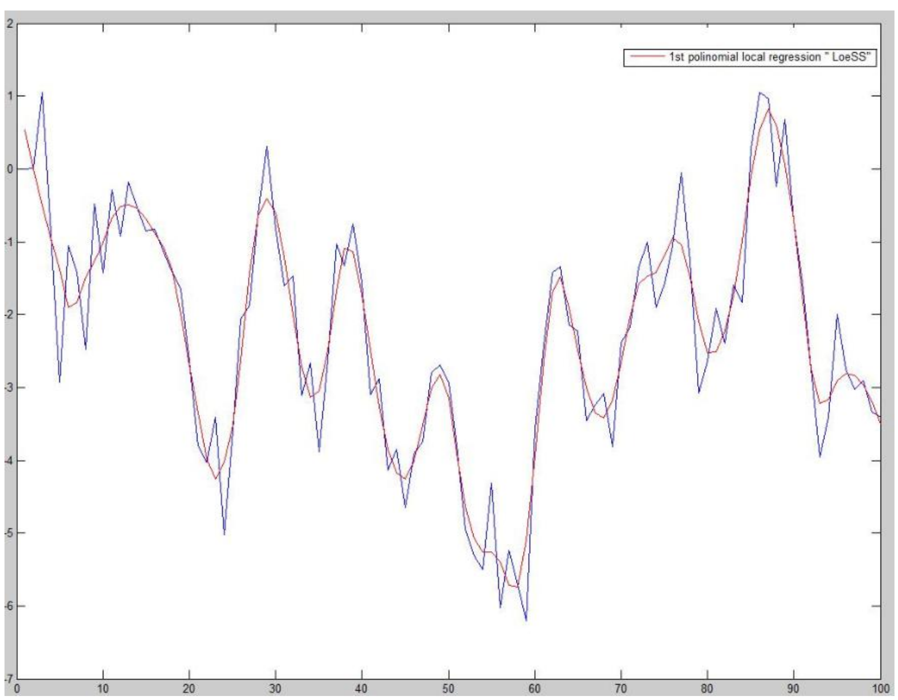

Figure C.1. Example of the use of LoeSS.