Master Thesis

Delving into the Spidyn Universe

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Abstract

The Spidyn indicator aims to detect pockets of predictability in time series based on detecting positive or negative unsustainable accelerations. In this Master´s Thesis we have applied Spidyn to financial data, specifically to stock price data, in order to detect unsustainable price accelerations which could develop into bubbles or crashes. The correct prediction of such behaviors would allow for profitable algorithmic trading to take place.

The main goal of this Master´s Thesis is to explore and analyze the parameter space of the Spidyn indicator with the purpose of finding a parameter set, or a reduced group of them, that may lead to better performance of the indicator, as well as studying the reason behind it.

The necessary tools developed to achieve such a goal constitute by themselves an important part of this Thesis, and both of them are aimed at allowing and encouraging future researchers on the topic to continue unraveling the complex Spidyn universe.

Acknowledgements

In the first place, I would like to thank my supervisor Prof. Didier Sornette, for generously having given me the opportunity to develop this great project with all the resources available to him, both human and technical. In the second place, I would like to make a special mention of Dr. Ryan Woodard, who throughout all these months has given me invaluable help, not just technical, but most importantly emotional, supporting me in those few moments of despair which is usually involved in good research.

I would also like to thank my parents, Luis and Ana, as well as my sister Anita and my girlfriend Cuca, for having supported me ever since the idea of carrying out my Master´s Thesis at ETH Zurich began to take shape in my mind.

Last but not least, I would like to thank all of those I have met during my stay in Zurich, and which have made this academic project turn into a complete and unforgettable experience.

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Chapter 1
Introduction

1.1. The Stock Market

A market has traditionally been a place where people traded goods and services, exchanging them for money or by providing themselves different goods or services in return. Essentially, it allows two parts, the buyer and the seller, to make the necessary arrangements for this exchange [12]. A stock market has basically the same purpose, to get buyers and sellers together, so they can exchange securities such as company stocks and derivatives at an agreed price. The type of participants trading in such markets has been changing from a majority of individual investors a few decades ago, to one of large institutional investors such as pension funds, mutual funds or hedge funds, among many others [13].

Many people feel attracted to the stock markets, fascinated by the possibility of quick gains, and encouraged by the increasing easiness of Internet trading [1]. People start their trading adventures lured by prospects of wealth and optimistic about their abilities to “beat the market”, forgetting its powerful and unpredictable displays of fury, which can be seen at its best in worldwide crashes, such as that which took place on October 19, 1987. Black Monday, as it is commonly referred, brought havoc to the financial markets like a Tsunami crossing the ocean. Figure 1.1 shows the behavior of the U.S. S&P 500, the English FTSE 100 and the Japanese Nikkei 225 during the months from July 1987 to January 1988. These Indexes, as well as most indexes around the world, suffered great losses which took many months to regain.

Figure 1.1: Behavior of the Indexes S&P 500, FTSE 100 and Nikkei 225 for the months between July 1987 and January 1988 [3].

1.2. The prediction of Prices and the Efficient Markets

Do the stock prices follow trends which can be used to predict future behaviors? This question has been asked, in different ways, by most of the people in contact with stock markets, and many studies have been made on this topic. As Maurice Kendall suggested in his controversial paper in 1953, and Louis Bachelier 53 years before him, stock prices seem to follow a random walk, meaning that stock price changes are independent of one another, and that future prices do not depend on past ones [11].

The *Efficient Market Hypothesis* states that all the information carried in the previous prices will be reflected in today´s stock price, and not in tomorrow´s. The reason behind this is that in competitive markets the prices adjust immediately to any effort by the investors to take advantage of the information in past prices. Suppose we could tell for sure from past prices Monday that the price of a certain stock, let’s say Google, was going to rise from 300$ on Monday to 400$ by Friday. What would happen when investors realize this is that they will start buying immediately until the price reached 400$, therefore destroying the trend and immediately having incorporated the information carried in the previous prices to the price of today. This would be the behavior if the market was efficient. Economists often refer to three levels of market´s efficiency [11]:

- *Weak form of Efficiency:* In this level, prices reflect the information contained in the record of past prices. Future price movements are determined entirely from information which is not found in the prices series, and therefore it is of no use to study past returns, and prices will follow a random walk.
- *Semistrong form of Efficiency:* The prices of stocks belonging to this type of market not only reflect past prices, but also all other publicly available information, such as published information contained in financial press. In this case, the prices will adjust immediately to information such as quarter earnings, new issues of stock, or mergers.
- *Strong form of Efficiency:* The prices of stocks with a strong form of efficiency reflect all the possible information, both public and private. In this type of market there would be no investors obtaining excess returns consistently, only temporarily luck or unlucky investors.

We have seen how markets are supposed to behave, but what happens when this premises are not met, what if we have inefficiencies in the markets. In this case arbitrage appears. Arbitrage is usually defined as a strategy which exploits these market inefficiencies in order to generate superior returns, supposedly being risk-free.

This arbitrage forces mispriced prices back to their supposed fair price. If a stock is underpriced, the arbitrage strategy consists on buying the stock until the moment the buying price is the same as its fair price, and the mispricing has disappeared. In the case of an overpriced stock, the strategy would consist on selling the stock until it reached this fair price.

1.3. Valuating Stocks

We have just seen how a mispricing may be used to arbitrage and obtain excess returns from the market, but how is a stock valuated in order to know if its positively, negatively or not mispriced at all? There are two main approaches to this problem, the fundamental analysis and the technical analysis [6]:

- *Fundamental Analysis:* This analysis evaluates a security by measuring its intrinsic value, examining economic, financial and other qualitative or quantitative factors. Everything which may affect a the security's values, such as macroeconomic factors concerning the economy or industry, as well as individual specific factors such as the financial condition of the firm or its management, is used in such analysis. From this analysis the value of the firm is drawn, and comparing it with the current market price trading decisions may be taken.

- *Technical Analysis:* This type of analysis is considered to be the opposite of the fundamental analysis. The attempt of pricing the stock derives from the statistics generated by market activity, such as past prices and volumes. The do not try to measure the intrinsic value of a stock, but instead use different tools such as price charts to identify patterns suggesting future activity. Technical indicators used by for the technical analysis are used to alert, predict and confirm, and are computed using price time series of stocks.

We have just seen two different and confronted ways of valuating a security, by scrutinizing a firm from the inside, or by examining what people think of the stock and the impression they have of it. The Spidyn indicator belongs to this second type of analysis, it is a technical indicator.

Chapter 2
The Spidyn Indicator

2.1. Description

The Spidyn Indicator is a technical indicator which aims to detect pockets of predictability in the time series based on detecting positive or negative unsustainable accelerations. In this Thesis we apply Spidyn to financial data, specifically to stock price data. These pockets or windows are short periods of the order of a few days in which we believe the stock has entered a mini-bubble or mini-crash. We seek an appropriate trading strategy such that Spidyn may be exploited for profitable algorithmic trading. Algorithmic trading systems use mathematical models on which they base their transaction decisions in the financial markets [6].

The Spidyn function accepts a time series and some parameters and returns a new time series of Spidyn indicators. The length of the output series is the length of the input series minus a parameter T, described below. The values of the Spidyn indicator usually lie in the range [-1, 1]. A main goal of this Thesis is to find parameters which lead to a successful trading strategy.

2.2 Parameters

The Spidyn algorithm was developed in 2004 by Didier Sornette and Didier Darcet, and the implementation of it was carried out by Yann Ageaon. It is provided as a black-box compiled library and it can be accessed by means of a Python wrapper developed by Ryan Woodard.

This wrapper is accessed through a python script developed during this Master Thesis, and which allows to easily modify the parameters involved in calculating the Spidyn indicator. Once the Spidyn indicators have been obtained, the python code also stores them in the newly created Fcozh data base, avoiding the tedious work that meant running through hundreds of folders and csv files as was the case before this implementation.

The input parameters passed to the Spidyn black box are the following:

- Data : The price time series of length N for the stock upon which the indicator is going to be computed.
- T : The Window size of the time series for which the indicator is computed on.
- P1 : The minimum coefficient of the polynomial to fit. This number corresponds to the degrees of freedom of the polynomial, and not the highest exponent of it. For example, a minimum coefficient of 2 would be equal to $P(x)=a_0+a_1x$ and not $P(x)=a_0+a_1x+a_2x^2$.

- P2 : The maximum coefficient of the polynomial to fit, and as well as the previous parameter, it makes reference to the number of degrees of freedom of the polynomial and not the highest exponent.
- Weight : Vector corresponding to the weights given to the polynomial equation defined by the parameters P1 and P2. In our research this parameter has been such that all the polynomials were equally weighted.

As we have learnt [2], the polynomials created by the parameters P1 and P2 specify the different order of derivatives used by Spidyn to generate its indicator. The higher P1 and P2, the higher the order of the derivatives we are taking into account. These derivatives are:

- Rate of change in Position is Velocity (1^{st} order difference)
- Rate of change in Velocity is Acceleration (2^{nd} order difference)
- Rate of change in Acceleration is Jerk/Jolt (3^{rd} order difference)
- Rate of change in Jolt is Snap (4^{th} order difference)
- Rate of change in Snap is Crackle (5^{th} order difference)
- Rate of change in Crackle is Pop (6^{th} order difference)

The higher order of the derivatives employed, the more aggressive the Spidyn indicator is. With the term aggressive, we want to reflect a behavior of the indicator in which sudden changes in prices are taking into account. If we refer to a more conservative behavior of Spidyn, we want to reflect the opposite behavior, taking into account softer and less abrupt changes.

2.3. Spidyn at Work

Spidyn works on a time series of past prices of size T, and by means of the polynomial fitting described by the parameters P1 and P2, compute an indicator for the day T+1. This process continues with a moving window of size T over the whole set of input data. Supposing we have a price time series of size N to explore, the number of indicators which will be computed by Spidyn is equal to (N-T+1). The reason behind this is that the indicator needs exactly T prices to compute the T+1 term, being equal to 0 those first T indicators. When all the time series has been explored, the last indicator will fall immediately outside its domain, thus the (+1) term.

The indicator is a real number of magnitude usually between ± 1, reflecting the unsustainable acceleration of the prices time series within the moving window. Figure 2.1 is an example of the Spidyn indicator for the stock Baxter for the month January to October 2007. If the indicator i(t) for a given date is larger in absolute value than a given threshold tIn>0, this may suggest the existence of recent mini-crashes or mini-bubbles. We hypothesize that i(t)<-tIn suggests a recent drop in the price, a crash, and i(t)>tIn suggests an increase in price, a bubble. Were such unsustainable acceleration in the change of prices unsustainable, an adequate trading strategy may be designed to profit from it.

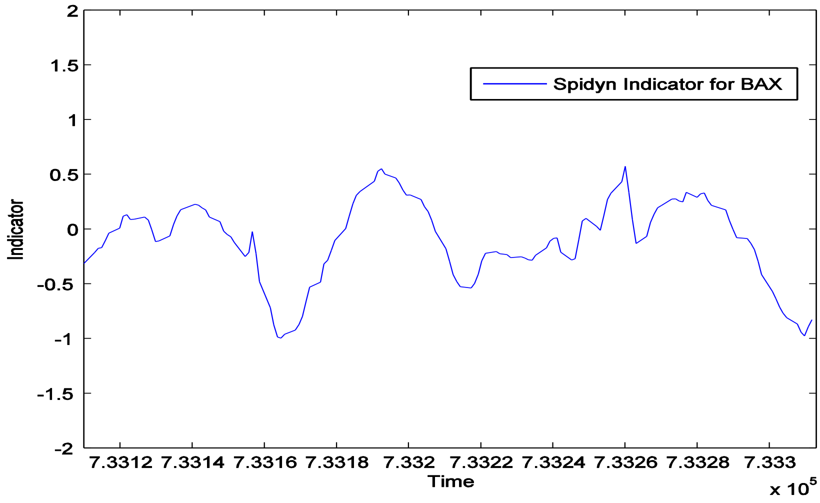

Figure 2.1: Indicator for the stock Baxter and for the parameters (30, 4, 7) from January to October 2007.

2.4. Trading Strategy

2.4.1. The Contrarian Strategy

The Spidyn indicator may be thought of as the petrol (energy source) which we need to move our vehicle (actual trades), but that alone isn´t enough, we need an engine. The trading strategy is our engine, which fueled by the indicator will automatically perform the necessary steps to make our vehicle advance efficiently. Once the Spidyn black-box has computed and delivered the indicator, it is up to our trading strategy to analyze it, extract as much information as possible from it and act accordingly.

As stated before, the indicator provides a measure of the actual situation of a stock, whether it is sustainable, on a bubble heading towards a crash, or in a bubble heading towards a rally, created by the optimistic/pessimistic mood of the traders, carried away by their emotions. “The behavior of financial markets is thought to result from varying attitudes towards risk, the heterogeneity in the framing of information, cognitive errors, self-control, and lack thereof, regret in financial decision making, and the influence of mass psychology” [1].

This irrational behavior may be exploited by strategies such as the *contrarian strategy*, which is based on the belief that certain crowd behaviors can lead to exploitable mispricing in the stock markets. This contrarian strategy is related to *value investing*, a type of investing strategy which also looks for mispriced investments, undervalued by the stock market. Although very similar in some aspects, they may differ in the fact that the value investor bases his opinion on financial metrics such as book value of price to earnings ratio, while contrarian investors focuses mainly on the feeling and atmosphere the investors have towards the stock [7].

The purpose of our contrarian strategy is to identify unsustainable accelerations which are pushing a stock to a rally or plunge and to act in opposition to the herd. If the stock price was rallying, we would believe a mini-bubble may be taking place and would suddenly end, so instead of buying we would sell the stock, waiting for the drop in prices. On the other hand, if the stock price was plunging in an unsustainable way as a result of irrational decisions, we wouldn´t follow the herd by selling, we would instead buy, with the belief that this crash would soon end and that the stock will recover.

This strategy may be followed in a variety of ways with different options. In our case, we have decided not to allow the possibility of *short selling*. Short selling allows one to profit from the decline in prices by borrowing a stock or financial instrument by paying a lending fee and selling it at the current market price with the belief that later on the stock would be worth less. It´s in that moment when the short seller repurchases the stock, called closing the position, at a (hopefully) lower price, returning the stock to the lender and keeping the difference between the prices. In our case this could be used if the Spidyn indicator detected a bubble and we didn´t have the stock in our portfolio. In that case we could borrow it for a fee, sell it and wait for the price to drop to cover the position and return the stock [8].

This type of practice has recently been criticized as contributing to the recent market volatility and severe drop of the prices of certain sectors, such as the financial sector, which made the U.S. Securities and Exchange Commission (SEC) decided to ban short-selling for nearly 800 financial companies to try to stop the falling stock prices [9].

Short selling may not only be harmful for the stock involved, but as stocks have no limit to the increase in price, the risk carried by the short seller is also high. A tragic example of the risks involved can be seen on one of Germany´s wealthiest men, Adolf Merckle, who committed suicide after being caught in a short selling squeeze by Porsche on VW shares, among other wrong trades [10].

We don´t expect such tragic outcomes. Our contrarian trading strategy will invest in long positions, meaning, we will buy the stocks and profit from the increase in price. To do so we will buy stocks when the crowd´s mood is pessimistic about a stock, causing it to unsustainably decrease its price, and profit from the change in trend when the price rises.

2.4.2. Strategy Parameters

The trading strategy described previously is based on that developed by former researcher Gilles Daniel and implemented in Matlab ®. We adapted that code to our new data base which manages and stores most of the information, as well as changes necessary for our research. Some of the most important parameters which describe the functioning of the strategy are the following:

- Investment Fraction : The fraction of our total wealth that will be invested each time we receive a buying signal. Our total wealth is defined by the amount of cash owned and the stocks in our portfolio valued at the closing price of the day before. Once we have calculated the amount of money which is going to be invested we check if we have that amount of money in cash. If we do, then the signal turns into an effective deal, but if we don´t then the deal is not made. This has a big effect on the performance of the portfolio, which will be seen clearly in the portfolio simulations.

- MaxLevarge : The maximum leverage allowed. In our case we have set this amount equal to one. This means that we are not leveraging, but trading only on our initial wealth. This behavior could belong to individual investors with a difficult access to leveraging. This option was not studied due to the large parameter space already used during this Thesis, but is a parameter we strongly advise on examining in the future.
- tIn : The threshold at which we enter a position, and has to be surpassed downwards so as to enter the market in a crash expecting the rebound.
- tOut : The threshold at which we exit a position, and has to be surpassed in an upward direction. Both parameters tIn and tOut are crucial in determining the response of the trading strategy to the Spidyn indicator. In our case and for the portfolio simulations tIn =tOut=-0.5, although some new scripts of code implemented by us will help analyzing other values.

It is important to make clear an important issue concerning the investment fraction. When the investment fraction is high, after only a few signals the initial wealth in cash is invested in stocks, which on one hand allows us to observe the gains and losses for the total of our wealth, but on the other hand makes us lose some Spidyn signals. The way we have programmed our trading strategy is the following:

Supposing we start with a wealth of 1 unit in cash and depending on the signals we receive on our first trading day we buy a few stocks, so now our total wealth may be seen as an addition of wealth invested in stocks and wealth invested in cash. We must remember that for every day and every stock we have an indicator, but that is not a signal. A signal is an indicator which has trespassed the threshold of the trading strategy. The following day we repeat the procedure and analyze the Spidyn signals in order to decide for each stock if we do nothing with it, if we sell it if we have it, or if we buy it. In order to buy the stock, first of all we calculate the amount which is going to be invested, which is our total wealth multiplied by the investment fraction. Once we have calculated this amount, we check to see if we have that amount in cash. If we have the buying deal is made, but if we don´t, the deal doesn´t take place, thus missing a signal. This could have been avoidable if leverage had been used in parameter MaxLeverage, which is a common practice for hedge funds and other financial institutions who have easy access to cheap leverage, but we decided to ignore this possibility, which would be recommendable to introduce for further analysis on Spidyn.

2.5. Data Input

2.5.1. Price Time Series

The Spidyn indicator is computed using the adjusted closing prices of stocks. The historical data used for our simulation comes from two sources: *CSRP* and *yahoo finance*. CRSP is a research center at the Booth School of Business of the University of Chicago functioning as a vendor of historical data. The data provided dates back to 1925, for stocks listed in NYSE [20]. This datasource has been used to obtain the prices for the in-sample simulations. Yahoo Finance provides information on stocks, historical data and prices among many others [3], and has been used as datasource for the out-of-sample simulations for which no prices where in the database.

The stocks employed in the simulations are those belonging to the S&P 500 Index, widely known as the best single gauge of the U.S. equity market and which includes 500 leading companies of the U.S. economy. It covers approximately 75% of the U.S. equities market and was created in 1923, and in 1957 expanded itself to include 500 companies. This index is market-value weighted, which means that changes in companies with higher market value will have a greater influence on the Index than a lower market value company [4].

The prices used in our Thesis are adjusted to splits, which means that stock splits have been taken into account in order to allow for historical comparison and accurately reflect the performance in today´s terms. In order to do so the old prices are adjust to reflect the recent splits [6].

The time period used for the simulation is January 2003 through December 2006. That period corresponds to what some people call a *Bull market*, which is characterized by optimism, investors´ confidence and expectations that the strong results will continue [6].We chose this period so that we can compare our new results with previous work carried out on this same period [18].

Chapter 3
In-Sample Simulations

3.1. Description

We have described the Spidyn indicator, its different parameters, the database and the trading strategy. Here we present the experiments we carried out, what we expect to learn from them, the results, and the conclusions.

We focus the main part of this Thesis in exploring the parameter space of the Spidyn indicator. Some parameters, such as the window size, had been previously studied [18], although in a lighter way, and some of them, such as P1 and P2, had not been previously explored.

By conducting our studies over these parameters and by the use of the database and the appropriate code we believe to be able to conduct a great amount of tests on different parameter sets. Our aim is to be able to find a set of parameters for the Spidyn indicator which allows us to outperform some usual Benchmarks such as the Index and the Buy & Hold strategy, as well as the performance of the parameter sets used by former Spidyn researchers.

In case we were successful in this quest, our results would allow subsequent researchers to conduct, based on these results, a more profound research on other aspects of the indicator without having to try it for the huge parameter space, allowing them to focus their effort on different issues.

In this Chapter we are going to perform a large variety of simulations in order to obtain a few sets of parameters which, for the testing period Between January 2003 and December 2006 outperform the rest of them.

As we have seen, the Spidyn indicator depends on several parameters whose combination provides us with one real number that will later determine the results of the trading strategy followed. This combination of the different possible parameters provides us with a fairly big parameter space in which to look for the best performing parameters. This study of the parameter space will present us with large quantities of data, which we will reduce and analyze.

The Spidyn parameters we explore are the window size (T), the beginning order of the polynomial (P1) and the ending order of the polynomial (P2). Previous studies [16-18] used:

- P1 = 2 [16-18]
- P2 =5 [16-18]
- T = [10, 30, 60, 150] for part of [18], but unknown for his portfolio simulations.

The parameter space explored were all combinations of:

- P1 = [1, 2, 3, 4]
- P2 = [4, 5, 6, 7]
- T = [10, 15, 20, 30, 45, 60, 90]

We tested all 112 combinations of T, P1, and P2. This choice of parameters was such that allowed us on the one hand to perform a great amount of simulations on different parameter sets, and on the other hand to be sufficiently close to the previous studies in order to use some of the previous results on the Spidyn indicator.

In order to reduce the large amount of data we decided to approach the search for a best performing set of parameter in the following way: First we chose three representative sectors of the S&P 500 (Financial, Health Care, and Information & Technology) and we analyzed for each of them the chosen parameter space. We grouped the results according to their Sharpe Ratio performance, obtaining sets of parameters which outperformed the rest. The next step was to follow the same procedure but with a few individual stocks belonging to each of the sectors, obtaining the performance for the same parameter space and grouping them accordingly. Finally, we repeated the procedure with the same parameter space but this time for the S&P 500 index, grouping the result in accordance with their Sharpe ratio performance and extracting the best performing parameter sets.

The motivation behind this procedure was to not only search for the best performing parameters, but also to test if the Spidyn indicator was capable of detecting stocks belonging to the same sector behaving in similar ways, which would indicate that different sectors follow different dynamics. If such a behavior was detected by our indicator, it could mean there may be some sort of predictability possible for us to exploit.

The outline of this main part of the experiments is shown in Figure 3.1:

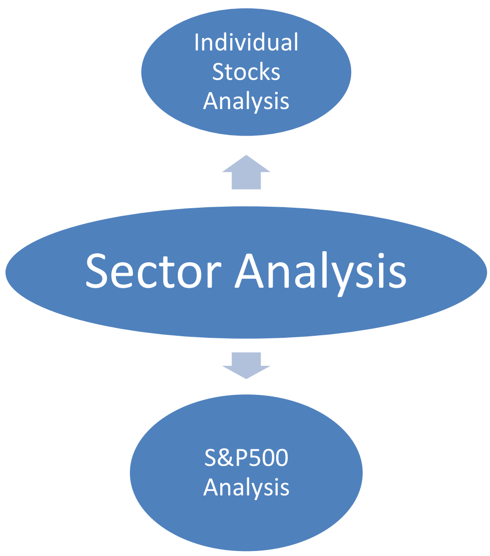

Figure 3.1: Outline of the experiments performed for the in-sample simulations.

Once we have carried out the necessary simulations and arrived to the conclusions on the best performing sets of parameters, we are in a position to check the results with an out of sample test. For this test we compared our results of the best performing parameter sets with those used previously [16-18] in order to compare their performance.

3.2. Sector Analysis

3.2.1. Methodology

As stated before, the sectors analyzed will be the three most important by weight in the S&P 500 index as classified by the Global Industry Classification Standard (GICS). The GICS methodology is the official Standard & Poor´s industry classification system, and is commonly accepted as a global classification using revenues as a key measure of the principal business activity of the companies. It is used for investment research, as well as for portfolio management and asset location [5].

There are 10 GICS sectors:

- Consumer Discretionary
- Consumer Staples
- Energy
- Financials
- Health Care
- Industrials
- Information and Technology
- Materials
- Telecommunications Services
- Utilities

The three most important sectors by market capitalization present in the S&P500 Index as for December 31, 2008 [4] are:

1. Information and Technology (15,27% of weight in the Index)
2. Health Care (14,79% of weight in the Index)
3. Financials (13,29% of weight in the Index)

These 3 sectors make up more than 40% of the index by weight, and are the ones chosen to carry on the simulations. The simulations consist on running the code written in Matlab by Gilles Daniel with the necessary changes made in order to allow us to include our greater parameter space.

We found that the investment fraction, which is the percentage of our wealth invested each time we receive a signal to invest, made a great difference when trying to evaluate the performance of the parameter sets. In order to take this into account, we decided to include this parameter in our search space, studying investment fractions (2, 5, 8, 10, 12, 15, 20, and 25%)

Before carrying out our simulations, we had to establish a way of determining between 2 sets of parameters which was the better performer, choosing two measures. The first and more obvious one was the percentage of wealth increase, but the flaw with this measure is that it doesn´t take into account the risks involved. On the other hand, if we use the Sharpe ratio to assess the performance of the different parameter sets we will be taking risk into account, as well as the returns. The Sharpe ratio measures the excess of returns per unit of risk and is defined as :

$$S = \frac{E[R - Rf]}{\sigma}$$

In our case, the risk free rate (Rf) is equal to zero both for our Spidyn portfolio, and the Index and Buy and Hold portfolios used as benchmark for comparison reasons, the returns (R) are the log-returns of the wealth and the standard deviation (σ)is that of the returns.

After carrying out the simulation over the parameter space for each sector we made a classification of the data according to the two different criteria, wealth increase and Sharpe ratio. When ordering the data in accordance to these two factors, we did it the following way:

When organizing the data according to the Sharpe Ratio, in case of tie we used the wealth increase to determine order, from greater wealth to smaller one. When arranging the classification in accordance to the Wealth increase, in case of tie we used the Sharpe Ratio to break the tie, from greater Sharpe Ratio to smaller one. After this arrangement has been made, we will choose the best performing parameters according to 2 approaches which will be explained in the next section, along with some examples.

During parts of the Thesis we will make reference to both of these performance indicators, but as stated before, due to the ability of the Sharpe ratio to incorporate a measure of risk, we will concentrate on the former. The Wealth increase will be therefore used just for comparison.

It is always thrilling to be the first one to open a present, the first to see a new car or even better, the first discovering something!, but to be the first to use a brand new data base system is not something everyone would be willing to do. Soon after starting with this Thesis, the project of a new data base for the group began to come to life. It was meant to help avoid saving loads of small files for the different data needed such as the indicators for each stock, and getting information on tickers and prices from different sources, favoring a greater consistency in the data, but there were some drawbacks. The most important of them and which seems to be currently solved was the amount of missing tickers. This initial limitation of the database forced us to conduct the main part of our research on a reduced S&P500 Index, fortunately with enough tickers on the index as well as in each sector to make it representative.

The total number of stocks of the S&P 500 Index was 193, which account for nearly a 40% of the total stocks, and for each of the chosen sectors we had:

- Information and Technology (36 out of 76 constituents, 47.4%)
- Health Care (20 out of 48 constituents, 41.6%)

- Financials (23 out of 81 constituents, 28.4%)

The number of stocks made up a 40.9% of our reduced S&P 193, and curiously enough, the stock belonging to these 3 chosen sectors make up a 41% of the S&P 500. We would have preferred a greater amount of stocks to perform our simulation, but after weeks of coding we were ready to start.

According to the methodology described, we performed the simulations of the portfolio trading strategy based on the Spidyn indicators for each sector. The procedure is the same for the three sectors, so we will only show once the whole procedure, and as reference the rest has been included as Appendix A.

To compare our results we will monitor two benchmark portfolios, the S&P 500 Index and a portfolio based on a Buy & Hold strategy. This simple strategy consists on buying the stocks belonging to our pool of stocks at the beginning and selling them in the end. Depending on the window size of our Spidyn indicator we would have to wait T days in order to make the first deal. Our Buy & Hold trading strategy has been designed to have as starting date the first day we can start dealing with our Spidyn strategy, in order to be consistent .It is also important to note that when comparing the Buy & Hold portfolio benchmark with the Index benchmark when dealing with the whole Index as a pool of stocks, both results shouldn´t be the same, due to the fact that the Indexes are usually weighted by market capitalization. This means that changes in the prices of stocks of bigger companies will have a greater influence on the Index than small ones. In the Buy & Hold portfolio, all stocks are equally weighted, every stock having the same influence over the performance of the portfolio.

When dealing with reduced pools of stocks such as when analyzing only stock of the Information and Technology Sector, the Index will remain the same, but the Buy & Hold strategy will only buy those stocks belonging to that sector.

3.2.2 Information & Technology Sector

For the simulation on the Information and Technology Sector, 36 stocks out of the 76 stocks that make up the sector according to GICS have been used. The results of running our Spidyn indicators together with our trading strategy have been classified according to their Sharpe ratio and their Wealth performance. The analysis presented below corresponds to that explained earlier. The results are separated according to the Sharpe ratio and Wealth increase.

3.2.2.1 Sharpe Ratio

Table 3.1 below shows the top 20 performers according to their Sharpe ratio. The abbreviations in the column heading of the table have the following definitions:

- *Ranking*: The position each parameter set has after being ordered y performance and filtered. One of the most used filters is when the parameter sets are arranged according to invest fraction. In this case, the value for position would be the same, but the *ranking* or local positioning would be for only this investment fraction.

- *Position*: The position each parameter set has after being ordered by performance without any filtering. In the case of the global performance without filtering, *Ranking* and *Position* are equivalent.
- *Wind*: The window size (T).
- *P1*: The starting degree of the polynomial.
- *P2*: The ending degree of the polynomial.
- *In Fr*: The investment fraction used in the trading strategy.
- *SP_S*: The annualized Sharpe ratio of the portfolio based on the Spidyn indicator.
- *SP_W*: The annualized Wealth increase of portfolio based on the Spidyn indicator (%).
- *In S*: The annualized Sharpe ratio of the S&P 500 Index.
- *In W*: The annualized Wealth increase of the S&P 500 Index (%).
- *BH S*: The annualized Sharpe ratio of a Buy and Hold portfolio.
- *BH W*: The annualized Wealth Increase of a Buy and Hold portfolio (%).

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	1	45	4	6	0.12	1.5	25	1.2	16	0.71	18
2	2	20	2	4	0.15	1.5	22	1.1	14	0.66	16
3	3	20	2	4	0.10	1.5	18	1.1	14	0.66	16
4	4	20	2	4	0.08	1.5	15	1.1	14	0.66	16
5	5	45	4	6	0.05	1.5	11	1.2	16	0.71	18
6	6	45	4	6	0.02	1.5	4.4	1.2	16	0.71	18
7	7	45	4	6	0.20	1.4	32	1.2	16	0.71	18
8	8	60	4	4	0.25	1.4	24	1.2	15	0.67	17
9	9	45	4	7	0.10	1.4	22	1.2	16	0.71	18
10	10	45	4	6	0.10	1.4	20	1.2	16	0.71	18
11	11	20	2	4	0.12	1.4	20	1.1	14	0.66	16
12	12	45	4	6	0.08	1.4	17	1.2	16	0.71	18
13	13	30	4	5	0.05	1.4	13	1.2	15	0.73	16
14	14	45	4	7	0.05	1.4	13	1.2	16	0.71	18
15	15	15	1	4	0.08	1.4	12	0.98	14	0.57	15
16	16	20	2	4	0.05	1.4	8.9	1.1	14	0.66	16
17	17	30	4	5	0.02	1.4	5	1.2	15	0.73	16
18	18	45	4	7	0.02	1.4	4.9	1.2	16	0.71	18
19	19	20	2	4	0.02	1.4	3.5	1.1	14	0.66	16
20	20	20	2	4	0.20	1.3	25	1.1	14	0.66	16

Table 3.1: Top 20 performing parameter sets according to Sharpe ratio.

Two approaches were used to analyze the data. The first one consists of analyzing individually the parameters of the top ten and top twenty results. The reason behind the choice of 20, and not only 10, is to allow us to get a glimpse of a bigger picture, not narrowing only on the top 10 which could only include parameter sets of a few investment fractions. This division also allows us to increase the efficiency of our tool by making it possible to notice strange behaviors in the data such as extreme differences between top 10 and top 20 results.

If in our first approach we treated the parameters individually, and not as a set, and we said that the investment fraction had a great influence on the result, this second approach tries to do exactly the opposite. We now evaluate each investment fraction separately to eliminate its influence (now the results of every investment fraction will have the same weight, not like before where some investment fraction nearly didn´t contribute). We now get the top 5 parameter sets of each investment fraction taking note of every time each set appears. This not only enables us to see the top performing parameter sets, but also to analyze the importance of the investment fraction.

Finally, we intend to compare the results obtained by the different approaches and obtain a few parameter sets which perform better than others for each sector.

1st Approach:

If we focus on the top 10 and top 20 performers we obtain the following results for the individual parameters:

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	7 “4´s”	70% of 4´s	12 “4´s”	60% of “4´s”
	3 “2´s”	30% of 2´s	7 “2´s”	35% of “2´s”
			1 “1´s”	5% of “1´s”
P2	5 “6´s”	50% of 6´s	6 “6´s”	30% of 6´s
	4 “4´s”	40% of 4´s	9 “4´s”	45% of 4´s
	1 “7”	10% of 7´s	3 “7´s”	15% of 7´s
			2 “5´s”	10% of 5´s
Window	6 “45´s”	60% of 45´s	9 “45´s”	45% of 45´s
	3 “20´s”	30% of 20´s	7 “20´s”	35% of 20´s
	1 “60”	10% of 60´s	1 “60”	5% of 60´s
			2 “30´s”	10%of 30´s
			1 “15´s”	5% of 45´s

Table 3.2: Summary of the results of Table 3.1

Table 3.2 Top 10 and Top 20 show the number of times a certain parameter has appeared, for example, under Top 20 we can see 12 “4´s”. This means that of the top 20 parameter sets, 12 of them had 4 as P1, and the next column in percentage show the percentage of parameter 4 appearing in the top 20. We can see that there a few individual parameters seem to dominate over the rest, and the percentage of the parameters don´t vary greatly from top 10 to top 20. According to these individual parameters the best performing set of parameters could be the following:

For the top 10:

- Window size: 45
- P1 : 4
- P2 : 6

For the top 20:

- Window size: 45
- P1 : 4
- P2 : 4

2nd Approach:

Next we analyzed the combination of sets of parameters which rank top 5 for each invest fraction. Here we can see how *Position* still refers to the global order of the parameters, taking into account all the investment fractions, while *Ranking* is a local positioning order for each investment fraction.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	6	45	4	6	0.02	1.5	4.4	1.2	16	0.71	18
2	17	30	4	5	0.02	1.4	5	1.2	15	0.73	16
3	18	45	4	7	0.02	1.4	4.9	1.2	16	0.71	18
4	19	20	2	4	0.02	1.4	3.5	1.1	14	0.66	16
5	34	30	3	5	0.02	1.3	3.9	1.2	15	0.73	16

Table 3.3: Top 5 parameter sets according to Sharpe ratio for In Fr 2%

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	5	45	4	6	0.05	1.5	11	1.2	16	0.71	18
2	13	30	4	5	0.05	1.4	13	1.2	15	0.73	16
3	14	45	4	7	0.05	1.4	13	1.2	16	0.71	18
4	16	20	2	4	0.05	1.4	8.9	1.1	14	0.66	16
5	32	30	3	5	0.05	1.3	9.9	1.2	15	0.73	16

Table 3.4: Top 5 parameter sets according to Sharpe ratio for In Fr 5%

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	4	20	2	4	0.08	1.5	15	1.1	14	0.66	16
2	12	45	4	6	0.08	1.4	17	1.2	16	0.71	18
3	15	15	1	4	0.08	1.4	12	0.98	14	0.57	15
4	28	30	4	5	0.08	1.3	18	1.2	15	0.73	16
5	31	60	4	7	0.08	1.3	14	1.2	15	0.67	17

Table 3.5: Top 5 parameter sets according to Sharpe ratio for In Fr 8%

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	3	20	2	4	0.10	1.5	18	1.1	14	0.66	16
2	9	45	4	7	0.10	1.4	22	1.2	16	0.71	18
3	10	45	4	6	0.10	1.4	20	1.2	16	0.71	18
4	26	30	4	5	0.10	1.3	20	1.2	15	0.73	16
5	29	60	4	7	0.10	1.3	16	1.2	15	0.67	17

Table 3.6: Top 5 parameter sets according to Sharpe ratio for In Fr 10%

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	1	45	4	6	0.12	1.5	25	1.2	16	0.71	18
2	11	20	2	4	0.12	1.4	20	1.1	14	0.66	16
3	21	45	4	7	0.12	1.3	24	1.2	16	0.71	18
4	23	20	3	4	0.12	1.3	22	1.1	14	0.66	16
5	25	30	3	5	0.12	1.3	21	1.2	15	0.73	16

Table 3.7: Top 5 parameter sets according to Sharpe ratio for In Fr 12%

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	2	20	2	4	0.15	1.5	22	1.1	14	0.66	16
2	22	45	4	6	0.15	1.3	23	1.2	16	0.71	18
3	24	60	4	7	0.15	1.3	22	1.2	15	0.67	17
4	47	60	2	7	0.15	1.2	15	1.2	15	0.67	17
5	65	30	4	4	0.15	1.1	21	1.2	15	0.73	16

Table 3.8: Top 5 parameter sets according to Sharpe ratio for In Fr 15%

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	7	45	4	6	0.20	1.4	32	1.2	16	0.71	18
2	20	20	2	4	0.20	1.3	25	1.1	14	0.66	16
3	27	60	4	4	0.20	1.3	19	1.2	15	0.67	17
4	62	60	4	7	0.20	1.1	23	1.2	15	0.67	17
5	66	30	2	5	0.20	1.1	21	1.2	15	0.73	16

Table 3.9: Top 5 parameter sets according to Sharpe ratio for In Fr 20%

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	8	60	4	4	0.25	1.4	24	1.2	15	0.67	17
2	37	45	4	6	0.25	1.2	29	1.2	16	0.71	18
3	59	20	2	6	0.25	1.1	35	1.1	14	0.66	16
4	60	45	3	6	0.25	1.1	26	1.2	16	0.71	18
5	104	15	1	5	0.25	1	31	0.98	14	0.57	15

Table 3.10: Top 5 parameter sets according to Sharpe ratio for In Fr 25%

Tables 3.3 to 3.10 show how for each investment fraction some parameter sets are appearing in all or most of them. By means of the Table 3.11 we can see more clearly the number of times the different parameter sets appear:

PARAMETER SET	WINDOW	P1	P2	NUMBER OF TIMES
1	45	4	6	8
2	20	2	4	7
3	45	4	7	4
4	30	4	5	4
5	60	4	7	4
6	30	3	5	3
7	60	4	4	2
8	15	1	4	1
9	20	3	4	1
10	60	2	7	1
11	30	4	4	1
12	30	2	5	1
13	20	2	6	1
14	45	3	4	1
15	15	1	5	1

Table 3.11: Number of times each parameter set appears in Tables 3.3-3.10

In Table 3.11 above, there are 15 different parameter sets out of a possible 40 in the top 5 of all invest fractions, and there are some which seem highly recurrent and which usually lie in the first places.

	Window	P1	P2
2nd Approach	45	4	6
2nd Approach	20	2	4
1st Approach	45	4	6
1st Approach	45	4	4

Table 3.12: Parameter sets obtained from the first and second approaches

Table 3.12 shows the parameter sets obtained by the two approaches. The first and third parameter sets, corresponding to different approaches match, but the second and fourth don´t. The fact that in the first approach we only focus on the parameters individually and for the second one we focus on the parameter sets as a whole causes this difference in results.

3.2.2.2 Wealth Increase

From Table 3.13 of the top 20 performers according to Wealth increase, we can see how the investment fraction has a great influence over the results, having the higher investment fractions a better performance according to Wealth increase than the lower ones. As seen in the previous chapter, this could be explained by the fact that when having lower investment fractions, it takes more time to be totally or at least significantly invested in the market, which leaves a big amount of money uninvested, decreasing both the gains and the losses.

As we saw from the previous approach, the Sharpe ratio does not seem to be as influenced as the Wealth increase by the investment fraction. We assume the reason behind this is that the amount of our wealth held in cash because of a smaller investment fraction doesn´t contribute to the increase in wealth or in returns, but it does contribute to a smaller volatility of our wealth. This also justifies our decision of choosing the Sharpe ratio to assess the performance of our sets of parameters.

To disentangle the effect of the investment fraction we decided to make a distinction in the data when evaluating the Wealth increase. In one group we evaluated the lower invest fractions (2, 5, 8 and 10%), and in another group we examined the higher invest fractions (12, 15, 20, and 25%). This distinction may also be related to the trading strategies followed by different types of investors. One could find large mutual funds or financial institutions which invest great quantities in a great variety of stocks and different investments and are looking for smaller but constant returns. This type of investors could belong to the first grouping of investment fraction, with a wider and more diversified investment portfolio.

If we were to center our attention on individual investors, amateur investors who probably invest part of their "surplus of income" and don´t have much time and means to analyze profoundly the stock market, we may find that they belong to the second group of investment fractions. Investors belonging to this group often prefer to choose just a selection of a few stocks, which they can follow on the little free time they have left from their work. Another example of this may be the Kimono Traders. Japanese housewives who in just a couple of years have turned out to become online speculators of currency, stock, bonds, or other investment opportunities [14].

For each group we will perform the two same approaches as carried out for the Sharpe ratio classification. After the division the results were as follow:

1ST GROUP (Investment fraction 2, 5, 8, and 10%)

1st Approach

We analyze the top 10 and 20 performers individually:

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	18	15	4	4	0.10	1.2	24	0.98	14	0.57	15
2	30	45	4	7	0.10	1.4	22	1.2	16	0.71	18
3	41	20	2	6	0.10	1.1	21	1.1	14	0.66	16
4	50	45	4	6	0.10	1.4	20	1.2	16	0.71	18
5	52	30	4	5	0.10	1.3	20	1.2	15	0.73	16
6	53	15	1	5	0.10	1.2	20	0.98	14	0.57	15
7	71	20	4	6	0.10	0.95	19	1.1	14	0.66	16
8	80	20	4	7	0.10	0.79	19	1.1	14	0.66	16
9	86	20	2	4	0.10	1.5	18	1.1	14	0.66	16
10	87	30	4	5	0.08	1.3	18	1.2	15	0.73	16
11	88	20	2	6	0.08	1.1	18	1.1	14	0.66	16
12	92	30	3	7	0.10	1	18	1.2	15	0.73	16
13	94	20	4	6	0.08	0.98	18	1.1	14	0.66	16
14	95	30	4	7	0.10	0.94	18	1.2	15	0.73	16
15	103	15	3	6	0.10	0.79	18	0.98	14	0.57	15
16	105	15	4	7	0.10	0.68	18	0.98	14	0.57	15
17	106	10	4	6	0.10	0.64	18	0.9	12	0.48	12
18	111	45	4	6	0.08	1.4	17	1.2	16	0.71	18
19	112	15	1	5	0.08	1.2	17	0.98	14	0.57	15
20	113	30	2	7	0.08	1.2	17	1.2	15	0.73	16

Table 3.13: Top 20 perfomers of group 1 investment fraction according to Wealth increase.

From Table3.13 above it is easy to observe how far behind the lower invest fraction simulations lay in comparison with the higher investment fractions when only the Wealth increase is taken into account. Bear in mind that now the *position* refers to the order of the parameter sets arranged in terms of Wealth increase. The parameter set with the highest Wealth increase from the group of low investment fractions is found in position 18th, as seen in the global *position*, and the second best is found in position 30th. We can also see how inside this group there is still a great difference in performance between the different invest fractions, being the top 20 dominated by the two highest invest fractions. This would mean that the first approach won´t be as revealing as it should be, and we should focus more on our second approach which allows us to see the best performing parameters for each invest fraction individually. In the following table we can see a summary of the first approach:

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	7 “4´s”	70% of 4´s	12 “4´s”	60% of 4´s
	2 “2´s”	20% of 2´s	4 “2´s”	20% of 2´s
	1 “1”	10% of 1´s	2 “1´s”	10% of 1´s
			2 “3´s”	10% of 3´s
P2	3 “6´s”	30% of 6´s	8 “6´s”	40% of 6´s
	3 “5´s”	30% of 5´s	4 “5´s”	20% of 5´s
	2 “7´s”	20% of 7´s	6 “7´s”	30% of 7´s
	2 “4´s”	20% of 4´s	2 “4´s”	10% of 4´s
Window	4 “20´s”	40% of 20´s	6 “20´s”	30% of 20´s
	2 “15´s”	20% of 15´s	5 “15´s”	25% of 15´s
	2 “45´s”	20% of 45´s	3 “45´s”	15% of 45´s
	2 “30´s”	20% of 30´s	5 “30´s”	25%of 30´s
			1 “10”	5% of 10´s

Table 3.14: Summary of the results of table 3.13

From Table 3.14 we can see there are several individual parameters appearing both in the top 10 and 20 positions, but there is still a slight greater recurrence of a few of them. In this case the most common parameters are:

For the top 10:

- Window size: 20
- P1 : 4
- P2 : 6 or 5

For the top 20:

- Window size: 20
- P1 : 4
- P2 : 6

2nd Approach

We next carried out the second approach in which we analyzed the parameter sets as a whole for each investment fraction. In this case we have the following classification:

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	503	20	4	6	0.02	1.1	5.5	1.1	14	0.66	16
2	505	10	4	6	0.02	0.77	5.4	0.9	12	0.48	12
3	511	20	3	6	0.02	1.1	5.3	1.1	14	0.66	16
4	517	20	4	4	0.02	1.2	5.2	1.1	14	0.66	16
5	525	30	4	5	0.02	1.4	5	1.2	15	0.73	16

Table 3.15 Top 5 parameter sets according to Wealth increase for investment fraction 2%.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	180	10	4	6	0.05	0.85	15	0.9	12	0.48	12
2	201	20	4	6	0.05	1	14	1.1	14	0.66	16
3	228	30	4	5	0.05	1.4	13	1.2	15	0.73	16
4	229	45	4	7	0.05	1.4	13	1.2	16	0.71	18
5	230	20	4	4	0.05	1.2	13	1.1	14	0.66	16

Table 3.16 Top 5 parameter sets according to Wealth increase for investment fraction 5%.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	87	30	4	5	0.08	1.3	18	1.2	15	0.73	16
2	88	20	2	6	0.08	1.1	18	1.1	14	0.66	16
3	94	20	4	6	0.08	0.98	18	1.1	14	0.66	16
4	111	45	4	6	0.08	1.4	17	1.2	16	0.71	18
5	112	15	1	5	0.08	1.2	17	0.98	14	0.57	15

Table 3.17 Top 5 parameter sets according to Wealth increase for investment fraction 8%.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	18	15	4	4	0.10	1.2	24	0.98	14	0.57	15
2	30	45	4	7	0.10	1.4	22	1.2	16	0.71	18
3	41	20	2	6	0.10	1.1	21	1.1	14	0.66	16
4	50	45	4	6	0.10	1.4	20	1.2	16	0.71	18
5	52	30	4	5	0.10	1.3	20	1.2	15	0.73	16

Table 3.18 Top 5 parameter sets according to Wealth increase for investment fraction 10%.

Tables 3.15 to 3.18 are summarized in Table 3.19:

PARAMETER SET	WINDOW	P1	P2	NUMBER OF TIMES
1	30	4	5	4
2	20	4	6	3
3	10	4	6	2
4	20	4	4	2
5	45	4	7	2
6	20	2	6	2
7	45	4	6	2
8	20	3	6	1
9	15	1	5	1
10	15	4	4	1

Table 3.19: Summary of Tables 3.15-3.18.

Although there are several different parameter set combinations as seen in Table 3.19, 10 out of a maximum of 20 and minimum of 5, we can still see some recurrence in the parameter sets. Compared with the previous results obtained by means of the 1^{st} approach, we can see that the parameter set

- Window size : 20
- P1 : 4
- P2 : 6

appears in 3 out of the 4 invest fractions as a best performer, and that the combination of P1=4 and P2 = 6 also appears quite often, in 7 of the 20 total parameter sets. Now we will repeat the same process to the second group of high investment fractions.

2ND GROUP

For this second group of invest fractions (12, 15, 20 and 25%) we used the same 2 approaches:

1st Approach:

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	1	20	2	6	0.25	1.1	35	1.1	14	0.66	16
2	2	45	4	6	0.20	1.4	32	1.2	16	0.71	18
3	3	15	1	5	0.25	1	31	0.98	14	0.57	15
4	4	45	4	6	0.25	1.2	29	1.2	16	0.71	18
5	5	10	1	7	0.20	0.61	29	0.9	12	0.48	12
6	6	45	4	7	0.25	1	28	1.2	16	0.71	18
7	7	10	2	7	0.20	0.61	28	0.9	12	0.48	12
8	8	10	4	7	0.25	0.45	27	0.9	12	0.48	12
9	9	45	3	6	0.25	1.1	26	1.2	16	0.71	18
10	10	60	4	7	0.25	1	26	1.2	15	0.67	17
11	11	30	2	7	0.25	0.86	26	1.2	15	0.73	16
12	12	45	4	6	0.12	1.5	25	1.2	16	0.71	18
13	13	20	2	4	0.20	1.3	25	1.1	14	0.66	16
14	14	15	3	6	0.20	0.71	25	0.98	14	0.57	15
15	15	10	2	7	0.15	0.69	25	0.9	12	0.48	12
16	16	60	4	4	0.25	1.4	24	1.2	15	0.67	17
17	17	45	4	7	0.12	1.3	24	1.2	16	0.71	18
18	19	20	2	6	0.12	1.1	24	1.1	14	0.66	16
19	20	30	2	7	0.20	0.93	24	1.2	15	0.73	16
20	21	30	4	5	0.25	0.9	24	1.2	15	0.73	16

Table 3.20: Top 20 perfomers of group 2 investment fraction according to Wealth increase.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	5 “4´s”	50% of 4´s	9 “4´s”	45% of 4´s
	2 “2´s”	20% of 2´s	7 “2´s”	35% of 2´s
	2 “1”	20% of 1´s	2 “1´s”	10% of 1´s
	1 “3”	10% of 3´s	2 “3´s”	10% of 3´s
P2	5 “7´s”	50% of 7´s	9 “7´s”	45% of 7´s
	4 “6´s”	40% of 6´s	7 “6´s”	35% of 6´s
	1 “5´s”	10% of 5´s	2 “5´s”	10% of 5´s
			2 “4´s”	10% of 4´s
Window	4 “45´s”	40% of 45´s	6 “45´s”	30% of 45´s
	3 “10´s”	30% of 10´s	4 “10´s”	20% of 10´s
	1 “20”	10% of 20´s	3 “20´s”	15% of 20´s
	1 “60”	10% of 60´s	2 “60´s”	10%of 60´s
	1 “15”	10% of 15´s	2 “15´s”	10% of 15´s
			3 “30´s”	15% of 30´s

Table 3.21: Summary of Table 3.20.

As seen in Table 3.21, both for the top 10 and top 20 results we get the same predominant parameters, which in our case are:

- Window size: 45
- P1 : 4
- P2 : 7 (but 6 is in top10 and 20 also close)

Results from the second approach are shown in Tables 3.22-3.25.

2nd Approach:

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	12	45	4	6	0.12	1.5	25	1.2	16	0.71	18
2	17	45	4	7	0.12	1.3	24	1.2	16	0.71	18
3	19	20	2	6	0.12	1.1	24	1.1	14	0.66	16
4	23	15	4	7	0.12	0.74	24	0.98	14	0.57	15
5	26	15	4	4	0.12	1	23	0.98	14	0.57	15

Table 3.22: Top 5 performers according to Wealth increase for investment fraction 12%.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	15	10	2	7	0.15	0.69	25	0.9	12	0.48	12
2	24	45	4	6	0.15	1.3	23	1.2	16	0.71	18
3	27	15	3	6	0.15	0.84	23	0.98	14	0.57	15
4	29	20	2	4	0.15	1.5	22	1.1	14	0.66	16
5	32	60	4	7	0.15	1.3	22	1.2	15	0.67	17

Table 3.23: Top 5 performers according to Wealth increase for investment fraction 15%.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	2	45	4	6	0.20	1.4	32	1.2	16	0.71	18
2	5	10	1	7	0.20	0.61	29	0.9	12	0.48	12
3	7	10	2	7	0.20	0.61	28	0.9	12	0.48	12
4	13	20	2	4	0.20	1.3	25	1.1	14	0.66	16
5	14	15	3	6	0.20	0.71	25	0.98	14	0.57	15

Table 3.24: Top 5 performers according to Wealth increase for investment fraction 20%.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	1	20	2	6	0.25	1.1	35	1.1	14	0.66	16
2	3	15	1	5	0.25	1	31	0.98	14	0.57	15
3	4	45	4	6	0.25	1.2	29	1.2	16	0.71	18
4	6	45	4	7	0.25	1	28	1.2	16	0.71	18
5	8	10	4	7	0.25	0.45	27	0.9	12	0.48	12

Table 3.25: Top 5 performers according to Wealth increase for investment fraction 25%.

PARAMETER SET	WINDOW	P1	P2	NUMBER OF TIMES
1	45	4	6	4
2	45	4	7	2
3	20	2	6	2
4	10	2	7	2
5	15	3	6	2
6	20	2	4	2
7	15	4	7	1
8	15	4	4	1
9	10	1	7	1
10	60	4	7	1
11	15	1	5	1
12	10	4	7	1

Table 3.26: Summary of the results of Tables 3.22-3.25.

There are several parameter sets in Table 3.26, and only a few of them repeat themselves throughout the different invest fractions. Although the results in this table are not totally revealing, one can see that the window size 45 was the dominant, as well as 4 for P1, but for P2, although 7 was dominant, 6 also appeared often both for the Top 10 and Top 20 positions of the first approach as on the top ranking of the whole parameter sets of the second approach.

3.2.3 Results for the Sector Analysis

For the remaining Financial and Health and Care sectors, the same two approaches are carried out, and the results of the simulations can be looked up in Appendiz A.1.

In order to extract conclusions from the simulations, the top performers for each of the two approaches are taken into account. If the performance of several parameter sets were found to be high, more than one parameter set may be stated for each approach. The summarized results obtained according to the Sharpe ratio performance and the Wealth increase are the following:

Sharpe Ratio Results:

For the Financial Sector: (Window, P1, P2)

- 1st Approach: (30, 1/2, 6/4)
- 2nd Approach: (30, 1, 4), (45, 2, 6), (30, 3, 7)

For the Health Care Sector:

- 1st Approach: (45/30, 4, 4)
- 2nd Approach: (45, 4, 7), (30, 3, 5), (45,4,4)

For the Information and Technology Sector:

- 1st Approach: (45, 4, 4/6)
- 2nd Approach: (45, 4, 6), (20, 2, 4), (45, 4, 7)

Wealth Increase results:

For the Financial Sector: (window, p1, p2)

- 1st Approach: (30, 4, 7)
- 2nd Approach: (30, 4, 7), (20, 4, 5), (15, 4, 4), (30, 3, 7)

For the Health Care Sector:

- 1st Approach: (10, 4, 7)
- 2nd Approach:
    - 1ST Group: (10, 4, 7), (10, 3, 5), (15, 4, 6), (30, 4, 7)
    - 2nd Group: (45, 4, 7), (15, 3, 7), (10, 4, 6), (30, 4,7)

For the Information and Technology Sector:

- 1st Approach: (20/45, 4, 7/6)
- 2nd Approach:
    - 1st Group: (30, 4, 5), (20, 4, 6), (45, 4, 7), (45, 4, 6), (10, 4, 6), (20, 4, 4)
    - 2nd Group: (45, 4, 6), (45, 4, 7), (20, 2, 6), (10, 2, 7), (15, 3, 6), (20, 2, 4)

3.2.4 Conclusion on Sectors

If we take a look at the results of the Sharpe ratio classification, we can see that the best performing parameter sets obtained by both approaches are similar, although they may differ at times in some parameters. This may be due to the fact that there are a few parameter sets which use combinations of the same parameters, so that by means of the 1st approach we know that these parameters are important, but when we analyze them using the 2nd approach we see that this does not result in one specific parameter set with those parameters repeating itself many times. Nevertheless we can still extract conclusions from both approaches:

If we focus on the Window size, we can see that the window of 45 days dominates over the rest, and that window of size 30 days has also an important weight in the results. There were a total of 7 window sizes (10, 15, 20, 30, 45, 60, and 90), so having had just 2 of them outstanding from the rest allows us to think that they may be used as general window sizes. A possible explanation behind this behavior could be that in order to obtain a good Sharpe Ratio, which is linked with low risk, it is necessary to use a Spidyn indicator which goes back between 30 and 45 days in time, allowing for the quantity of data accumulated during those days to "get a grasp" of the risk, while producing the indicator. It may not seem too much time back, especially if we compare it to the 60 and 90 days window also included in the parameter space, but as seen when analyzing the Wealth increase, higher returns, which is also linked directly to the Sharpe ratio, seem to be related with shorter window sizes. It seems logical therefore to think that a balance between taking into account long periods of time in order to reduce risks, and short ones in order to increase the returns should be suitable.

We can also think that the reason for not achieving the best Sharpe Ratio with windows as large as 90 days is because our indicator was designed and meant for it to be a short term indicator. It may be reasonable to believe that when the time span it uses to get the data is too long, the signals it may detect might tend to get distorted. Here we can see a compromise between acting with just the data of few days with the risk involved, and the security of having larger amounts of data, but loosing it´s efficiency detecting in detecting pockets of predictability in the short term.

If we now focus on parameters P1 and P2 we can see that there are a greater number of parameters appearing. For some sectors such as the Health care and the Information and technology, the parameter 4 seems to appear often for P1, but then several options are found for P2.

As specified in the description of the Spidyn parameters in section 2.2., depending on the derivatives used, Spidyn will perceive, and at the same time reflect in its indicator, different changes in trend. When taking into account the lower derivatives such as Velocity or Acceleration, the changes are more subtle and take more time to be perceived and incorporated into the Spidyn indicator. If the higher order derivatives were to be taken into account, the changes on the prices showing signs of mini-crashes or mini-bubbles would quickly be detected and incorporated into the indicator which will then be used by the programmed trading strategy to trade on it. As well as for the window size, when dealing with the parameters in charge of specifying the derivatives taken into account, there seems to be a dilemma between a conservative approach, which would wait for a clearer signal that a mini-crash or mini-bubble has been detected, and a more aggressive approach which would detect a greater amount of signals indicating this events.

As seen in the results above, there seems to be a predominance of higher parameters for P1, and a not so clear pattern for P2, but this analysis will be complemented with that of the individual stocks in the next section.

When dealing with the Wealth increase results, and compared with those of Sharpe ratio, there seems to be a much higher number of top performing parameter sets without a clear predominance of just a few.

If we focus on the Window sizes we can see that although windows of 45 and 30 days are common, 10, 15 and 20 days window are also present, which means that Spidyn indicators obtained by looking at only a few days worth of prices seems to be adequate for quick wealth gains, in comparison to what was found for the Sharpe ratio. It seems that, in order to obtain higher results, it may be profitable to focus on the quick changes of the markets, which are reflected on the few days worth of information we want the Spidyn to focus on, although that could mean sacrificing risk.

If we now focus on P1 and P2 we can see that the predominant parameters for both are quite high, P1 being usually 4 and sometimes 3, and P2 being usually 7 or 6. As we said before, this suggests that the higher and more aggressive derivatives perform better than the smaller order ones in detecting quick changes in the prices, sending more indicators which surpass the buying and selling thresholds. This may in turn generate higher loses, as well as gains, and will therefore increase the volatility of the returns, decreasing the Sharpe ratio, as we assumed when analyzing previously the results according to performance by Sharpe ratio.

A very important result obtained here is that not only have we found a few parameter sets which seem to outperform the rest for each sector, and the difference between them according to the measurement employed, but also that the experiments carried out by former researcher [16-18], seem not to have conducted conducted with the best set of parameters, or even good/acceptable ones, because P1=2 and P2 =5 have not appeared in our results when dealing with the top performers.

3.3 Stock Analysis

3.3.1 Description

We have just made an analysis on the parameter sets which perform better for the different sectors and have arrived to a few conclusions stated in the previous section. What we will now attempt is to repeat the simulations carried out before but on 15 random stocks belonging to the different sectors studied (Financials, Health Care and Information and Technology), and compare the results of the analysis with the previous results.

In order to perform the simulations, some changes were be made on the main code, specifically on the configuration and main files. The most relevant change is that we will no longer have investment fraction, and the trading strategy for the individual stocks will change to a “in or out” strategy. This means that when the Spidyn indicator surpasses the In Threshold, if we are not in the stock we will buy it with all our wealth, and if we already have it we will continue in the stock. In the same way, if it trespasses our Out Threshold, if we don´t own it we will do nothing, we will not sell short, and if we have it we will sell all of it.

3.3.2 Methodology

Working with simulations on all the parameter space for 15 stocks of each sector produced a great amount of information which had to be analyzed. In order to allow us to make this task easier, we decided to resort to Cluster Analysis, a technique consisting of assigning objects into groups of similar characteristics and which can lead to discovery of patterns in data.

There are different ways of clustering the data, and a Hierarchical Agglomerative approach seemed the most appropriate[19]. This approach consists on considering each individual element as a cluster, and then merging them successively into larger ones. We conducted this clustering on all three parameters, the Window Size (T), and the beginning and ending polynomial parameters (P1 and P2). The clustering process was as described by Figures 3.2-3.4:

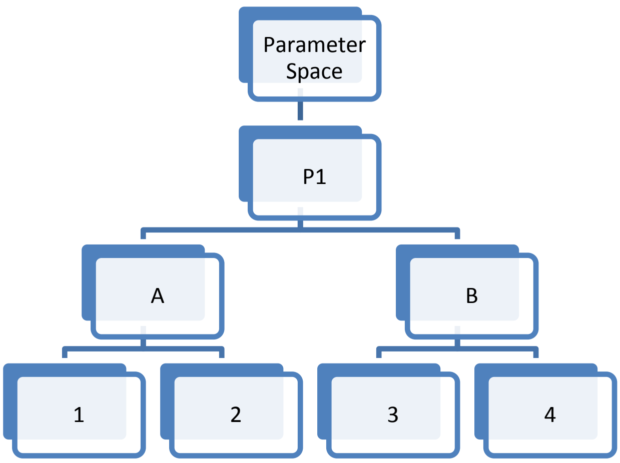

Figure 3.2: Clustering process for parameter P1.

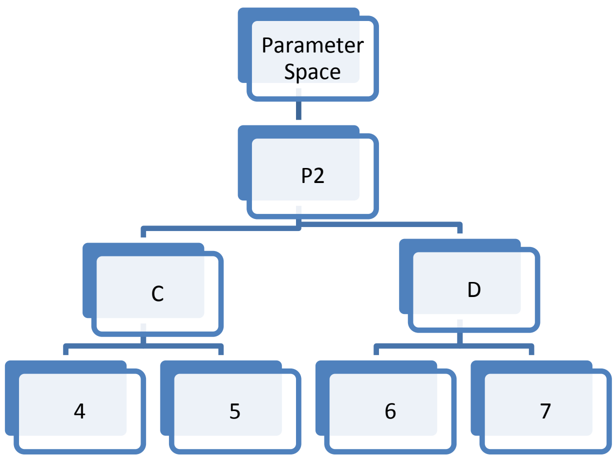

Figure 3.3: Clustering process for parameter P2.

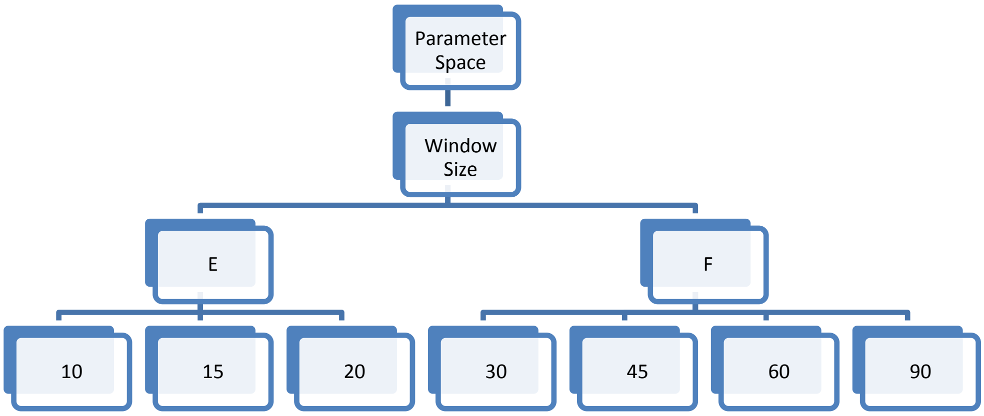

Figure 3.4: Clustering process for Window size.

The following table also represents the clustering grouping:

PARAMETER	GROUP
P1 = [1, 2]	A
P1 = [3, 4]	B
P2 = [4, 5]	C
P2 = [6, 7]	D
T = [10, 15, 20]	E
T = [30, 45, 60, 90]	F

Figure 3.4: Summary of Clustering grouping

This clustering will be used on both the following stock results as for a further analysis between the sectors and the individual stocks.

3.3.3 Information & Technology Stocks

We performed the same analysis as in section 3.2 but on 15 random stocks of Table 3.27 belonging to the sector of Information and Technology:

TICKER	DESCRIPTION
ADBE	Adobe Systems Inc
ADPT	Adaptec Inc
ADSK	Autodesk Inc
CB	The Chubb CP
CNXT	Conexant Systems Inc
CPWR	Compuware Corp
CSG	CSG Systems International Inc
CVG	Convergys Corp
GLW	Corning Inc
INTC	Intel Corporation
MET	MetLife Inc
MSFT	Microsoft Corporation
MV	Metavante Technologies Inc
NSM	National Semiconductor Corporation
TXN	Texas Instruments Inc

Table 3.27: Tickers and Descriptions of the 15 random stocks for the I&T sector.

In order to clarify the procedure followed, we will show the procedure for just one stock and use the result of the rest of them. In the case of ADOBE SYSTEMS INC (ADBE), we have for the top 10 performers according to the Sharpe ratio the following parameter sets:

Sharpe Ratio:

Position	Wind	p1	p2	SP_S	SP_W	In S	In W	BH S	BH W
1	15	4	7	1	20	1.2	14	0.79	29
2	10	3	4	0.93	17	1.1	14	0.74	28
3	15	2	7	0.83	15	1.2	14	0.79	29
4	15	3	7	0.79	14	1.2	14	0.79	29
5	60	3	5	0.78	5.9	1	12	0.71	27
6	10	4	6	0.73	15	1.1	14	0.74	28
7	10	4	4	0.73	14	1.1	14	0.74	28
8	15	3	6	0.73	13	1.2	14	0.79	29
9	60	2	6	0.73	4.7	1	12	0.71	27
10	60	4	4	0.66	5.7	1	12	0.71	27

Table 3.28: Top 10 performing parameter sets according to Sharpe ratio.

Which if we classify according to the previous cluster segmentation we find the following result:

- T = E(7)
- P1 = B(8)
- P2 = D(6)

We now take a look at the top 10 performing parameter sets according to wealth:

Wealth:

Position	Wind	p1	p2	SP_S	SP_W	In S	In W	BH S	BH W
1	15	4	7	1	20	1.2	14	0.79	29
2	10	3	4	0.93	17	1.1	14	0.74	28
3	15	2	7	0.83	15	1.2	14	0.79	29
4	10	4	6	0.73	15	1.1	14	0.74	28
5	15	3	7	0.79	14	1.2	14	0.79	29
6	10	4	4	0.73	14	1.1	14	0.74	28
7	10	3	7	0.61	14	1.1	14	0.74	28
8	15	3	6	0.73	13	1.2	14	0.79	29
9	10	2	7	0.58	13	1.1	14	0.74	28
10	10	1	7	0.53	12	1.1	14	0.74	28

Table 3.29: Top 10 performing parameter sets according to Wealth increase.

- T = E(10)
- P1 = B(7)
- P2 = D(8)

The collection of best performing parameters we arrived to in the sector analysis will also be cluster analyzed:

Sharpe Ratio:

Wind	p1	p2
45	4	4
45	4	6
20	2	4
45	4	7

Table 3.30: Top performing parameter sets for the I&T Sector according to Sharpe ratio.

- T = F(3)
- P1 = B(3)
- P2 = C/D

Wealth:

Wind	p1	p2
20	4	7
20	4	6
45	4	7
45	4	6
30	4	5
10	4	6
20	4	4
20	2	6
10	2	7
15	3	6
20	2	4

Table 3.31: Top performing parameter sets for the I&T Sector according to Wealth increase.

- T = E(8)
- P1 = B(8)
- P2 = D(8)

We can now compare the results of the stocks to the results of the sector they belong to, as well as similarly to the procedure of the sector analysis, obtain the most predominant parameters, in this case clusters. The results of the sector are just for comparison, since only the individual stock results will count to obtain a "clustered" predominant parameter set. During the count, the clusters get a point if they are the most predominant in their stock, and if there is a tie between two clusters, half a point will be given to each.

Sharpe Ratio:

PARAMETER	T	P1	P2
Inf & Tec Sector	**F**	**B**	**C/D**
ADBE	E	B	D
ADPT	F	B	C/D
ADSK	F	A/B	C
CB	F	B	C
CNXT	E/F	B	C/D
CPWR	F	B	C
CSC	E/F	B	D
CVG	F	B	C
GLW	F	A/B	C/D
INTC	F	B	C
MET	F	B	C
MSFT	F	B	C
MV	E	B	C/D
NSM	F	B	C/D
TXN	F	A/B	C/D
TOTAL	**F (12)**	**B (13,5)**	**C (10)**

Table 3.32: Results of the Cluster Analysis on the 15 random stocks of I&T sector according to Sharpe ratio.

Wealth:

PARAMETER	T	P1	P2
Inf & Tec Sector	**E**	**B**	**D**
ADBE	E	B	D
ADPT	E	B	C
ADSK	E	B	D
CB	E/F	B	D
CNXT	E	B	D
CPWR	F	B	C/D
CSC	E	B	D
CVG	E	B	D
GLW	E	A/B	D
INTC	E	B	C
MET	E	B	C
MSFT	E	B	C
MV	E	B	D
NSM	E	B	D
TXN	F	B	C/D
TOTAL	**E (12,5)**	**B (14,5)**	**D (10)**

Table 3.33: Results of the Cluster Analysis on the 15 random stocks of I&T sector according to Wealth increase.

3.3.4 Results of Individual Stocks

Now that we have the results of the stocks and the sectors to which they belong, we can conduct a broader analysis in which we can see if the parameter sets which in the previous section we concluded were the best performing also were best performing or at least above the median performers for the stocks when studied individually.

FINANCIAL SECTOR

Sharpe Ratio:

PARAMETER	T	P1	P2
Financial Sector	**F**	**A**	**D**
ABK	F	B	C
ALL	E	B	C
AOC	E/F	B	C
BAC	E	B	C
BEN	F	A/B	D
CAT	F	A/B	C
CB	F	B	C
CINF	E	B	C
CMA	E/F	B	C/D
FITB	F	A	C/D
JPM	F	A	C/D
MER	F	B	D
MIL	F	B	C/D
NCC	E/F	A	C/D
STT	E	A/B	C/D
TOTAL	**F (9,5)**	**B (10,5)**	**C (10)**

Table 3.34: Results of the Cluster Analysis on the 15 random stocks of Financial sector according to Sharpe ratio.

Wealth:

PARAMETER	T	P1	P2
Financial Sector	**E/F**	**B**	**C/D**
ABK	E	B	C
ALL	E	B	C
AOC	E	B	C/B
BAC	E	B	C
BEN	E	B	D
CAT	E	B	D
CB	E/F	B	D
CINF	E	B	D
CMA	E	B	C
FITB	F	A/B	C
JPM	E	B	D
MER	E/F	B	D
MIL	E/F	B	C
NCC	E	B	C
STT	E	A/B	C/D
TOTAL	**E (12,5)**	**B (14)**	**C (8)**

Table 3.35: Results of the Cluster Analysis on the 15 random stocks of Financial sector according to Wealth increase.

HEALTH CARE SECTOR

Sharpe Ratio:

PARAMETER	T	P1	P2
Health Care Sector	**F**	**B**	**C**
ABT	F	B	C/D
AGN	F	B	C/D
BDX	E/F	B	D
BSX	F	B	C/D
CAH	E	A/B	D
HUM	F	B	D
JNJ	F	A	C/D
MDT	F	A	C
PFE	F	B	D
PKI	F	B	C/D
STJ	E	B	D
SYK	E	B	C/D
THC	F	A/B	D
TMO	F	B	C
UNH	F	B	D
TOTAL	**F (11,5)**	**B (12)**	**D (10)**

Table 3.36: Results of the Cluster Analysis on the 15 random stocks of Health Care sector according to Sharpe ratio.

Wealth:

PARAMETER	T	P1	P2
Health Care Sector	**E**	**B**	**D**
ABT	F	B	C/D
AGN	E	B	D
BDX	E	B	D
BSX	E	B	D
CAH	E	A/B	D
HUM	E/F	B	D
JNJ	E	B	C/D
MDT	F	A/B	D
PFE	F	B	D
PKI	E	B	D
STJ	E	B	D
SYK	E	B	D
THC	F	B	C
TMO	E	B	D
UNH	F	B	C
TOTAL	**E (9,5)**	**B (14)**	**D (12)**

Table 3.37: Results of the Cluster Analysis on the 15 random stocks of Health Care sector according to Wealth increase.

INFORMATION AND TECHNOLOGY SECTOR

Sharpe Ratio:

PARAMETER	T	P1	P2
Inf & Tec Sector	**F**	**B**	**C/D**
ADBE	E	B	D
ADPT	F	B	C/D
ADSK	F	A/B	C
CB	F	B	C
CNXT	E/F	B	C/D
CPWR	F	B	C
CSC	E/F	B	D
CVG	F	B	C
GLW	F	A/B	C/D
INTC	F	B	C
MET	F	B	C
MSFT	F	B	C
MV	E	B	C/D
NSM	F	B	C/D
TXN	F	A/B	C/D
TOTAL	**F (12)**	**B (13,5)**	**C (10)**

Table 3.38: Results of the Cluster Analysis on the 15 random stocks of Information & Technology sector according to Sharpe ratio.

Wealth:

PARAMETER	T	P1	P2
Inf & Tec Sector	**E**	**B**	**D**
ADBE	E	B	D
ADPT	E	B	C
ADSK	E	B	D
CB	E/F	B	D
CNXT	E	B	D
CPWR	F	B	C/D
CSC	E	B	D
CVG	E	B	D
GLW	E	A/B	D
INTC	E	B	C
MET	E	B	C
MSFT	E	B	C
MV	E	B	D
NSM	E	B	D
TXN	F	B	C/D
TOTAL	**E (12,5)**	**B (14,5)**	**D (10)**

Table 3.39: Results of the Cluster Analysis on the 15 random stocks of Information & Technology sector according to Wealth increase.

As seen in Tables 3.34-3.39, the grouping made before has greatly simplified the results, making it easier to reach the following conclusions, both on the different sectors as for the parameters individually:

3.3.5. Conclusions on Stocks

Sector by sector analysis

<u>Financial Sector:</u>

The Wealth Increase for this sector does not have a clear trend, because both for the window size (T) and the second parameter (P2) there is a tie. If we then focus on the stocks, we can see that for parameter P1 the majority match with the cluster of the sector, B. We can see there is a different behavior for the window size and P2, although for the sector as a whole both of them are tied. When analyzing the individual stocks we can see that a great number of them (12.5 over 15) have low window sizes (E), while for the parameter P2 there is nearly a tie between both groups (C (8) and D (7)). We must remember that when there is a tie between the groupings, half a point is given for each group, thus the decimals appearing in these results.

These results suggest that when looking for greater Wealth Increase, there is a predominance of smaller window sizes, as well as larger P1. If we now focus on P2 where there is a tie between clusters we could think that the parameter which fits best in this case in somewhere in the middle, maybe a 5 or a 6, but this still needs to be tested further.

When looking at the Sharpe Ratio for this sector, we cannot extract too many conclusions because of the diversity of the results. From the results we can see that parameters P1 and P2 of the individual stocks don´t match those of the sector, but match those of the Wealth increase. What we can extract from these results is that the window size seems to have increased, which could mean as stated before, that when you have more data to calculate the indicator you may have a better insight of the risks involved, taking them into account and reducing them, thus increasing the Sharpe Ratio.

<u>Health Care Sector:</u>

In this case we have a defined set of best performing parameters from the sector analysis, which we can compare in an easier way to the stocks analyzed belonging to the sector. We can observe that the majority of the stocks match their sector in all of the parameters for Wealth Increase and when classified according to Sharpe Ratio both T and P1 match as well, while for the P2 it differs. This may show that for Health Care we may have found a more robust set of parameters, meaning that the Spidyn indicator may capture in a better way the signals coming from this sector, or even that the sector in itself is prone to a more irrational behavior, allowing the Spidyn indicator to capture and exploit such behaviors.

If we analyze the meaning of the parameters, we can see that for the Wealth Increase we have a low window size, and high P1 and P2. This may suggest that, as well as before, it seems to be more profitable to only look at a few days of data in order to capture more changes in the signal. When looking at the high P1 and P2, we can conclude that there is much more importance given to the higher order derivatives, a more aggressive approach of Spidyn.

When looking at the parameters of the sector and stocks according to the Sharpe Ratio, we can see the window size is larger, just as for the previous sector. We can also see how the sector as a whole seems to have a milder aggressive approach, based on an aggressive first parameter P1 but a more conservative P2, while when dealing with the individual stocks we have both a high P1 and P2, suggesting a more aggressive behavior.

Information and Technology Sector:

For this sector we can see that there are a clear set of parameters which define this sector, although for the P2 of Sharpe ratio there is a tie. When looking at the Wealth Increase we can see that both the sector analysis as well as the individual stock analysis match. In this case we also have a small window size, and high P1 and P2 which means more weight is being assorted into the highest order derivatives, signaling a very aggressive approach in order to increase only the wealth, without taking risk into consideration.

If we look at the Sharpe Ratio we can see that the window size and P1 matches, while P2 was tied for the sector. From this result we can suggest again that there has been an increase in the window size needed to take risk into account successfully, and that P1 is still on the aggressive side. When looking at P2, we can imagine that a more conservative parameter should be employed, as seen in the individual stocks results and in the fact that for the sector there was a tie, so the global P1 and P2 suggest we are dealing with a moderately aggressive indicator.

Parameter analysis

Window size (T):

For the Wealth Increase we can see that for all sectors and individual stocks there is a clear predominance of smaller window sizes (T= 10, 15, and 20 days). This may suggest that when only the wealth (returns) are taken into account, the smaller window sizes perform better because they are more sensible to the changes in the markets and therefore may react better to them.

If we are looking at the Sharpe Ratio, we can see the opposite, there is a predominance of larger window sizes (T= 30, 45, 60, and 90 days). If we think about this in the same way as for the previous analysis, a greater window size means you are taking into account a greater amount of data in order to "construct" the Spidyn indicators. The effect this could have for the trading strategy could be that fewer signals are issued; only when after many days, the prices still seem to reflect there is a mini-crash or bubble which is taking place and can be profited. The less signals we have, the less deals take place, so the returns may not be as high as those in which smaller window sizes are used, this should also mean a fewer risks and a smaller deviation (standard deviation) at a cost of losing some opportunities.

We are going to give the Sharpe Ratio a greater importance when deciding on which parameters to use because it takes into account the risk, in the form of standard deviation, as well as the returns, which is the only measurement of the Wealth Increase. When taking a look at the predominant window sizes, one can see that the most recurrent of the higher window sizes are 30 and 45, so our choice would be between these two. This also proves that our election of window sizes was appropriate, due to the fact that we explored the parameter universe surrounding our choice. We could go further and make smaller divisions like T = 40 and 50, but we think that the divisions are small enough to be effective.

Parameter P1 :

If we take a look at both the Wealth Increase as to the Sharpe Ratio, we can see that for all sectors (maybe excluding Sharpe Ratio of Financials) there is a clear predominance of large P1´s, which means, according to the definition of this parameter together with P2 that the lower order derivatives are not taken into account as much as the higher order ones when determining the Spidyn Indicator. This is a discovery of great importance because in previous research on Spidyn, both by Gilles as by Allan, the parameter chosen for P1 was 2, which lies in the lower P1 group. This discovery may be used for future research as a “cornerstone” in order to improve the results. It may also mean (*I think I interpreted this from last talk with Prof. Sornette)* that we are not using what most trend followers do. What they do is use concepts such as velocity and acceleration to draw the graphs, resistances levels, etc. What we are using instead are higher order derivatives which doesn´t have to do with the practices commonly used.

Parameter P2 :

For this parameter, opposing what happened with P1, there is a difference between Wealth Increase and Sharpe Ratio. Although it is not completely clear, there is a tendency in which when looking at the Wealth, the best performers are those with higher P2, while for the Sharpe Ratio, the best performers are those with lower P2. This means that although for both cases there seems to be an aggressive approach because of P1, there is also a difference between them, and the Wealth, as for the Window size, seems to be more aggressive and searches quicker changes in trends than the Sharpe ratio, whose best performers are a bit less aggressive, showing signs of taking risk into consideration.

3.4. S&P 500 Index Analysis

3.4.1. Methodology

We performed an analysis similar to that of the sector analysis and individual stocks which may help us in our quest to determine if there is a common set of parameters which may outperform the rest not only for a certain sector, but also for the whole of the index. In this case, as for the Stock analysis we also used the cluster analysis with the same grouping.

3.4.2. Results

The results for the Index analysis according to the Wealth increase and the Sharpe ratio was the following:

<u>Wealth:</u>

1st Approach:

Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	10	1	7	0.25	1.1	260	1.1	14	1.2	17
2	15	4	7	0.25	1.4	220	1.2	14	1.3	17
3	10	4	5	0.25	1.3	190	1.1	14	1.2	17
4	10	3	7	0.15	1.5	180	1.1	14	1.2	17
5	10	2	6	0.25	1.1	160	1.1	14	1.2	17
6	10	3	6	0.25	0.99	160	1.1	14	1.2	17
7	10	1	6	0.2	1.3	150	1.1	14	1.2	17
8	10	3	5	0.25	1.2	150	1.1	14	1.2	17
9	15	4	6	0.2	1.7	140	1.2	14	1.3	17
10	20	4	7	0.25	1.4	140	1.2	14	1.3	18
11	15	4	7	0.2	1.3	140	1.2	14	1.3	17
12	10	2	5	0.25	1.3	140	1.1	14	1.2	17
13	10	4	6	0.2	1.2	140	1.1	14	1.2	17
14	15	4	4	0.2	2	130	1.2	14	1.3	17
15	10	3	5	0.2	1.4	130	1.1	14	1.2	17
16	10	4	5	0.2	1.3	130	1.1	14	1.2	17
17	10	4	7	0.15	1.2	130	1.1	14	1.2	17
18	10	1	5	0.25	1.3	120	1.1	14	1.2	17
19	20	3	7	0.25	1.3	110	1.2	14	1.3	18
20	10	2	6	0.2	1	110	1.1	14	1.2	17

Table 3.40: Top 20 performing parameter sets for the S&P 500 Index according to the Wealth increase.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	4 “4´s”	40% of 4´s	9 “4´s”	45% of 4´s
	3 “3´s”	30% of 3´s	5 “3´s”	25% of 3´s
	2 “1´s”	20% of 1´s	3 “1´s”	15% of 1´s
	1 “2”	10% of 2´s	3 “2´s”	15% of 2´s
P2	4 “7´s”	40% of 7´s	7 “7´s”	35% of 7´s
	4 “6´s”	40% of 6´s	6 “6´s”	30% of 6´s
	2 “5´s”	20% of 5´s	6 “5´s”	30% of 5´s
			1 “4”	5% of 4´s
Window	7 “10´s”	70% of 10´s	14 “10´s”	70% of 10´s
	2 “15”	20% of 15´s	4 “15´s”	20% of 15´s
	1 “20”	10% of 20´s	2 “20´s”	10% of 20´s
GROUPING	E, B, D		E, B, D	
TOTAL		**E, B, D**		

Table 3.41: Summary of the results of Table 3.40.

2nd Approach:

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	458	10	1	7	0.02	1.5	21	1.1	14	1.2	17
2	478	20	4	5	0.02	1.7	20	1.2	14	1.3	18
3	479	30	4	7	0.02	1.7	20	1.1	13	1.2	17
4	480	15	1	7	0.02	1.6	20	1.2	14	1.3	17
5	482	15	4	7	0.02	1.5	20	1.2	14	1.3	17

Table 3.42: Top 5 performing parameter sets for investment fraction 2% according to Wealth increase.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	154	15	2	7	0.05	1.9	45	1.2	14	1.3	17
2	192	10	1	6	0.05	1.6	39	1.1	14	1.2	17
3	202	15	1	7	0.05	1.7	38	1.2	14	1.3	17
4	228	10	2	7	0.05	1.2	35	1.1	14	1.2	17
5	237	20	4	7	0.05	1.6	34	1.2	14	1.3	18

Table 3.43: Top 5 performing parameter sets for investment fraction 5% according to Wealth increase.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	96	10	4	7	0.08	1.1	55	1.1	14	1.2	17
2	103	15	3	7	0.08	1.6	53	1.2	14	1.3	17
3	123	10	3	6	0.08	1.3	50	1.1	14	1.2	17
4	129	15	4	7	0.08	1.4	49	1.2	14	1.3	17
5	143	10	3	7	0.08	1	47	1.1	14	1.2	17

Table 3.44: Top 5 performing parameter sets for investment fraction 8% according to Wealth increase.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	47	10	1	6	0.1	1.6	77	1.1	14	1.2	17
2	54	10	3	7	0.1	1.2	72	1.1	14	1.2	17
3	56	10	2	7	0.1	1.2	71	1.1	14	1.2	17
4	66	10	4	6	0.1	1.2	67	1.1	14	1.2	17
5	81	15	2	7	0.1	1.4	58	1.2	14	1.3	17

Table 3.45: Top 5 performing parameter sets for investment fraction 10% according to Wealth increase.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	39	10	3	6	0.12	1.3	84	1.1	14	1.2	17
2	45	10	3	5	0.12	1.4	78	1.1	14	1.2	17
3	58	10	2	5	0.12	1.5	70	1.1	14	1.2	17
4	73	10	4	5	0.12	1.3	64	1.1	14	1.2	17
5	95	20	3	7	0.12	1.2	55	1.2	14	1.3	18

Table 3.46: Top 5 performing parameter sets for investment fraction 12% according to Wealth increase.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	4	10	3	7	0.15	1.5	180	1.1	14	1.2	17
2	17	10	4	7	0.15	1.2	130	1.1	14	1.2	17
3	26	10	2	6	0.15	1.3	100	1.1	14	1.2	17
4	28	10	2	5	0.15	1.6	99	1.1	14	1.2	17
5	34	10	3	5	0.15	1.4	90	1.1	14	1.2	17

Table 3.47: Top 5 performing parameter sets for investment fraction 15% according to Wealth increase.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	7	10	1	6	0.2	1.3	150	1.1	14	1.2	17
2	9	15	4	6	0.2	1.7	140	1.2	14	1.3	17
3	11	15	4	7	0.2	1.3	140	1.2	14	1.3	17
4	13	10	4	6	0.2	1.2	140	1.1	14	1.2	17
5	14	15	4	4	0.2	2	130	1.2	14	1.3	17

Table 3.48: Top 5 performing parameter sets for investment fraction 20% according to Wealth increase

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	1	10	1	7	0.25	1.1	260	1.1	14	1.2	17
2	2	15	4	7	0.25	1.4	220	1.2	14	1.3	17
3	3	10	4	5	0.25	1.3	190	1.1	14	1.2	17
4	5	10	2	6	0.25	1.1	160	1.1	14	1.2	17
5	6	10	3	6	0.25	0.99	160	1.1	14	1.2	17

Table 3.49: Top 5 performing parameter sets for investment fraction 25% according to Wealth increase.

INVEST FRACTION	WINDOW	P1	P2
2%	E	B	D
5%	E	A	D
8%	E	B	D
10%	E	A	D
12%	E	B	C
15%	E	B	D
20%	E	B	D
25%	E	B	D
TOTAL	**E(8)**	**B(6)**	**D(7)**

Table 3.50: Summary of the results of Tables 3.42-3.47 grouped for Cluster analysis

Sharpe Ratio:

1st Approach

Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	45	4	6	0.2	2.2	65	1	12	1.1	15
2	60	4	7	0.08	2.1	37	1	12	1.1	14
3	15	4	4	0.2	2	130	1.2	14	1.3	17
4	30	3	5	0.08	2	33	1.1	13	1.2	17
5	15	3	4	0.25	1.9	93	1.2	14	1.3	17
6	20	4	4	0.1	1.9	51	1.2	14	1.3	18
7	20	3	5	0.1	1.9	50	1.2	14	1.3	18
8	15	2	7	0.05	1.9	45	1.2	14	1.3	17
9	20	2	4	0.1	1.9	39	1.2	14	1.3	18
10	15	1	4	0.12	1.9	37	1.2	14	1.3	17
11	60	4	7	0.1	1.9	36	1	12	1.1	14
12	30	2	7	0.05	1.9	29	1.1	13	1.2	17
13	60	4	7	0.05	1.9	26	1	12	1.1	14
14	20	2	4	0.05	1.9	25	1.2	14	1.3	18
15	20	2	5	0.2	1.8	68	1.2	14	1.3	18
16	20	4	4	0.15	1.8	67	1.2	14	1.3	18
17	20	2	4	0.2	1.8	57	1.2	14	1.3	18
18	15	1	4	0.25	1.8	57	1.2	14	1.3	17
19	45	3	6	0.2	1.8	47	1	12	1.1	15
20	20	2	4	0.12	1.8	41	1.2	14	1.3	18

Table 3.51: Top 20 performing parameter sets for the S&P 500 Index according to the Sharpe ratio.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	4 “4´s”	40% of 4´s	7 “4´s”	35% of 4´s
	3 “3´s”	30% of 3´s	4 “3´s”	20% of 3´s
	2 “2´s”	20% of 2´s	7 “2´s”	35% of 2´s
	1 “1”	10% of 1´s	2 “1´s”	10% of 1´s
P2	5 “4´s”	50% of 4´s	10 “4´s”	50% of 4´s
	2 “5´s”	20% of 5´s	3 “5´s”	15% of 5´s
	2 “7´s”	20% of 7´s	5 “7´s”	25% of 7´s
	1 “6”	10” of “6´s”	2 “6´s”	10% of 6´s
Window	4 “15´s”	40% of 15´s	5 “15´s”	25% of 15´s
	3 “20”	30% of 20´s	8 “20´s”	40% of 20´s
	1 “30”	10% of 30´s	2 “30´s”	10% of 30´s
	1 “45”	10% of 45´s	2 “45´s”	10% of 45´s
	1 “60”	10% of 60´s	3 “60´s”	15% of 60´s
GROUPING	E, B, C		E, B, C	
TOTAL		**E, B, C**		

Table3.52: Summary of the results of Table 3.49

2nd Approach

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	30	15	3	4	0.02	1.8	19	1.2	14	1.3	17
2	31	45	4	6	0.02	1.8	14	1	12	1.1	15
3	32	60	4	7	0.02	1.8	12	1	12	1.1	14
4	33	20	2	4	0.02	1.8	11	1.2	14	1.3	18
5	34	15	1	4	0.02	1.8	10	1.2	14	1.3	17

Table 3.53: Top 5 performing parameter set for investment fraction 2% according to Sharpe

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	8	15	2	7	0.05	1.9	45	1.2	14	1.3	17
2	12	30	2	7	0.05	1.9	29	1.1	13	1.2	17
3	13	60	4	7	0.05	1.9	26	1	12	1.1	14
4	14	20	2	4	0.05	1.9	25	1.2	14	1.3	18
5	25	20	4	5	0.05	1.8	32	1.2	14	1.3	18

Table 3.54: Top 5 performing parameter set for investment fraction 5% according to Sharpe ratio.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	2	60	4	7	0.08	2.1	37	1	12	1.1	14
2	4	30	3	5	0.08	2	33	1.1	13	1.2	17
3	22	30	4	7	0.08	1.8	39	1.1	13	1.2	17
4	24	15	2	4	0.08	1.8	33	1.2	14	1.3	17
5	26	45	4	6	0.08	1.8	31	1	12	1.1	15

Table 3.55: Top 5 performing parameter set for investment fraction 8% according to Sharpe ratio.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	6	20	4	4	0.1	1.9	51	1.2	14	1.3	18
2	7	20	3	5	0.1	1.9	50	1.2	14	1.3	18
3	9	20	2	4	0.1	1.9	39	1.2	14	1.3	18
4	11	60	4	7	0.1	1.9	36	1	12	1.1	14
5	23	30	3	5	0.1	1.8	37	1.1	13	1.2	17

Table 3.56: Top 5 performing parameter set for investment fraction 10% according to Sharpe ratio.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	10	15	1	4	0.12	1.9	37	1.2	14	1.3	17
2	20	20	2	4	0.12	1.8	41	1.2	14	1.3	18
3	39	15	3	4	0.12	1.7	47	1.2	14	1.3	17
4	43	45	4	7	0.12	1.7	40	1	12	1.1	15
5	50	30	1	6	0.12	1.7	33	1.1	13	1.2	17

Table 3.57: Top 5 performing parameter set for investment fraction 12% according to Sharpe ratio.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	16	20	4	4	0.15	1.8	67	1.2	14	1.3	18
2	21	60	3	7	0.15	1.8	40	1	12	1.1	14
3	40	45	4	7	0.15	1.7	46	1	12	1.1	15
4	41	15	2	4	0.15	1.7	45	1.2	14	1.3	17
5	42	20	2	4	0.15	1.7	41	1.2	14	1.3	18

Table 3.58: Top 5 performing parameter set for investment fraction 15% according to Sharpe ratio.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	1	45	4	6	0.2	2.2	65	1	12	1.1	15
2	3	15	4	4	0.2	2	130	1.2	14	1.3	17
3	15	20	2	5	0.2	1.8	68	1.2	14	1.3	18
4	17	20	2	4	0.2	1.8	57	1.2	14	1.3	18
5	19	45	3	6	0.2	1.8	47	1	12	1.1	15

Table 3.59: Top 5 performing parameter set for investment fraction 20% according to Sharpe ratio.

Ranking	Position	Wind	p1	p2	In Fr	SP_S	SP_W	In S	In W	BH S	BH W
1	5	15	3	4	0.25	1.9	93	1.2	14	1.3	17
2	18	15	1	4	0.25	1.8	57	1.2	14	1.3	17
3	37	45	4	5	0.25	1.7	72	1	12	1.1	15
4	38	60	4	7	0.25	1.7	66	1	12	1.1	14
5	71	20	3	4	0.25	1.6	77	1.2	14	1.3	18

Table 3.60: Top 5 performing parameter set for investment fraction 25% according to Sharpe ratio.

INVEST FRACTION	WINDOW	P1	P2
2%	E	B	C
5%	E	A	D
8%	F	B	D
10%	E	B	C
12%	E	A	C
15%	E	B	C
20%	E	B	C
25%	E	B	C
TOTAL	**E(7)**	**B(6)**	**C(6)**

Table 3.61: Summary of the result of Tables 3.51-3.58.

3.4.4. Conclusions on S&P 500 Index

As we can see from the results of the simulations run for the 193 stocks of the SP500, the parameters P1 and P2 both for the Wealth increase, and more importantly, to the Sharpe ratio, behave exactly as those studied in the previous case of the sector and the stocks belonging to the sectors. When dealing with Wealth Increase both of them belong to the higher group, and so give a greater importance to the higher order derivatives, being more aggressive. If taking the Sharpe Ratio into consideration, we can see that P1 belongs to the high order derivatives group and P2 to the lower one, showing a milder aggressiveness.

In the case of the window size there is a difference with the previous sector/stocks case. For the Wealth Increase there is a smaller window size as expected from previous results, but when dealing with the Sharpe Ratio classification we observe there is also a small window size, which differs from the greater window size from the previous analysis. If we look at the first approach of the Sharpe ratio analysis, we can see that when analyzed the window size, the results were that for the top 20 performers, the most representative group, the windows 20 and 30 days make out 50% of the total, meaning that although with the clustering the final result pointed out a small window size, it is not as small as it could be. To confirm this supposition, we can see the results for the Wealth increase, in which we can see that for the top 20 performers, 70% of the window size parameters correspond to a 10 days window, the smallest of all, and not one single window size belonging to the larger window sizes. These results may still keep us excited about the possibility of accomplishing our goal.

3.5. In-Sample Conclusions

The analysis of the sections 3.2-3.4 corresponding to the simulations of the Sector, the stocks, and the S&P 500 Index, seem to have been alike. The most important conclusions which can be extracted from this chapter are those concerning the Window size and parameters P1 and P2.

There seems to be a predominance of window sizes of 30 and 45 days when analyzed according to the Sharpe ratio. This length is higher than the resulting one when classified according to the Wealth performance. The reason behind this could be that when dealing only with returns, if we only use a few days worth of data to compute the indicator, the indicator seems to capture more changes of trend which may be used by the strategy to increase the returns. If most of these changes in trend happen to be successfully predicted, the possibilities of increasing our wealth is very high. On the other hand, the fact that we are taking into account a small amount of information may also generate errors in this prediction which would be paid with greater losses. If we take a very big Window size, of the size of 60 or 90 days, there seem to be less changes in trend predicted, because over a longer period of time only a few of them continue, losing the power of Spidyn to predict short term unsustainable accelerations. It therefore seems sensible to arrive to the conclusion that according to the Sharpe ratio performance, in order to achieve a constantly good performance, a medium sized Window size of size 30 or 45 days, which has turned out to be the most usual ones in our best performing parameter sets, takes into account a balanced mixture of both the high returns of low windows and the risk awareness of higher window sizes.

The results for parameter P1 seem to be consistent both for the performance according to the Sharpe ratio as for the Wealth increase. Higher P1 such as 3 or 4 seem to perform better than the lower ones such as 1 or 2. The meaning behind the parameter P1 is, as has been explained earlier, the aggressiveness of the changes in prices the indicator is looking for. The higher the parameter P1 the quicker the changes are detected.

Parameter P2 seems to have different results depending on how the performance is assessed. When only the Wealth increase is taken into account, parameter P2 seems to be of a higher order such as 6 or 7, while when Sharpe ratio is being used for assessment, the parameter seems to be of a lower order such as 4 or 5. The definition of parameter P2, as well of that of P1, has to do with the order of derivatives employed. As well as for the Window size, where there is a difference between the results for Sharpe ratio and Wealth increase, the difference seems to depend on the amount of risk wanted to take into account and the type of changes in prices to look for. In the case of the most aggressive type, only looking at the returns, higher P2, together with high P1, might mean the indicator is looking for very sudden changes in prices, and when there seems to be a small change, it is reflected in the indicator. In the case of the assessment according to Sharpe ratio, in the lower P2 suggest that it doesn´t take into account all of the changes in trends when they are too aggressive, but instead weights for this change to be captured by lower order derivatives which would account for a smaller amount of risk.

Finally, from the conclusion stated in this section as well as from the results seen in the previous ones, it seem possible that the parameters used for former research [16-18] are not the optimal ones. Parameters P1 =2 and P2=5 don´t seem to appear as best performing, and the fact that P1 corresponds to the low order groups, when we have seen how both Sharpe ratio and Wealth increase the higher order ones seem to perform better , reflect the same hypothesis. This finding will be tested in the following chapter.

Chapter 4
Validation and Verification

4.1. Purpose

We have now finished analyzing the sectors, the individual stocks belonging to the sectors and the S&P 500 Index. Our next move, and one of vital importance when using "Data Snooping", is the process of verification and validation on other samples of data "to test our hypothesis". This process will consist on simulating a group of "best parameter sets" on a period of time which hasn't been used to obtain these parameter sets, an out of sample simulation.

We chose the period between January 2007 and October 2007, which is considered by many the change in regime, the end of the previous bubble and start of the actual crash [2]. The reason behind this choice comes from the supposition that the Spidyn indicator may be sensible to the market regimes. This supposition is based on former research [18] which carried out simulations on Bullish and Bearish regimes, obtaining different results for each. The new period of time had no price time series included in the data base, so the new data was downloaded directly from Yahoo Finance, and the indicators calculated and stored in the fcozh database. Because of this new procedure, we were able to collect information on a greater amount of stocks, specifically 431 out of 500 instead of the 193 used for the previous simulations. This really makes this new simulation out-of-sample, because not only are we using a time period not used before, but we are also dealing with stocks that had not been analyzed. The sectors have now the following number of stocks belonging to them, in comparison with the constituents of the S&P 500:

- Financial sector: 68 out of 76 constituents.
- Health Care sector: 47 out of 48 constituents.
- Information & Technology sector : 65 out of 81 constituents.

The hypotheses which are going to be tested are two:

1. *Have we found a collection of parameter sets which perform better than the ones employed in previous research [16-18]?*
2. *Does the same collection of parameter sets not only perform better than the former ones, but indeed outperform the rest of the parameter space?*

For the out of sample simulations the investment fraction of the trading strategy will be kept at an 8%, a level which is halfway through those used in the previous simulations, and for which the deal to signal percentage is high enough to consider relatively many signals, but not low enough to be most of the time uninvested, as will be seen in Chapter 5. We have also seen previously that the Sharpe ratio is less affected by this parameter than the Wealth increase, so we could expect this decision to have a smaller impact on the results. The parameter sets chosen to simulate are a collection of parameter sets extracted from the best performing sectors, individual stocks of each sector, and the S&P 500 in the following way:

4.1. Selection of Parameter Sets

In the previous sections we had found a series of patterns by use of the agglomerative clustering analysis, which has proved useful in simplifying data to extract patterns of behavior. The problem about this approach is that we need actual parameters to introduce into the Spidyn and trade upon. To solve this inconvenience we have come upon two different groups of parameter sets, both of which are going to be tested against the parameter set used in previous work [16-18]. From those studies not all of the parameters used are clearly stated, only the use of P1=2 and P2=5. The window size, which is also a parameter of great importance, was not clearly stated, therefore, in order to compare the simulations of the new found parameters against the previous ones, we have used window sizes of 30 and 45 and parameters P1 = 2 and P2 = 5 for previous parameter sets.

The two different groups of parameter sets which can be tested against the previous ones consist of:

1. An analysis of the sector best performing parameters according to the Sharpe ratio, the best performing parameters for the individual stocks of a sector, and the best performing parameters of the S&P 500.
2. The conclusion of the In Sample Simulations of the previous chapter.

4.2.1. 1st Group of Parameter Sets

This analysis will be similar to those performed for the previous chapter, one example of each will be shown and the rest can be looked up in Appendix B.1.

4.2.1.1 Sector

The following example shows how to arrive to the Health Care Sector parameter set. From every investment fraction the parameters of the top 5 performing parameter sets according to Sharpe ratio will be taken into account to find the best performing parameter sets:

	Investment Fraction (%)								
Window Size	2	5	8	10	12	15	20	25	**TOTAL**
10	0	0	0	0	0	2	0	0	**2**
15	0	0	0	0	0		1	0	**1**
20	0	0	0	0	0	0	1	1	**2**
30	3	3	3	3	3	1	1	2	**19**
45	2	2	2	2	2	2	1	2	**15**
60	0	0	0	0	0	0	1	0	**1**
90	0	0	0	0	0	0	0	0	**0**

Table 4.1: Window size for the top 5 parameter sets of each investment fraction of the Health Care sector.

	Investment Fraction (%)								
P1	2	5	8	10	12	15	20	25	**TOTAL**
1	0	0	0	0	0	1	0	0	**1**
2	1	1	1	1	1	0	1	0	**6**
3	1	1	1	1	1	1	2	2	**10**
4	3	3	3	3	3	3	2	3	**23**

Table 4.2: Parameter P1 for the top 5 parameter sets of each investment fraction of the Health Care sector.

	Investment Fraction (%)								
P2	2	5	8	10	12	15	20	25	**TOTAL**
4	2	2	2	2	2	1	0	2	**13**
5	1	1	1	1	1	2	1	1	**9**
6	0	0	0	0	0	1	1	0	**2**
7	2	2	2	2	2	1	3	2	**16**

Table 4.3: Parameter P2 for the top 5 parameter sets of each investment fraction of the Health Care sector.

The resultant parameter set is:

- Window size = 30 days
- P1 = 4
- P2 = 7

4.2.1.2. Individual Stocks

To take into account the results of the individual stocks belonging to a sector, we will conduct the same procedure but replacing the different investment fractions with the different stocks of the sector. The results can be looked up in Appendix B.2 and as an example, the stocks belonging to the Financial sector were as follow:

	Stock															
Window Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
10	0	5	1	3	0	0	0	1	3	0	0	1	0	1	0	15
15	1	3	2	1	0	0	0	5	0	1	2	0	2	0	4	21
20	2	3	2	1	0	0	0	5	0	1	2	0	2	0	4	22
30	1	0	3	2	1	4	4	3	1	2	3	2	5	4	4	39
45	0	0	0	1	3	1	4	0	2	2	2	6	1	0	0	22
60	5	0	1	0	5	0	1	1	2	2	1	0	0	0	0	18
90	1	0	1	0	0	1	0	0	0	3	1	0	0	1	0	8

Table 4.4: Window size for the top 5 parameter sets of each stock of the Financial sector.

	Stock															
P1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
1	1	1	2	1	2	1	1	1	**2**	4	3	0	0	4	3	26
2	3	1	1	1	3	5	2	3	**1**	2	3	2	3	2	2	34
3	3	2	3	4	2	2	4	1	**2**	2	2	3	3	2	2	37
4	3	6	4	4	3	2	3	5	**5**	2	2	5	4	2	3	53

Table 4.5: Parameter P1 for the top 5 parameter sets of each stock of the Financial sector.

	Stock															
P2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
4	3	2	5	3	2	3	1	3	**3**	3	2	3	2	1	1	37
5	4	4	1	4	1	3	6	3	**2**	2	3	1	3	4	4	45
6	0	2	3	1	4	3	3	2	**4**	3	2	3	3	2	1	36
7	3	2	1	2	3	1	0	2	**1**	2	3	3	2	3	4	32

Table 4.6: Parameter P2 for the top 5 parameter sets of each stock of the Financial sector.

The resultant parameter set is:

- Window size = 30 days
- P1 = 4
- P2 = 5

4.2.1.3. The S&P 500

When dealing with the S&P 500 Index, the procedure is the same as for the sector, taking into account the different investment fractions.

	Investment Fraction (%)							
Window Size	2	5	8	10	12	15	20	25	**TOTAL**
10	0	0	0	0	0	0	0	0	**0**
15	2	1	1	0	2	1	1	2	**10**
20	1	2	0	3	1	2	2	1	**12**
30	0	1	2	1	1	0	0	0	**5**
45	1	0	1	0	1	1	2	1	**7**
60	1	1	1	1	0	1	0	1	**6**
90	0	0	0	0	0	0	0	0	**0**

Table 4.7: Window size for the top 5 parameter sets of each investment fraction of the Index.

	Investment Fraction (%)								
P1	2	5	8	10	12	15	20	25	**TOTAL**
1	1	0	0	0	2	0	0	1	**4**
2	1	3	1	1	1	2	2	0	**11**
3	1	0	1	2	1	1	1	2	**9**
4	2	2	3	2	1	2	2	2	**16**

Table 4.8: Parameter P1 for the top 5 parameter sets of each investment fraction of the Index.

	Investment Fraction (%)								
P2	2	5	8	10	12	15	20	25	**TOTAL**
4	3	1	1	2	3	3	2	3	**18**
5	0	1	1	2	0	0	1	1	**6**
6	1	0	1	0	1	0	2	0	**5**
7	1	3	2	1	1	2	0	1	**11**

Table 4.9: Parameter P2 for the top 5 parameter sets of each investment fraction of the Index.

The resultant parameter set is:

- Window size = 20 days
- P1 = 4
- P2 = 4

The summarized results of all of them are the following:

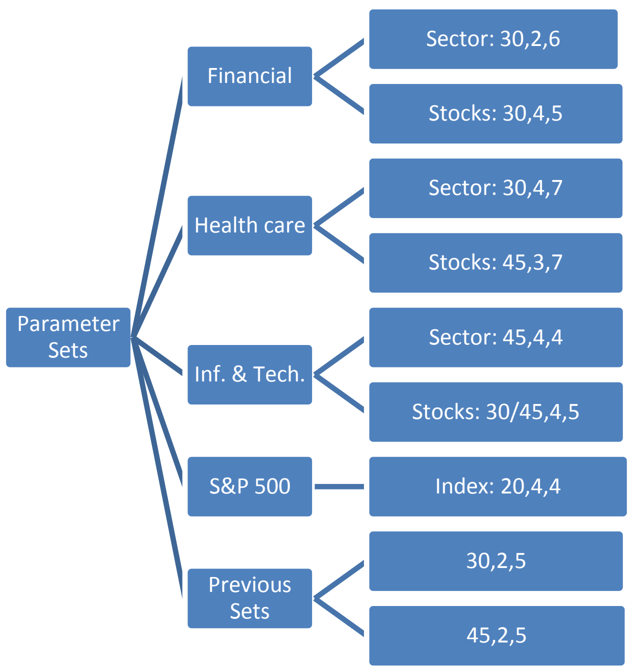

Figure 4.1: Summary of the parameter sets belonging to Group 1.

As seen from the results, they are similar to what we were expecting, window sizes of 30 and 45, high parameters for P1 and low parameters for P2, although this was not so clear, as stated form previous results and confirmed by this ones.

4.2.2. 2nd Group of Parameter Sets

For this group of parameter sets we will use the conclusions we obtained from the previous chapter. The previous results drove us to the conclusion that according to a measure of Sharpe ratio, the best performing parameters should belong to a window size of between 30 and 45 days, a high parameter for P1, such as 3 or 4, and a low parameter for P2 such as 4 or 5. In this case, the parameter space explored during the simulation will be:

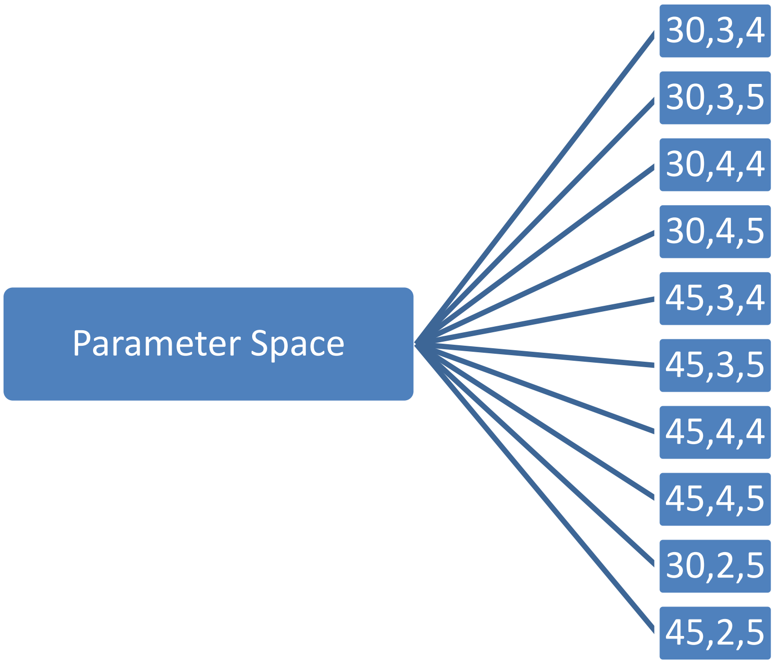

Figure 4.2: Summary of the parameter sets belonging to Group 2.

Once the out of sample period and the parameter sets have been chosen, and the reasons behind their choice have been explained, we are ready to begin our simulations.

4.3. Group 1 Simulations

4.3.1. 1st Hypothesis Results

We will now test the parameter sets against those used in former researches for the period starting January 2007 and ending on October of the same year. The simulations will then be arranged by means of the Sharpe ratio because of the same reasons it was employed to assess the performance of the in sample simulations. First we will see a sector classification, with the former parameter sets, and those belonging to the Sector and Stocks analysis, and finally we will see the simulation carried out for all of the S&P 500 and the all of the previous parameter sets. For each sector, the parameter sets obtained for the sector analysis and stock analysis of each sector will used in the simulation. Taking as an example the Financial sector, only the parameter sets obtained for the whole sector (30,2,6) and for the stocks belonging to the Financial sector (30,4,5) will be used.

Financial Sector									
Source	Wind	p1	p2	SP_S	SP_W(%)	In S	InW(%)	BH S	BH W(%)
STOCK	30	4	5	-0.51	-7.6	0.57	7.9	-0.59	-11
SECTOR	30	2	6	-0.6	-8.3	0.57	7.9	-0.59	-11
ALAN	45	2	5	-0.97	-7.7	1.1	16	-0.25	-4.6
ALAN	30	2	5	-1.3	-13	0.57	7.9	-0.59	-11

Table 4.10: Comparison of the parameter sets belonging to the Financial sector of Group 1 and former parameter sets.

Health Care Sector									
Source	Wind	p1	p2	SP_S	SP_W	In S	In W	BH S	BH W
SECTOR	30	4	7	2.1	23	0.57	7.9	0.16	2.5
STOCKS	45	3	7	1.8	17	1.1	16	0.69	9.3
ALAN	30	2	5	-0.3	-1.6	0.57	7.9	0.16	2.5
ALAN	45	2	5	-0.39	-1.3	1.1	16	0.69	9.3

Table 4.11: Comparison of the parameter sets belonging to the Health Care sector of Group 1 and former parameter sets.

Information & Technology Sector									
Source	Wind	p1	p2	SP_S	SP_W(%)	In S	InW(%)	BH S	BH W(%)
ALAN	45	2	5	0.5	3.7	1.1	16	0.78	14
STOCKS	45	4	5	0.35	4.4	1.1	16	0.78	14
STOCKS	30	4	5	0.23	3	0.57	7.9	0.35	6.3
SECTOR	45	4	4	-0.056	-0.6	1.1	16	0.78	14
ALAN	30	2	5	-0.092	-0.99	0.57	7.9	0.35	6.3

Table 4.12: Comparison of the parameter sets belonging to the Information & Technology sector of Group 1 and former parameter sets.

S&P 500 Index									
Source	Wind	p1	p2	SP_S	SP_W (%)	In S	InW(%)	BH S	BH W(%)
F SECTOR	30	2	6	2.6	110.0	0.57	7.9	0.0071	0.62
HC STOCKS	45	3	7	1.6	53.0	1.1	16	0.37	6.8
S&P 500	20	4	4	1	35.0	0.65	9.4	0.21	4
IT & F STOCKS	30	4	5	0.42	13.0	0.57	7.9	0.0071	0.62
I&T STOCKS	45	4	5	0.35	11.0	1.1	16	0.37	6.8
I&T SECTOR	45	4	4	0.17	4.6	1.1	16	0.37	6.8
ALAN	30	2	5	0.079	1.8	0.57	7.9	0.0071	0.62
HC SECTOR	30	4	7	-0.41	-15.0	0.57	7.9	0.0071	0.62
ALAN	45	2	5	-0.57	-9.8	1.1	16	0.37	6.8

Table 4.13: Comparison of the parameter sets belonging to the whole Group 1 and former parameter sets.

4.3.2. 2nd Hypothesis Results

For these simulations we will test the chosen parameter sets against the whole parameter space explored in Chapter 3. Because of the length of the results, only the first results will be shown, and then our parameter sets with the position they lie in out of the 112 possible parameter set combinations. The complete table can be looked up in Appendix B.3.

Financial Sector										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	InW(%)	BH S	BHW(%)
1		20	2	5	1.1	17	0.65	9.4	-0.4	-7.6
2		60	4	7	0.93	12	0.94	15	-0.26	-4.8
3		90	1	4	0.86	2	0.35	3.6	-0.94	-19
51	STOCK	30	4	5	-0.51	-7.6	0.57	7.9	-0.59	-11
54	SECTOR	30	2	6	-0.6	-8.3	0.57	7.9	-0.59	-11
78	ALAN	45	2	5	-0.97	-7.7	1.1	16	-0.25	-4.6
92	ALAN	30	2	5	-1.3	-13	0.57	7.9	-0.59	-11

Table 4.14: Comparison of the parameter sets belonging to the Financial sector of Group 1 and former parameter sets with the rest of parameter space.

Health Care Sector										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
1		60	2	5	2.4	8.4	0.94	15	0.5	6.9
2		10	1	4	2.3	22	0.61	9.6	0.5	6.6
3		20	4	5	2.2	25	0.65	9.4	0.37	5.1
4		15	4	4	2.1	23	0.65	8.9	0.5	6.6
5	SECTOR	30	4	7	2.1	23	0.57	7.9	0.16	2.5
11	STOCK	45	3	7	1.8	17	1.1	16	0.69	9.3
84	ALAN	30	2	5	-0.3	-1.6	0.57	7.9	0.16	2.5
89	ALAN	45	2	5	-0.39	-1.3	1.1	16	0.69	9.3

Table 4.15: Comparison of the parameter sets belonging to the Health Care sector of Group 1 and former parameter sets with the rest of parameter space.

Information & Technology Sector										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
1		60	1	4	2.5	5.5	0.94	15	0.79	14
2		20	1	5	2.2	24	0.65	9.4	0.54	9.6
3		60	1	6	2.1	14	0.94	15	0.79	14
59	ALAN	45	2	5	0.5	3.7	1.1	16	0.78	14
65	STOCK	45	4	5	0.35	4.4	1.1	16	0.78	14
75	STOCK	30	4	5	0.23	3	0.57	7.9	0.35	6.3
84	SECTOR	45	4	4	-0.056	-0.6	1.1	16	0.78	14
88	ALAN	30	2	5	-0.092	-0.99	0.57	7.9	0.35	6.3

Table 4.16: Comparison of the parameter sets belonging to the Information & Technology sector of Group 1 and former parameter sets with the rest of parameter space.

S&P Index										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
1		20	2	5	3.4	160.00	0.65	9.4	0.21	4
2	F. SECTOR	30	2	6	2.6	110.00	0.57	7.9	0.0071	0.62
3		20	1	6	2.2	100.00	0.65	9.4	0.21	4
4		10	1	5	1.7	120.00	0.61	9.6	0.31	5.5
5		10	4	4	1.6	120.00	0.61	9.6	0.31	5.5
6	HC. STOCKS	45	3	7	1.6	53.00	1.1	16	0.37	6.8
34	F.&IT. STOCKS	30	4	5	0.42	13.00	0.57	7.9	0.0071	0.62
36	IT. STOCKS	45	4	5	0.35	11.00	1.1	16	0.37	6.8
41	IT. SECTOR	45	4	4	0.17	4.60	1.1	16	0.37	6.8
46	PREVIOUS	30	2	5	0.079	1.80	0.57	7.9	0.0071	0.62
73	HC. SECTOR	30	4	7	-0.41	-15.00	0.57	7.9	0.0071	0.62
80	PREVIOUS	45	2	5	-0.57	-9.80	1.1	16	0.37	6.8

Table 4.17: Comparison of the parameter sets belonging to the whole Group 1 and former parameter sets with the rest of parameter space.

4.3.3. Conclusions

The results of section 4.3.1 describing the simulations of the first group of parameter sets against those previously used, seem to suggest that the first hypothesis seems to be successfully proven. In the case of the Financial sector and the Health Care sector, Tables 4.10-4.11, both the best performing parameter set according to the individual stocks and the sector outperform the parameter set previously used. In the Financial Sector, the difference between the worst performing of our chosen parameter sets and the best of the previous ones is of 0.4 annualized Sharpe ratio, and the performance in relation with the Buy & Hold strategy on the same sector has a similar Sharpe ratio, although a worse Wealth increase. If we now take a look at the Health Care sector, Table 4.11, the difference between the lower performer of the chosen parameter set and the best performing previous parameter set is a stunning 2.1 difference in Sharpe ratio. If we compare it to the Buy & Hold threshold strategy for the same sector we can see that our chosen set outperforms greatly the performance of the benchmark strategy, both in Wealth, and more importantly, in Sharpe ratio.

If we now observe the results for the Information and Technology sector, Table 4.12, we can see that although one of the former parameter sets (30, 2, 5) is indeed in last place, the other one (45, 2, 5) is in first place outperforming the rest of our chosen parameter sets for at least 0.15 Sharpe ratio. In this case none of the parameter sets obtains better Sharpe ratio or wealth than the Buy & Hold strategy. Although there hasn´t been an overwhelming result owing to this last sector, it is fair to say that the parameter sets which seemed to over perform the rest for the In Sample simulations for each sector seem to perform better than the former parameter sets in the Out of Sample simulations.

If we now see the effect this has over the total S&P 500 Index, table 4.13, we can see that except for one of the chosen parameter sets, the other 7 parameter sets including the parameter set obtained from the previous S&P 500 analysis, outperform the previous parameter sets. It is worth mentioning that the top performers of the chosen parameter sets outperform the Index and especially the Buy & Hold benchmark greatly.

When focusing on the results of section 4.3.2 regarding the second hypothesis on whether the first group of parameter sets outperformed the rest, we found out that for the different sectors the performance was average or a bit less for both the Financial and Information and technology sectors, tables 4.14 and 4.16, while for the Health Care sector, table 4.15, its performance was in the top 10% of the 112 possible combinations of parameter sets.

This could just be coincidence, or could it be something else. It may be possible that a few sectors could have different behaviors in such a way as to make a few Spidyn parameters semi-optimal throughout different periods. If this was to be proven right, this could mean that Spidyn could be used not only for general trading on whole Indexes, but could also successfully be exploited dealing with only specific sectors of which we could find this sets of overperforming parameters.

The Table 4.17 showing the whole combination of parameter sets, including the ones of group 1 and the former ones suggest a slight above average behavior for the group 2 parameter sets, with 2 of them ranking in the top 6. Meanwhile, the former parameter sets seem slightly below average. Although the parameter sets belonging to group 1 seem to perform above average, choosing them before the rest of the possible combinations isn´t a clear solution.

It is also important to notice the fact that the top positions belong to low window sizes. This behavior contrasts with those of the sectors in which, although some low window sizes are present, higher window sizes ranked in top positions. In this context it is curious to see how the best performing parameter for the S&P Index has P1 = 2 and P2 =5 as parameters, which correspond to the parameters used in past research, although the window size is smaller than the one which we found performed better for the in-sample simulations. This is also true for the Financial sector, as seen in Table 4.14 with the same window size T = 20, and for the sector of Health care, Table 4.15 where we can see how parameter P1 and P2 also rank first, although this time with window size T = 60.

4.4. Group 2 Simulations

4.4.1. 1st Hypothesis Results

We will now test the parameter sets of the second group against those used for previous research, and will arrange the results according to the Sharpe ratio in order to evaluate the performance of the different portfolios. First we will show a sector classification, with the former parameter sets, and those belonging to this second group, and finally we will see the simulation carried out for all of the S&P 500 and the previous parameter sets.

Financial Sector								
Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
30	4	5	-0.51	-7.6	0.57	7.9	-0.59	-11
45	4	4	-0.52	-6.9	1.1	16	-0.25	-4.6
30	4	4	-0.63	-7.9	0.57	7.9	-0.59	-11
45	4	5	-0.67	-8.2	1.1	16	-0.25	-4.6
45	3	4	-0.71	-7.5	1.1	16	-0.25	-4.6
30	3	5	-0.92	-11	0.57	7.9	-0.59	-11
45	2	5	-0.97	-7.7	1.1	16	-0.25	-4.6
30	2	5	-1.3	-13	0.57	7.9	-0.59	-11
45	3	5	-1.4	-13	1.1	16	-0.25	-4.6
30	3	4	-1.9	-18	0.57	7.9	-0.59	-11

Table 4.18: Comparison of the parameter sets belonging to the Group 2 and former parameter sets for the Financial sector.

Health Care Sector								
Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
30	4	5	0.76	7.6	0.57	7.9	0.16	2.5
45	4	5	0.47	3.3	1.1	16	0.69	9.3
45	4	4	0.41	2.5	1.1	16	0.69	9.3
30	3	5	0.35	2.5	0.57	7.9	0.16	2.5
30	4	4	0.32	2.6	0.57	7.9	0.16	2.5
45	3	4	-0.0042	-0.016	1.1	16	0.69	9.3
45	3	5	-0.26	-1.3	1.1	16	0.69	9.3
30	2	5	-0.3	-1.6	0.57	7.9	0.16	2.5
45	2	5	-0.39	-1.3	1.1	16	0.69	9.3
30	3	4	-0.71	-3.8	0.57	7.9	0.16	2.5

Table 4.19: Comparison of the parameter sets belonging to the Group 2 and former parameter sets for the Health Care sector.

Information & Technology Sector								
Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
45	3	4	1	9.4	1.1	16	0.78	14
45	2	5	0.5	3.7	1.1	16	0.78	14
45	4	5	0.35	4.4	1.1	16	0.78	14
30	4	5	0.23	3	0.57	7.9	0.35	6.3
45	4	4	-0.056	-0.6	1.1	16	0.78	14
30	2	5	-0.092	-0.99	0.57	7.9	0.35	6.3
30	3	5	-0.38	-4.7	0.57	7.9	0.35	6.3
30	4	4	-0.44	-6.2	0.57	7.9	0.35	6.3
45	3	5	-0.48	-4.4	1.1	16	0.78	14
30	3	4	-0.55	-5.7	0.57	7.9	0.35	6.3

Table 4.20: Comparison of the parameter sets belonging to the Group 2 and former parameter sets for the Information & Technology sector.

S&P 500 Index								
Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
30	4	5	0.42	13	0.57	7.9	0.0071	0.62
45	4	5	0.35	11	1.1	16	0.37	6.8
45	4	4	0.17	4.6	1.1	16	0.37	6.8
45	3	4	0.16	3.1	1.1	16	0.37	6.8
30	4	4	0.083	1.9	0.57	7.9	0.0071	0.62
30	2	5	0.079	1.8	0.57	7.9	0.0071	0.62
30	3	4	-0.063	-1.4	0.57	7.9	0.0071	0.62
45	3	5	-0.082	-1.7	1.1	16	0.37	6.8
45	2	5	-0.57	-9.8	1.1	16	0.37	6.8
30	3	5	-0.75	-17	0.57	7.9	0.0071	0.62

Table 4.21: Comparison of the parameter sets belonging to the Group 2 and former parameter sets for the whole Index.

4.4.2. 2nd Hypothesis Results

These out-of-sample simulations will test the whole parameter space explored in Chapter 3 against our 2nd Group of chosen parameters. Because of the length of the results, only the first parameter sets, and those in the specified group will be shown. The rest may be looked up under Appendix B.3.

Financial Sector										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
1		20	2	5	1.1	17	0.65	9.4	-0.4	-7.6
2		60	4	7	0.93	12	0.94	15	-0.26	-4.8
3		90	1	4	0.86	2	0.35	3.6	-0.94	-19
4		10	2	7	0.83	27	0.61	9.6	-0.34	-6.2
51	GROUP 2	30	4	5	-0.51	-7.6	0.57	7.9	-0.59	-11
52	GROUP 2	45	4	4	-0.52	-6.9	1.1	16	-0.25	-4.6
57	GROUP 2	30	4	4	-0.63	-7.9	0.57	7.9	-0.59	-11
61	GROUP 2	45	4	5	-0.67	-8.2	1.1	16	-0.25	-4.6
63	GROUP 2	45	3	4	-0.71	-7.5	1.1	16	-0.25	-4.6
75	GROUP 2	30	3	5	-0.92	-11	0.57	7.9	-0.59	-11
78	Alan	45	2	5	-0.97	-7.7	1.1	16	-0.25	-4.6
92	Alan	30	2	5	-1.3	-13	0.57	7.9	-0.59	-11
96	GROUP 2	45	3	5	-1.4	-13	1.1	16	-0.25	-4.6
108	GROUP 2	30	3	4	-1.9	-18	0.57	7.9	-0.59	-11

Table 4.22: Comparison of the parameter sets belonging to the whole Group 2 and former parameter sets with the rest of parameter space for the Financial sector.

Health Care Sector										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
1		60	2	5	2.4	8.4	0.94	15	0.5	6.9
2		10	1	4	2.3	22	0.61	9.6	0.5	6.6
3		20	4	5	2.2	25	0.65	9.4	0.37	5.1
4		15	4	4	2.1	23	0.65	8.9	0.5	6.6
33	GROUP 2	30	4	5	0.76	7.6	0.57	7.9	0.16	2.5
50	GROUP 2	45	4	5	0.47	3.3	1.1	16	0.69	9.3
56	GROUP 2	45	4	4	0.41	2.5	1.1	16	0.69	9.3
59	GROUP 2	30	3	5	0.35	2.5	0.57	7.9	0.16	2.5
61	GROUP 2	30	4	4	0.32	2.6	0.57	7.9	0.16	2.5
71	GROUP 2	45	3	4	-0.004	-0.016	1.1	16	0.69	9.3
80	GROUP 2	45	3	5	-0.26	-1.3	1.1	16	0.69	9.3
84	ALAN	30	2	5	-0.3	-1.6	0.57	7.9	0.16	2.5
89	ALAN	45	2	5	-0.39	-1.3	1.1	16	0.69	9.3
102	GROUP 2	30	3	4	-0.71	-3.8	0.57	7.9	0.16	2.5

Table 4.23: Comparison of the parameter sets belonging to the whole Group 2 and former parameter sets with the rest of parameter space for the Health Care sector.

Information & Technology Sector										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
1		60	1	4	2.5	5.5	0.94	15	0.79	14
2		20	1	5	2.2	24	0.65	9.4	0.54	9.6
3		60	1	6	2.1	14	0.94	15	0.79	14
4		60	3	4	2.1	13	0.94	15	0.79	14
30	GROUP 2	45	3	4	1	9.4	1.1	16	0.78	14
59	ALAN	45	2	5	0.5	3.7	1.1	16	0.78	14
65	GROUP 2	45	4	5	0.35	4.4	1.1	16	0.78	14
75	GROUP 2	30	4	5	0.23	3	0.57	7.9	0.35	6.3
84	GROUP 2	45	4	4	-0.056	-0.6	1.1	16	0.78	14
88	ALAN	30	2	5	-0.092	-0.99	0.57	7.9	0.35	6.3
92	GROUP 2	30	3	5	-0.38	-4.7	0.57	7.9	0.35	6.3
93	GROUP 2	30	4	4	-0.44	-6.2	0.57	7.9	0.35	6.3
94	GROUP 2	45	3	5	-0.48	-4.4	1.1	16	0.78	14
98	GROUP 2	30	3	4	-0.55	-5.7	0.57	7.9	0.35	6.3

Table 4.24: Comparison of the parameter sets belonging to the whole Group 2 and former parameter sets with the rest of parameter space for the Information & Technology sector.

Information & Technology Sector										
Position	Source	Wind	p1	p2	SP_S	SP_W(%)	In S	In W(%)	BH S	BH W(%)
1		20	2	5	3.4	160.00	0.65	9.4	0.21	4
2		30	2	6	2.6	110.00	0.57	7.9	0.0071	0.62
3		20	1	6	2.2	100.00	0.65	9.4	0.21	4
4		10	1	5	1.7	120.00	0.61	9.6	0.31	5.5
34	GROUP 2	30	4	5	0.42	13.00	0.57	7.9	0.0071	0.62
36	GROUP 2	45	4	5	0.35	11.00	1.1	16	0.37	6.8
41	GROUP 2	45	4	4	0.17	4.60	1.1	16	0.37	6.8
42	GROUP 2	45	3	4	0.16	3.10	1.1	16	0.37	6.8
45	GROUP 2	30	4	4	0.083	1.90	0.57	7.9	0.0071	0.62
46	PREVIOUS	30	2	5	0.079	1.80	0.57	7.9	0.0071	0.62
56	GROUP 2	30	3	4	-0.063	-1.40	0.57	7.9	0.0071	0.62
57	GROUP 2	45	3	5	-0.082	-1.70	1.1	16	0.37	6.8
80	PREVIOUS	45	2	5	-0.57	-9.80	1.1	16	0.37	6.8
84	GROUP 2	30	3	5	-0.75	-17.00	0.57	7.9	0.0071	0.62

Table 4.25: Comparison of the parameter sets belonging to the whole Group 2 and former parameter sets with the rest of parameter space for the whole Index.

4.4.3. Conclusions

From section 4.4.1 where the first hypothesis is tested against the second group, we can see that for the Financial and the Health Care sectors, Tables 4.18 and 4.19, the chosen parameters seem to outperform the previous parameter sets employed. In the case of the Financial sector, 75% of the parameter sets belonging to the collection of parameters being tested performed better than the former parameter sets, while for the Health Care sector 87.5% of the sets performed better.

When looking at the Information and Technology sector, Table 4.20, there seems to be a difference with respect to the previous sectors, and one of the former parameter sets ranks second while the other one lies in a middle position. This divergence between the sectors has also been found in the results of section 4.3, with the first group of parameter sets. In that section we saw how the parameters chosen performed better than the former ones for the Financial and Health care sectors, but did not for the Information & Technology sector. This behavior, repeated for two different collections of parameter sets, may be evidence supporting the supposition that there may be differences between the behaviors of sectors and the stocks belonging to each sector, in a sense that some sectors may behave in a more irrational way, allowing Spidyn to detect and exploit it.

If we now focus on the whole of the S&P Index, Table 4.21 we can see that more than 60% of the parameter sets belonging to the second group perform better than the best of the former parameter set, while nearly 90% of them perform above the second one. These results may suggest that for the whole index, as well as for most of the sectors, the parameter sets belonging to the second chosen group perform better than those used for previous research.

It is important to make notice of the fact that these parameter sets, having been tested for the three sectors and the index, seem to perform in a similar way throughout the simulations. In the following table we can see the parameter sets ordered according to their Sharpe ratio results, where we can see how the difference in their arrangement between the different sectors and the Index is smaller as one could have thought of.

Fin. Sector	HC. Sector	I&T Sector	S&P500
30,4,5	30,4,5	45,3,4	30,4,5
45,4,4	45,4,5	45,2,5	45,4,5
30,4,4	45,4,4	45,4,5	45,4,4
45,4,5	30,3,5	30,4,5	45,3,4
45,3,4	30,4,4	45,4,4	30,4,4
30,3,5	45,3,4	30,2,5	30,2,5
45,2,5	45,3,5	30,3,5	30,3,4
30,2,5	30,2,5	30,4,4	45,3,5
45,3,5	45,2,5	45,3,5	45,2,5
30,3,4	30,3,4	30,3,4	30,3,5

Table 4.26: Summary of the parameter sets arranged by performance and sector.

This may also suggest that inside this collection of parameter sets we have thought could perform better than the rest, there are even a few that outperform the rest. In this case we can see how the parameter sets (T=30, P1=4, P2=5), (T=45, P1=4,P2=5) and (T=45,P1=45,P1=4,P2=4) seem to outperform the rest of parameters for most of the situations, even for the Information and Technology sectors in which we have seen there is a discrepancy in the results.

If we take a look at the result of section 4.4.2 in which we are comparing the collection of parameters belonging to the second group for each sector, Tables 4.22-4.24, we can see that as well as for the previous section, the parameter sets of the second group tend to perform on average, when not worse, than the rest of parameters.

Table 4.25 shows how the parameter sets belonging to group 2 perform against the rest of parameters for the whole Index, and the results suggest that they perform on average or slightly above . They all seem to have a similar performance, performing similarly to the Buy & Hold benchmark.

4.5. Conclusions on the Out-of-Sample Validation

The purpose of this validation was to test the conclusions on the best performing parameters we arrive to on Chapter 3 and to try to answer the two hypothesis that were formulated and which could be described as the main points of our Master Thesis.

The first hypothesis we wanted to tests involved finding out if the parameter sets we found from Chapter 3 as being best performing, and therefore performing better that the former parameter set used by previous researcher for the in-sample simulations, also performed better than this former parameter set in the out-of-sample simulations.

From the sections 4.3.1 and 4.4.1 we can see that the results for the Financial and Health Care sectors, as well as for the S&P 500 Index Tables 4.10-4.13 and 4.18-4.21 show clearly a better performance for the newly chosen parameter set over the old ones. In the case of the Information &Technology sector there also seems to be in both cases, Tables 4.12 and 4.20, a change in this trend, performing the old parameter equal, if not a bit better, than the new ones. This situation left us with the following idea going round and round our heads. May it be possible that the because of different characteristics of the sectors, some tend to behave in ways which allow the Spidyn indicator to use all of its predictive force, while other sectors are more immune to our indicator? If this was true, then it might turn out that for some sectors with characteristics that make them more susceptible to unsustainable accelerations the Spidyn indicator may be used for trading more successfully than for the whole Index. If focusing on a few sectors instead of the whole pool of stocks, this may help in the implementation of Spidyn for real-life trading.

The answer to our first hypothesis seems to be that the parameter sets belonging to the two groups analyzed do perform better than the former ones, both for the Index as a whole as for 2 out of 3 sectors. It is important to note that when referring to former parameter sets, not only are we taking into account P1 and P2, but also the window size. The reason behind this explanation comes from the results of the testing of the second hypothesis.

The second hypothesis, whether the parameter sets belonging to group 1 and group 2 outperformed the rest of parameter sets seems not so optimistic. In fact, these chosen parameter sets belonging to the 2 groups seem to perform on average, or underperform, for most of the sectors.

If we focus on the S&P 500 Index, we have a slightly more optimistic view. For the 2nd group of parameter sets, the results seem on average, Table 4.25, but for the 1st group, table 4.17, the results seem to perform just above average, with 2 parameter sets in the top 6 positions.

The top rated parameter set (T = 20, P1=2, P2=5), Table 4.25, shows a Share ratio of 3.4 an a Wealth increase of 160%, which is outstanding when compared to the second parameter set and especially to the Index and the Buy & Hold benchmarks. Parameter P1 and P2 are the same as those used in previous research, and which our first hypothesis tried to demonstrate was worst than our selection of parameter sets. Short window sizes may have for a short period of time greater Wealth increase, as seen in Chapter 3, which would increase the Sharpe ratio, but probably in a larger period of time this small windows may find problem with their volatility and risk, therefore diminishing their Sharpe ratio.

It may be sensible to think that although some parameter set, such as those belonging to the best performing for the Financial sector and to the Health Care stocks, seem to perform well when dealing against the whole parameter space for the whole S&P 500 Index, it seems far-fetched to assume that the parameter sets chosen from the results of the in-sample simulations outperform the rest. The second hypothesis seems therefore refuted.

The out-of sample simulations carried on less than a year when the in-sample simulations were carried on 4 years of data may not be long enough to extract conclusive results. This should be taken into account when analyzing these results, as well as for further studies on Spidyn.

Chapter 5
Other Measures

5.1. Definitions

On previous Chapters we have dealt mainly with the annualized Sharpe ratio and annualized Wealth increase, there are many more important measures involved in portfolio strategies. Some strategies may have similar Sharpe ratios or Wealth variations, and these measurements may be useful to distinguish between them.

In the case of our trading strategy based on the Spidyn indicator, there are a few important measures which help us understand better the way Spidyn works, and how it interacts with our strategy. Some of them are:

- Number of Signals
- Number of Deals
- Deals/Signals (%)
- Time/Deal (Days)
- Successful Deals (%)
- Sharpe/Deal

5.2. Number of Signals

From a price time series of length N, for M number of stocks we have a total M*(N-T+1) indicators, but not all of them are signals. Depending on the threshold employed by our trading strategy we will have a different *number of signals*. If the threshold was set so high that the indicator never trespassed the threshold the number of signals would be zero, while if it was low enough, we could have the same number of signals as indicators. The number of signals therefore depends on the parameters used when calculating the Spidyn indicator such as the window size, P1 and P2, and the threshold. In the next graph we can see an example of how changing the window size for the Financial sector simulation for the out-of–sample period keeping parameters P1=4 and P2=7 fixed, changes the number of signals:

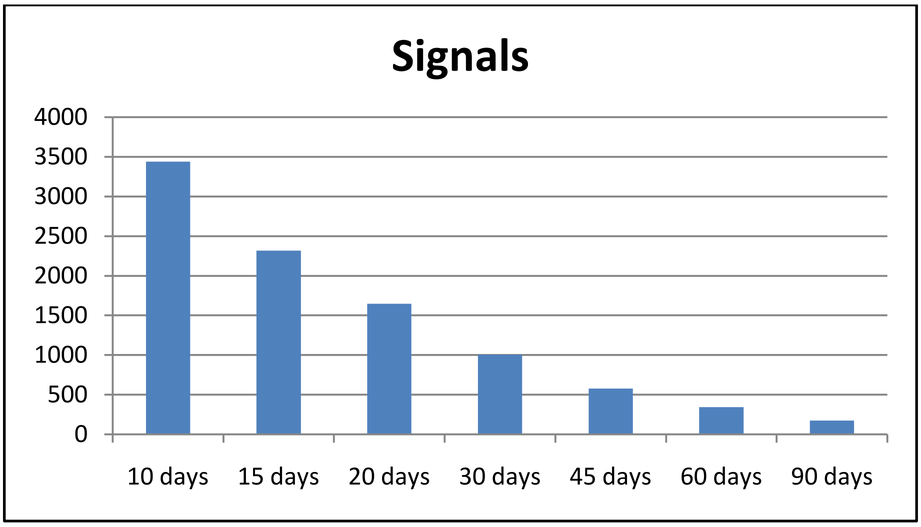

Figure 5.1: Number of signals for different Window sizes and P1=4, P2=7 for the Financial sector.

The Figure 5.1 shows how the amount of signals decreases when the window size increases. As said previously in Section 3.5, a reason behind this could be that when the indicator is computed on a smaller amount of data, small changes in trends can be perceived by the Spidyn as possible bubbles or crashes, and therefore will emit larger indicators which would more easily trespass the threshold than lower ones. When dealing with indicators computed over larger windows, if the Spidyn has issued a large indicator meaning a possible unsustainable price acceleration over so many days it must be a big change which has continued for a long time. This may mean that although fewer signals are detected by the trading strategy, this may founded on more information, decreasing the risk. It may also mean that if after many days have passed by unsustainable acceleration noticed by Spidyn could have already been corrected and our deal wouldn´t turn out to be successful. To take both possibilities into account, the choice of windows between 30 and 45 seems a sensitive choice.

The following figure shows the amount of signals depending on the sectors for the out-of-sample simulation period:

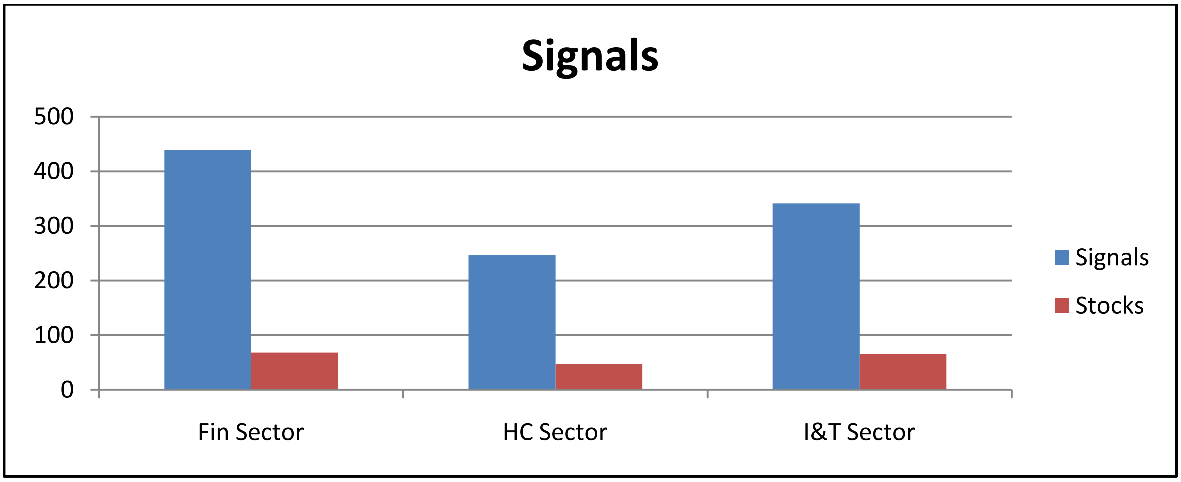

Figure 5.2: Number of signals and stocks for each sector and parameters T=30, P1=4, P2=7.

As seen in Figure 5.2, the average number may vary from one sector to the other. The reason behind seems to be the amount of stock belonging to each group. It is easy to see the relation between both of them, being the Health Care sector the one with least amount of stocks (47) , followed by the Information & Technology(65) and the Financial sector(68). The more stocks belonging to a group the more signals that group receives.

5.3 Number of Deals

Once the trading strategy detects a signal, it analyzes a set of other parameters such as the invest fraction, the day the signal has been issued or if we have the stock and if the conditions are met a deal is closed. The total number of these deals for the whole of the stocks under analysis is the *number of deals*. The number of signals limit the maximum number of deals, but apart from that it is independent from it. The following graph represents the number of deals with respect to the invest fraction for the Information & Technology sector, parameters T=45, P1=4, and P2=4, and a fixed number of 246 signals.

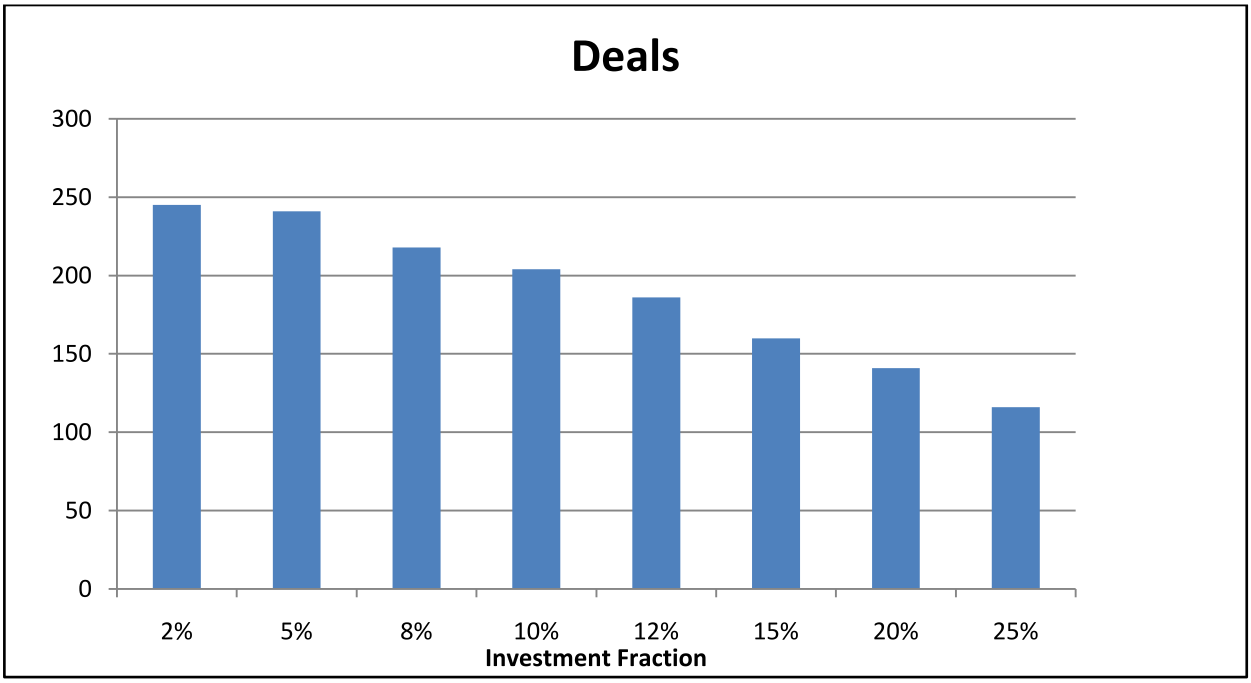

Figure 5.3: Number of deals with respect to the investment fraction for the Information & Technology sector and parameters T=45, P1=4, P2=4.

Figure 5.3 shows how the number of deals diminishes when the investment fraction increases, even though the amount of signals is always the same and equal to 246. In the next section we will see this behavior better.

The number of deals is also a very important measure to take into account some costs which will reduce our gains and that we haven´t taken into account during the portfolio simulations, transaction costs. These are the costs include the commissions paid when buying and selling a stock, the total amount increases with the number of deals.

Supposing we had an initial wealth of 1000€ and in one year we had a 10% profit, that is, 100€. If we did so by doing 10 deals, and there was a fix transaction costs per deal of 1€, then our gain would really be of 90€, a 9%. If instead we managed to achieve that same 10% of profit by making 100 trades, at 1€ per trade the total costs would be of 100€, leaving us without profits.

The following figure shows the average number of deals for each sector and Index for the out-of-sample simulations:

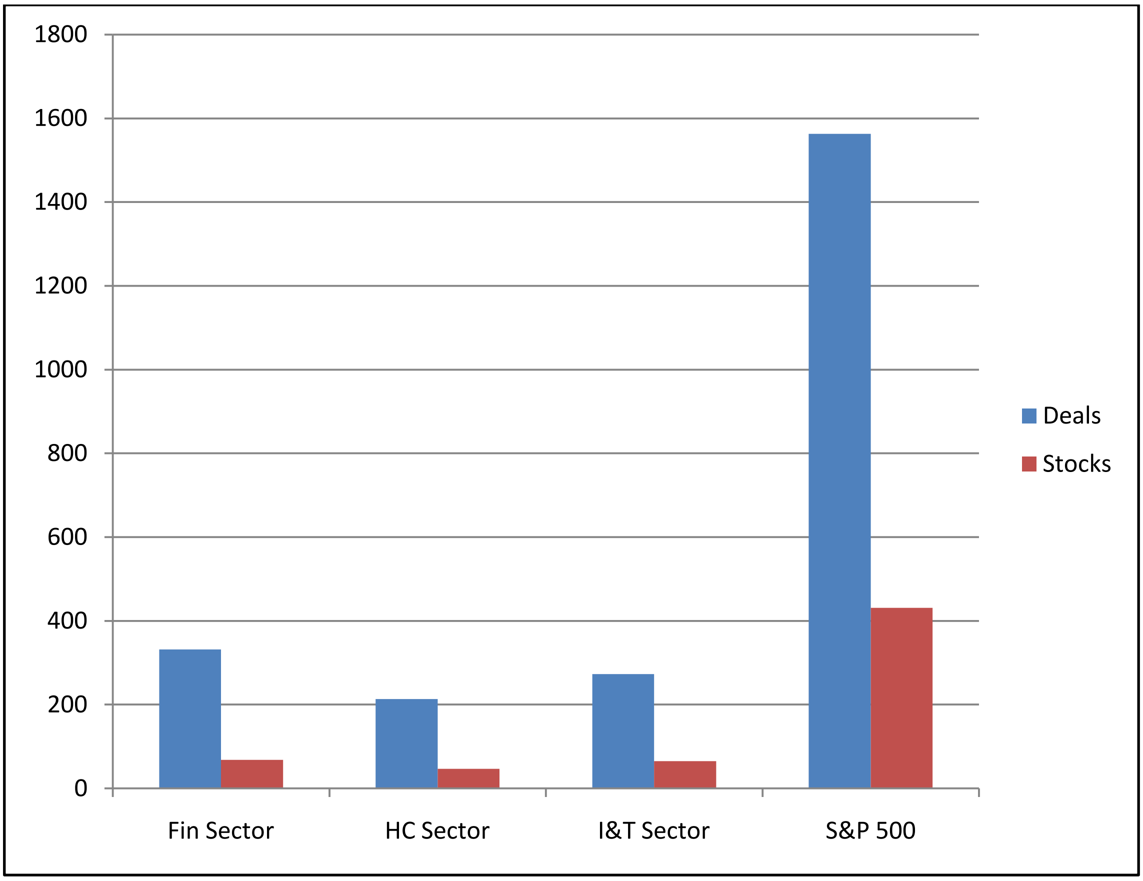

Figure 5.4: Average number of deals for each sector and Index for the out-of-sample period

As seen in Figure 5.4, the average number of deals for the different parameter sets has been between 200 to 320 deals, while for the S&P 500 Index it averages nearly 1600 Deals. As for the Figure 5.2 of the signals per sector, the same relation seems to be true here. The more stocks in our pool of stocks, the more signals we get, the more deals that may be made, depending on the investment fraction.

5.4 Deals to Signals

From the previous definitions it follows that not all signals turn into deals, therefore the existence of the measurement *deals/signals*. This ratio is influenced greatly by the investment fraction. As seen in Chapter 2, the greater the investment fraction, more wealth is invested in each deal and the sooner the moment when no more cash is available for buying with the buying signals. In the same way, when you invest large amounts in each deal the less different stocks you have in your portfolio. This causes that when you have a selling signal, if you do not own stocks from that stock you won't be able to sell it (remember we do not allow short-selling). This makes trading strategies with higher investment fractions to carry out fewer signals to effective deals, as seen in the following graph belonging to the Financial sector out-of-sample period, and for the parameter set (T=30, P1=4, P2=5) for the different investment fractions:

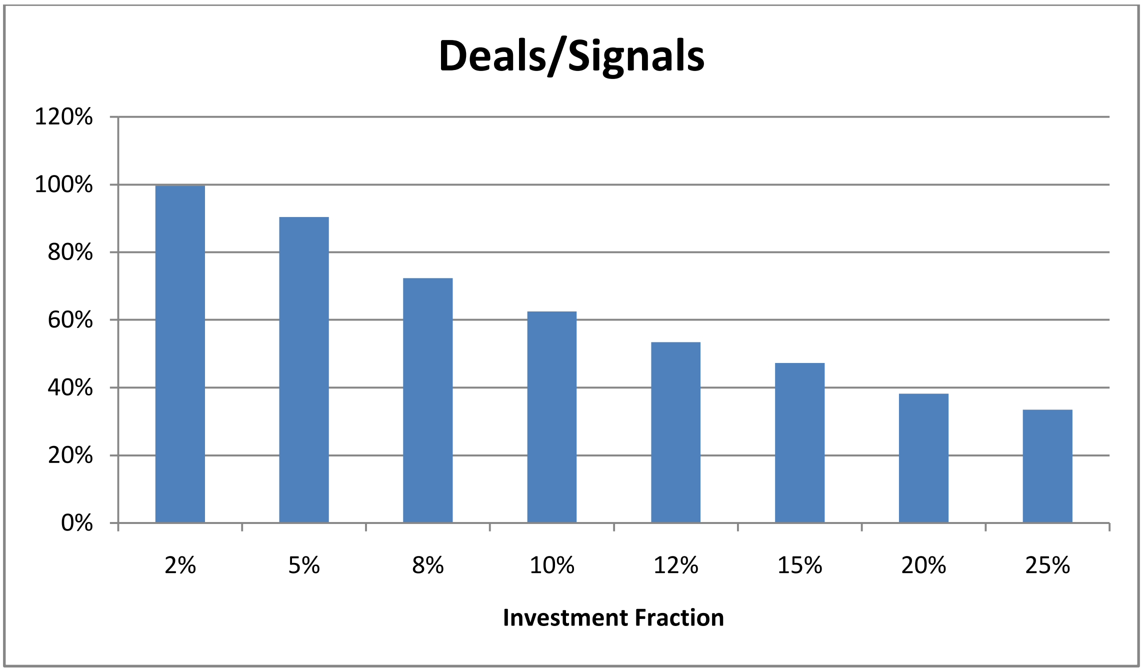

Figure 5.5: Deals/Signals for the Financial sector in out-of-sample period, and for the parameter set (T=30, P1=4, P2=5) for the different investment fractions:

The number of signal efficiently turned into deal goes from the 100% when the investment fraction is a low 2%, to a 35% when the investment fraction is up to 25%. With an investment fraction of 8% the percentage of deals to signals is usually around 70% in this case.

For the out-of-sample portfolio simulations a invest fraction of 8% was chosen, this allowed for the following Deal to Signal ratios:

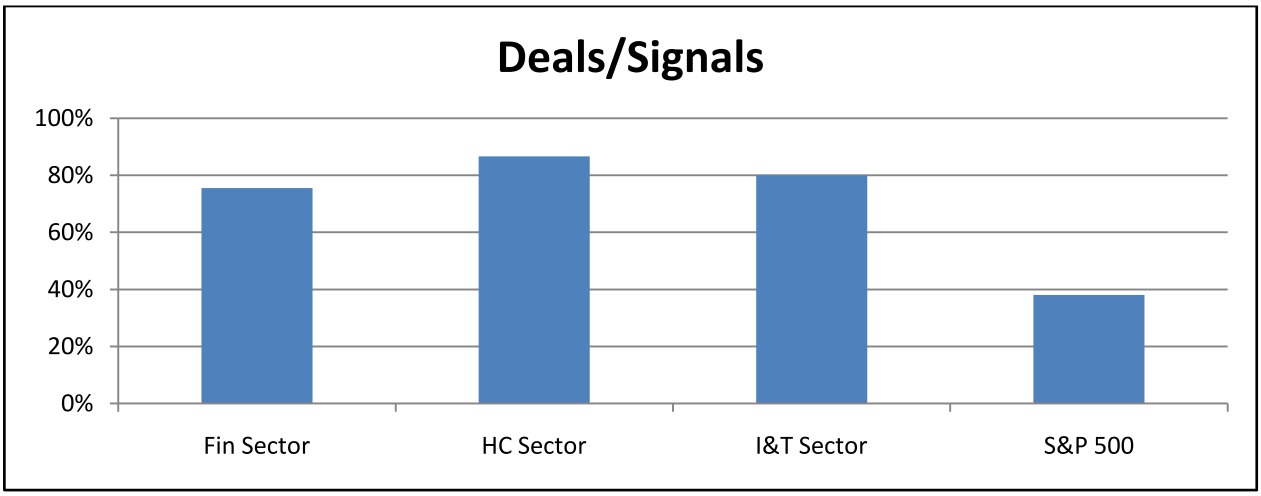

Figure 5.6: Average Deal/Signals for each sector and Index in out-of-sample period.

The ratio of Deals to Signals remains over 70% for the three sectors, as seen in Figure 5.6, and for the whole Index decreases to 35%. We believed this investment fraction to be appropriate instead of a higher one which would have lost a greater amount of signals, or lower ones which could have large amounts of wealth uninvested for long periods of time.

5.5. Time per Deal

The number of days elapsed between the opening of a position, investing a portion of our wealth on a certain stock, and closing that position, selling the stock, is the *time per deal*. Depending on the type of strategy the time could go from milliseconds for some kinds of algorithmic strategies, in which the speed of connection to the stock market makes the difference, and which has brought some derivative exchanges such as Eurex to evolve into providing low latency access of down to milliseconds per round trip [15], to up to years with long-term strategies.

In our out-of-sample portfolio simulations, the average time per deal for the different sectors and Index were the following:

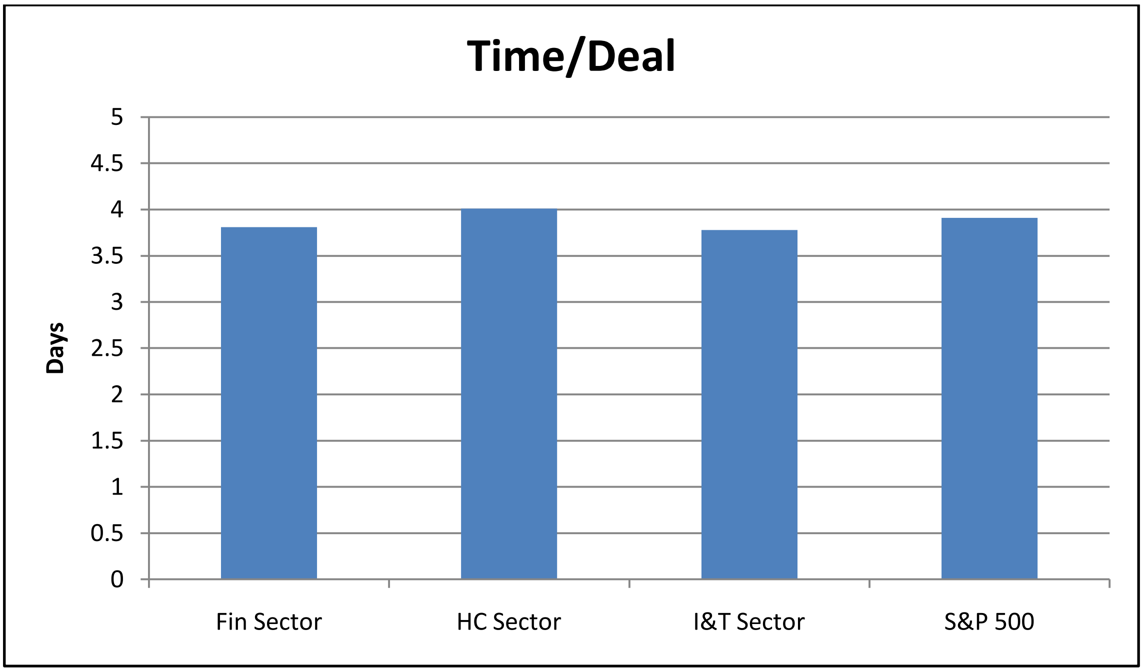

Figure 5.7: Average Time/Deal for the different sectors and Index for the out-of-sample period.

Figure 5.7 shows that there is not a great difference between the three sector and the Index, while for other measures such as the number of deals and signals the difference was great. This suggests that the average time it take for a deal to be completed, that is, bought and then sold, is independent of the amount of deals or signals, or even of the amount of stocks in the pool of options. This makes sense because Spidyn gives us the same indicators for each stock independently of the rest of our possible portfolio. Only the individual stock is taken into account. Nevertheless we have to bear in mind that although the average is around 4, it is not unusual to have deals on both extremes, such as deals lasting 15 days, and some lasting 1.

5.6. Successful Deals

The definition of deal, as defined before, means a signal has effectively been transformed into a buying or selling deal. What we don´t know is the amount of deals in which we have made money on, which means selling for a higher price than we paid for, the percentage of *successful deals* shows just that.

In the following graph we can see the different ratios of successful deals to deals for the three studied sectors and the Index for the out-of-sample period divided into the different parameter groups.

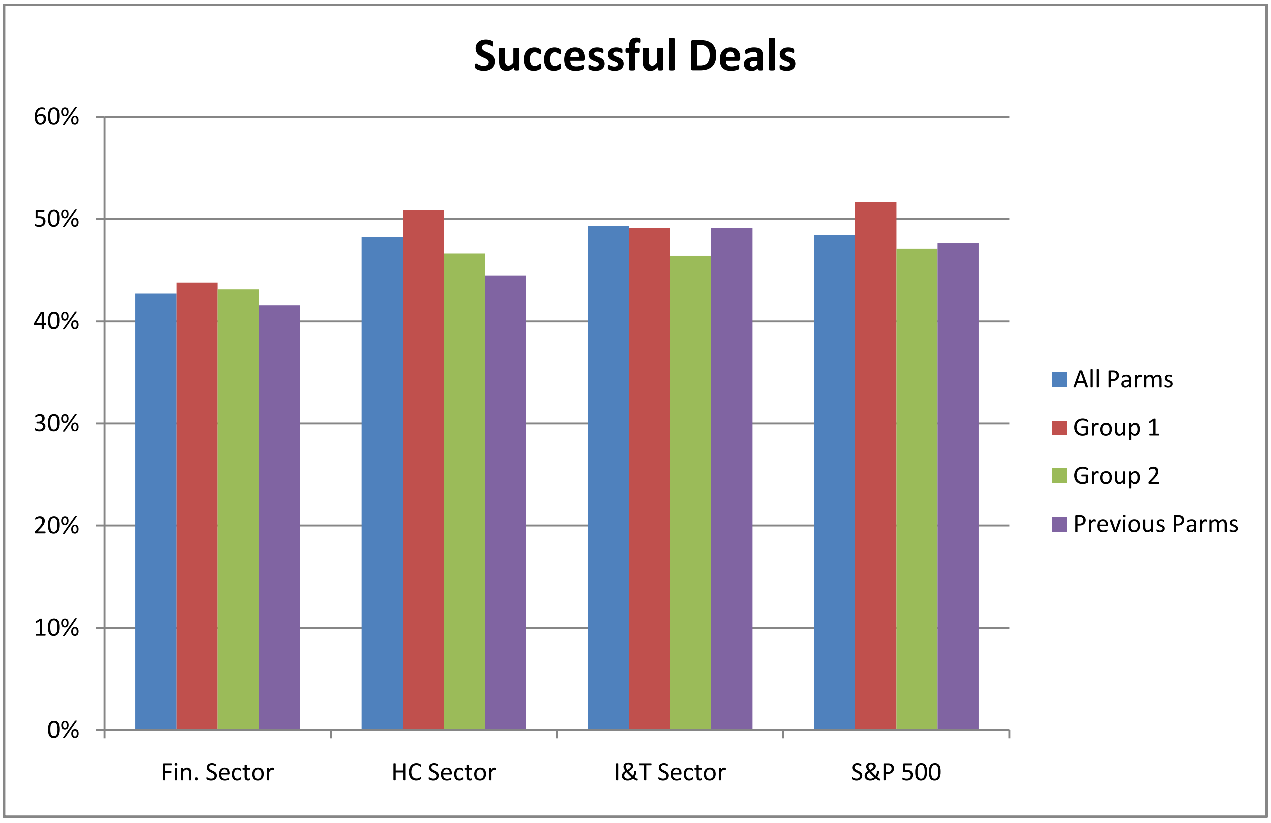

Figure 5.8: Successful deals (%) for the sectors and Index for the out-of-sample period and for each group of parameter sets.

In Figure 5.8 we can see for the different sectors and the Index the percentage of successful deals. If trading randomly, the percentage of successful deals, if the period was long enough, should be equal to 50%, according to commonly accepted hypothesis that price trajectories are identical to a random walk, and therefore every new day the price trajectory is as random as if it was decided by the flip of a coin [1]. It is to our surprise that we can see how just once this 50% barrier is crossed, which means when only dealing with the number of times our prediction was successful we did worst than trading randomly. However, this measure is not to alarm us. It may well be that in the case of unsuccessful trades the loss were small, while with the fewer successful deals the gains were really high. This would indeed be a profitable case for us, and could be measured by the gains per deal, or even better, by the Sharpe per deal.

From the same figure we can see how the parameter sets belonging to Group 1 seem to have greater amount of successful deals throughout the different sectors and even the index.

5.7. Sharpe/Deal

This important measure gives us an idea of how profitable the average of the deals has been. Instead of giving us the average of the returns, this measure is also takes into account the extra risks involved in the returns, giving us a more detailed explanation of what is really happening while our trading strategy is at work.

In the following graph we can see the average Sharpe per Deal for the different sectors and the index in the out-of-sample period.

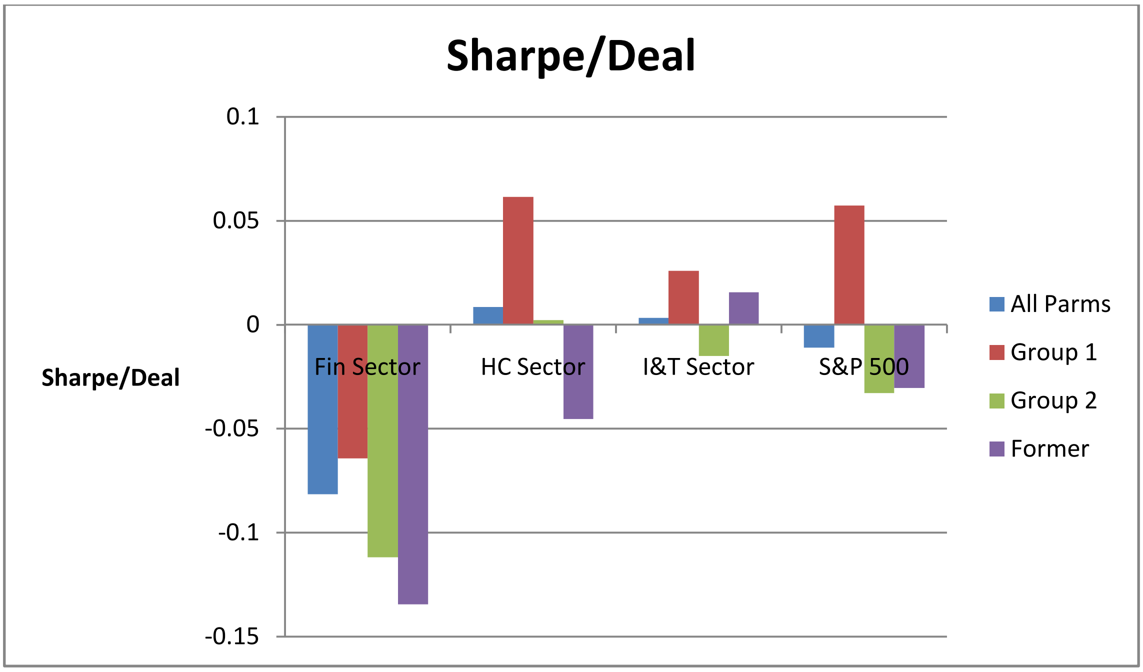

Figure 5.9: Average Sharpe/Deal for the different sectors and the Index for the out-of-sample period and the different groups of parameter sets.

Figure 5.9 shows there are several groups of parameter sets which have a negative Sharpe/Deal. By definition, this means that investing in a risk free asset would have been of better use to us. Being the risk free rate used for calculating the Sharpe ratio equal to zero, in the negative cases we would have invested our money better by not investing at all!

Nevertheless we can see how group 1 seems to perform better than others in this measurement as well, outperforming the rest even in the Financial sector where all parameter set groups seemed to exhibit negative performance.

5.8. Conclusion

The measures introduced in this chapter help us expand our knowledge on the way the Spidyn indicator behaves. It has also provided support for some of the decisions we have taken over the simulations, such as deciding on choosing a Window size =30/45 in order to receive enough signals, Figure 5.1, or having chosen an investment fraction of 8% to carry out the out-of-sample simulations, allowing us to detect sufficient signals, 70 % for the sectors and more than 30% for the Index, while having enough wealth invested, Figures 5.5 and 5.6.

Seeing the percentage of successful deals, together with the average Sharpe/Deal of the different groups of parameter sets has also proved helpful in our task of identifying the best performing parameters, and similarly to the results of section 4.5, we have seen how the parameter sets of Group 1 seem to perform better than the rest of parameters chosen to carry out the simulations, such as the Group 2 or the former parameter sets.

Chapter 6
Conclusion

The goal of this Thesis was to explore part of the Spidyn´s parameter space which could help us gain an insight into Spidyn and how it worked and behaved. Achieving such an understanding in the field of complex systems is not easy, and any new step forward taken in this direction and contributing in a useful way will be worth the time and effort put into this project.

When struck with the question on which part of the Spidyn were we to focus on, we decided on three of the main parameters used for the computing of the indicator, namely the Window size (T), the minimum coefficient of the polynomial to fit (P1), and the maximum coefficient of the polynomial to fit (P2). Specifically the parameters tested were: T = [10, 15, 20, 30, 45, 60, 90], P1 = [1, 2, 3, 4], and P2 = [4, 5, 6, 7].If we were to find a set of the aforesaid parameters, or even a collection of them, this may be useful in different ways. It may allow for a better performance in real-life trading using the Spidyn indicator and the adequate trading strategy, and it could also be used as "a cornerstone/ strong foundations" for future research on Spidyn.

Building on past knowledge [16-18], our research was focused on a Bullish Regime, years 2003 to 2006, and meant to predict mini-crashes taking place in this upward price trend. The trading strategy on itself played a very important part in the simulations, and some changes were made to the previous existing strategy [16-17] in order to carry out the desired simulations.

In order to assess the performance of the portfolio simulations some measures were described, although the single most important measure employed was the Sharpe ratio, due to its ability to capture the excess in the returns, taking into account not only the expected returns, but also the risk implied in these returns by means of the standard deviation of the returns.

When dealing with the simulations, we decided to focus on a few different sectors belonging to the S&P 500 Index, such as the Information & Technology, Health Care and Financial sectors, and from there work ourselves to the individual stocks and to the whole Index. The results we obtained from this approach seemed to suggest that lower window sizes seemed to have better returns by ignoring part of the risk implied, while very high window sizes missed many possible mini-crashes. Therefore a medium window size such as 30 or 45 days seemed the better positioned to achieve equilibrium between high returns and lower risks or volatility.

When dealing with the parameters P1 and P2, which account for the degree of the polynomial to fit, and therefore with the order of the derivatives used for prediction, we saw that parameter P1 tends to be high, being equal to three or four, while the parameter P2 although not as clear as P1, seemed to belong to the lower ones, such as four and five. This suggests that although P1 being high means an aggressive approach [2], P2 belonging to the lower range softens this aggressiveness. When dealing only with returns and performance, both of these parameters were on the high range, meaning a very aggressive behavior. This difference may correspond to the ignorance of risk of the latter.

From the results we also discovered that the former parameters used in previous research [16-18], happened to behave under average, which lead us to believe that even if we didn´t find semi-optimal set of parameters for Spidyn, we may achieve a more modest goal of at least improving what was used previously.

These two ideas were the hypotheses tested during our out-of-sample portfolio simulations, in order to validate and verify the conclusions we arrived on Chapter 3. The time period used for this simulations went from January 2007 to October 2007. The intention behind choosing this brief period was to continue our simulations on a period with a similar regime, to change as little as possible, and October 2007 seemed to many economists the starting point of the crash we are now in [2].

The two hypotheses to be tested were therefore the following: “Do our chosen collection of parameter sets outperform the previously used ones?”, and the second and more ambitious “Do our chosen collection of parameter sets outperform the rest of possible parameter sets?” These hypotheses were tested in chapter 4 with similar simulations as those carried out in Chapter 3, with different outcome.

The results seemed to suggest that our collection of parameter sets seemed to perform on average better than the ones previously employed, confirming our first hypothesis. Nevertheless, it is true that the different behavior between the sectors made us formulate another question. “Could it be possible that different sectors respond differently to Spidyn?” If this was to be proved true, it may suggest that the dynamics and characteristics of different sectors may make them more or less vulnerable to unsustainable accelerations on the prices of their stocks caused by human irrationality. This could then be applied to our trading strategy by trading on those sectors in which Spidyn may be more successful, while avoiding those which don´t.

When testing out our second hypothesis, the results seemed to be inconclusive. The performance of our collection of parameter sets was average or slightly under for the different sector tried, while for the Index they seemed to perform above average, although not as clearly as to validate the hypothesis. A suggestion for future research is to carry out this same simulation on different periods of time with similar regimes, or even for the same period of time in different Indexes of countries, which could lend itself to interesting comparison between the behavior of sectors in the same period of time but different geographical location.

Some other measures such as the Sharpe per Deal and ratio of Successive Deals were also introduced, which shed a bit of light on the influence of some of Spidyn and the trading strategy parameters, as well as closing in on which of the big collection of parameters seemed to perform better.

The conclusion we can extract from the Master thesis, is that although every little step brings hundreds of new questions, we seemed to have found a trend in the behavior of the Spidyn indicator regarding the parameters T, P1, and P2. Giving an exact number for each of these is not an easy task, but at least having decreased the parameter space from more than 100 different parameter sets to just less than 10 seems a great achievement which we wish could contribute in making Spidyn a successful predictor.

Chapter 7
Where to go Next

We have found working on Spidyn´s complexity awe-inspiring as well as an enriching experience. Unfortunately for us, as more and more questions began emerging, less and less time was left to carry them out. It is our hope to note down in this section the most interesting ideas we would have liked to research further on, as well as some experiments for which the necessary arrangements such as code and strategy had been made, but not carried out.

Different Indexes and Countries: One of our first ideas when starting this Thesis was to examine the results of the use of Spidyn in different indexes and countries. There were several reasons behind this motivation, but we will just emphasize a few of them. We believe that carrying out the same simulations for important international indexes in different countries may be useful for observing possible common trends between the same sectors in different countries that may not hold for different sectors in the same country. As seen throughout this Thesis, and especially in Chapter 4, the sectors seem to behave differently, maybe allowing Spidyn to perform more accurate predictions depending on the sector. One of the possible ways of testing this out would be by testing these same 3 sectors, during the same time period.

Different indexes also means that the market participants may not be the same, like more hedge funds and institutional investors operating on the S&P 500 than on the Spanish IBEX-35. If this was the case, it might also be true that the behavior of these investors was not the same for both, and therefore Spidyn might react differently in each index, allowing us to identify the best place to implement a real-life trading strategy based on the Spidyn indicator.

Finally, the period used both for the in-sample as for the out-of-sample simulations comes from the belief, as stated before, that the Spidyn indicator might be sensitive to market regimes. Getting data from different indexes may also allow us to perform more simulations and compare them for the same periods of time, not having to worry about the consistency in the market regimes, due to the usual connection between international markets, as seen in Figure 1.1.

The use of stocks coming from different indexes was something we had in mind when writing the Python and Matlab scripts, and therefore the necessary steps needed for its implementation have already been taken. In Appendix C we have shown the necessary changes that have to be done in order to use this option.

Use of Quantiles: Quantiles were explored to be used for the trading strategy thresholds in previous research [18], with some interesting results. It was our intention to incorporate this to our work, but we finally had to give up in our attempt in favor of a more extensive analysis of the rest of parameters.

The code we developed allows us to work with quantiles in a variety of ways, as will be described further in Appendix C. Not only do we have growing windows to calculate the quantiles, but also moving windows of varying lengths which can be used to have not only stock dependant quantiles, but also time dependant ones. The possibilities offered by these different windows are huge. Not only can they be used with a variety of parameters to obtain better performance for our Spidyn based portfolios, but they may also be used in further research as a tool to determine changes in market regimes, if the measures of both quantiles are monitored and compared.

Weights: During the different research on Spidyn [16-18], different parameters were studied, but some of them including the weights remained constant. Both the Python and MySQL database have been developed to include possible changes in this parameter which we also kept constant through our research.

Out-of-Sample Period: Constraints due to changes in market regimes have made us choose for the out-of-sample validation a short period of time when compared with the in-sample-period of a few years. If the suggestion on using different indexes was to be followed, using the same period for the in-sample simulations and the out-of-sample one but changing the indexes and therefore the stocks might be an interesting idea to follow.

Leverage: There has been no leverage during this Thesis, but in order to get all of the Spidyn signals transformed into deals, as seen in section 5.4, leverage could be used. By means of borrowing the necessary money, the necessary money could be borrowed, a common practice for hedge funds and other financial institutions. The result may be a portfolio on really all of the signals emitted by Spidyn, without some of the constraints we had on our trading strategy.

Portfolio of Parameter Sets: A very interesting suggestion made by our Tutor, Prof. Dr. Didier Sornette, was to perform a portfolio of different portfolios, each one of them for a different set of parameters. By doing this we could have a group of the best performing parameter sets running individual portfolios, each of them being part at the same time of a global portfolio in an equally weighted way, or even better, maybe with different weights according on the market regimes or the actual performance of each portfolio, just as if they were traded stocks.

By doing this we may also find out if the Spidyn indicators of the different parameter sets detect the same opportunities and unsustainable accelerations, or if they detect different ones. Both of these conclusions would be useful with our strategy of portfolio of portfolios. In case the acceleration detected was the same one, if most of the portfolios detected it we would profit from the different portfolios investing in it. In case they detected different ones, then having each individual portfolio capturing different unsustainable accelerations would make us globally capture all of them.

We encourage further researchers on the Spidyn indicator to pursue this idea further maybe in combination of some of the above, as it seems a solid starting place for a great number of questions in need of answers.

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Appendix

Appendix A

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	8 “1´s”	80% of 1´s	8 “1´s”	40% of “1´s”
	2 “2´s”	20% of 2´s	7 “2´s”	35% of “2´s”
			4 “3´s”	20% of “3´s”
			1 “4”	5% of “4´s”
P2	8 “4´s”	80% of 4´s	8 “4´s”	40% of 4´s
	2 “6”	20% of 6´s	9 “6´s”	45% of 6´s
			2 “7´s”	10% of 7´s
			1 “5”	5% of 1´s
Window	8 “30´s”	80% of 30´s	10 “30´s”	50% of 30´s
	2 “45´s”	20% of 45´s	6 “45´s”	30% of 45´s
			4 “60´s”	20% of 60´s

Table A.1: Summary of the results according to Sharpe ratio for the Financial sector 1st approach.

Parameter Set	Window	P1	P2	Number of times
1	30	1	4	8
2	45	2	6	8
3	30	3	7	5
4	60	3	6	5
5	30	2	7	3
6	60	4	6	2
7	20	2	5	1
8	30	4	6	1
9	30	4	7	1
10	45	3	5	1
11	45	4	7	1
12	30	1	6	1
13	60	2	6	1
14	30	4	4	1
15	45	2	5	1

Table A.2: Summary of the 2nd approach for the Financial sector according to Sharpe ratio.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	6 “4´s”	60% of 4´s	11 “4´s”	55% of “4´s”
	4 “3´s”	40% of 3´s	7 “3´s”	35% of “3´s”
			2 “2´s”	10% of “1´s”
P2	5 “7´s”	50% of 7´s	10 “7´s”	50% of 7´s
	1 “6”	10% of 6´s	3 “6´s”	15% of 6´s
	3 “5´s”	30% of 5´s	4 “5´s”	20% of 5´s
	1 “4”	10% of 4´s	3 “4´s”	15% of 4´s
Window	5 “30´s”	50% of 30´s	8 “30´s”	40% of 30´s
	2 “20´s”	20% of 20´s	3 “20´s”	15% of 20´s
	2 “15´s”	20% of 15´s	4 “15´s”	20% of 15´s
	1 “10”	10% of 10´s	3 “10´s”	15% of 10´s
			1 “60”	5% of 60´s
			1 “45”	5% of 45´s

Table A.3: Summary of the results according to Wealth increase for the Financial sector 1st approach, 1st group.

Parameter Set	Window	P1	P2	Number of times
1	30	4	7	4
2	20	4	5	4
3	15	4	4	4
4	10	3	7	2
5	10	4	7	2
6	30	3	7	2
7	15	3	7	1
8	10	3	5	1

Table A.4: Summary of the 2nd approach for the Financial sector according to Wealth increase, 1st group.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	6 “4´s”	60% of 4´s	12 “4´s”	60% of “4´s”
	3 “3´s”	30% of 3´s	6 “3´s”	30% of “3´s”
	1 “1”	10% of 1´s	1 “1”	5% of “1´s”
			1“2”	5% of “2´s”
P2	4 “7´s”	40% of 7´s	9 “7´s”	45% of 7´s
	2 “6´s”	20% of 6´s	3 “6´s”	15% of 6´s
	2 “5´s”	20% of 5´s	6 “5´s”	30% of 5´s
	2 “4´s”	20% of 4´s	2 “4´s”	10% of 4´s
Window	4 “30´s”	40% of 30´s	7 “30´s”	35% of 30´s
	2 “20´s”	20% of 20´s	4 “20´s”	20% of 20´s
	2 “15´s”	20% of 15´s	4 “15´s”	20% of 15´s
	2 “10´s”	20% of 10´s	3 “10´s”	15% of 10´s
			2 “45´s”	10% of 45´s

Table A.5 : Summary of the results according to Wealth increase for the Financial sector 1st approach, 2nd group.

Parameter Set	Window	P1	P2	Number of times
1	30	4	7	3
2	20	4	5	3
3	30	3	7	2
4	15	3	7	2
5	10	4	5	2
6	15	4	7	1
7	15	3	5	1
8	20	4	6	1
9	15	1	7	1
10	30	4	4	1
11	30	4	6	1
12	15	3	4	1
13	10	3	7	1

Table A.6: Summary of the 2nd approach for the Financial sector according to Wealth increase, 2nd group.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	9 “4´s”	90% of 4´s	14 “4´s”	70% of “4´s”
	1 “3”	10% of 3´s	3 “3´s”	15% of “3´s”
			3 “2´s”	15% of “2´s”
P2	6 “4´s”	60% of 4´s	10 “4´s”	50% of 4´s
	3 “7´s”	30% of 7´s	7 “7´s”	35% of 7´s
	1 “5”	10% of 5´s	3 “5´s”	15% of 5´s
Window	8 “45´s”	80% of 45´s	10 “45´s”	50% of 45´s
	2 “30´s”	20% of 30´s	10 “30´s”	50% of 30´s

Table A.7: Summary of the results according to Sharpe ratio for the Health Care sector 1st approach.

PARAMETER SET	WINDOW	P1	P2	NUMBER OF TIMES
1	45	4	7	8
2	30	3	5	8
3	45	4	4	7
4	30	4	7	6
5	30	2	4	5
6	10	1	5	1
7	10	4	6	1
8	15	3	7	1
9	20	2	7	1
10	60	4	6	1
11	20	3	4	1

Table A.8: Summary of the 2nd approach for the Health Care sector according to Sharpe ratio.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	6 “4´s”	60% of 4´s	9 “4´s”	45% of “4´s”
	2 “3´s”	20% of 3´s	6 “3´s”	30% of “3´s”
	2 “2´s”	20% of 2´s	4 “2´s”	20% of “2´s”
			1 “1”	5% of “1´s”
P2	7 “7´s”	70% of 7´s	12 “7´s”	60% of 7´s
	2 “6´s”	20% of 6´s	2 “6´s”	10% of 6´s
	1 “5”	10% of 5´s	5 “5´s”	25% of 5´s
			1 “4”	5% of 4´s
Window	4 “10´s”	40% of 10´s	10 “10´s”	50% of 10´s
	3 “15´s”	30% of 15´s	5 “15´s”	25% of 15´s
	2 “20´s”	20% of 20´s	3 “20´s”	15% of 20´s
	1 “30”	10% of 30´s	2 “30´s”	10%of 30´s

Table A.9: Table A.5: Summary of the results according to Wealth increase for the Health Care sector 1st approach, 1st group.

PARAMETER SET	WINDOW	P1	P2	NUMBER OF TIMES
1	10	4	7	4
2	10	3	5	4
3	15	4	6	4
4	30	4	7	4
5	10	4	6	3
6	15	2	7	1

Table A.10: Summary of the 2nd approach for the Health Care sector according to Wealth increase, 1st group.

Parameter	Top 10	Top 10 (%)	Top 20	Top 20 (%)
P1	4 “3´s”	40% of 3´s	9 “3´s”	45% of “3´s”
	4 “4´s”	40% of 4´s	6 “4´s”	30% of “4´s”
	2 “2´s”	20% of 2´s	3 “2´s”	15% of “2´s”
			2 “1´s”	10% of “1´s”
P2	6 “7´s”	60% of 7´s	9 “7´s”	45% of 7´s
	2 “5´s”	20% of 5´s	6 “5´s”	30% of 5´s
	1 “6”	10% of 6´s	1 “6´s”	10% of 6´s
	1 “4”	10% of 4´s	4 “4´s”	20% of 4´s
Window	3 “10´s”	30% of 10´s	10 “10´s”	50% of 10´s
	3 “15´s”	30% of 15´s	3 “15´s”	15% of 15´s
	2 “20´s”	20% of 20´s	2 “20´s”	10% of 20´s
	1 “30”	10% of 30´s	3 “30´s”	15%of 30´s
	1 “45	10% of 45´s	2 “45´s”	10% of 45´s

Table A.11: Summary of the results according to Wealth increase for the Health Care sector 1st approach, 2nd group.

PARAMETER SET	WINDOW	P1	P2	NUMBER OF TIMES
1	45	4	7	3
2	15	3	7	2
3	10	4	6	2
4	30	4	7	2
5	20	2	7	2
6	15	4	6	1
7	10	2	5	1
8	10	1	5	1
9	15	3	6	1
10	10	1	6	1
11	10	3	5	1
12	15	2	7	1
13	10	4	5	1
14	20	3	4	1

Table A.12: Summary of the 2nd approach for the Health Care sector according to Wealth increase, 2nd group.

Appendix B

Appendix B.1

	Investment Fraction (%)								
Window Size	2	5	8	10	12	15	20	25	**TOTAL**
10	0	0	0	0	0	0	0	0	**0**
15	0	0	0	0	0	0	0	0	**0**
20	1	0	0	0	0	0	0	0	**1**
30	3	3	3	3	3	1	2	2	**20**
45	1	1	1	1	1	2	2	2	**11**
60	0	1	1	1	1	2	1	1	**8**
90	0	0	0	0	0	0	0	0	**0**

Table B.1: Window size for the top 5 parameter sets of each investment fraction of the Financial sector.

	Investment Fraction (%)								
P1	2	5	8	10	12	15	20	25	**TOTAL**
1	1	1	1	1	1	1	2	1	**9**
2	3	2	2	1	1	1	1	3	**14**
3	1	2	2	2	2	2	0	0	**11**
4	0	0	0	1	1	1	2	1	**6**

Tables B.2: Parameter P1 for the top 5 parameter sets of each investment fraction of the Financial sector.

	Investment Fraction (%)								
P2	2	5	8	10	12	15	20	25	**TOTAL**
4	1	1	1	1	1	1	1	2	**9**
5	1	0	0	0	0	1	0	1	**3**
6	1	2	2	3	2	3	3	2	**18**
7	2	2	2	1	2	0	1	0	**10**

Table B.3: Parameter P2 for the top 5 parameter sets of each investment fraction of the Financial sector.

	Investment Fraction (%)								
Window Size	2	5	8	10	12	15	20	25	**TOTAL**
10	0	0	0	0	0	0	0	0	**0**
15	0	0	1	0	0	0	0	1	**2**
20	1	1	1	1	2	1	1	1	**9**
30	2	2	1	1	1	1	1	0	**9**
45	2	2	1	2	2	1	1	2	**13**
60	0	0	1	1	0	2	2	1	**7**
90	0	0	0	0	0	0	0	0	**0**

Table B.4: Window size for the top 5 parameter sets of each investment fraction of the Information & Technology sector.

	Investment Fraction (%)								
P1	2	5	8	10	12	15	20	25	**TOTAL**
1	0	0	1	0	0	0	0	1	**2**
2	1	1	1	1	1	2	2	1	**10**
3	1	1	0	0	2	0	0	1	**5**
4	3	3	3	4	2	3	3	2	**23**

Table B.5: Parameter P1 for the top 5 parameter sets of each investment fraction of the Information & Technology sector.

	Investment Fraction (%)								
P2	2	5	8	10	12	15	20	25	**TOTAL**
4	1	1	2	1	2	2	2	1	**12**
5	2	2	1	1	1	0	1	1	**9**
6	1	1	1	1	1	1	1	3	**10**
7	1	1	1	2	1	2	1	0	**9**

Table B.6: Parameter P2 for the top 5 parameter sets of each investment fraction of the Information & Technology sector.

Appendix B.2

	Stock															
Window Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
10	0	0	2	0	5	4	2	0	0	1	2	4	0	2	0	22
15	0	2	1	0	3	0	1	0	0	1	5	2	1	0	0	16
20	1	2	2	0	0	0	1	0	0	1	1	1	2	1	2	14
30	6	2	1	1	0	1	4	2	0	1	1	2	1	2	2	26
45	1	3	3	3	1	2	2	3	3	0	1	0	2	2	4	30
60	0	0	0	2	0	1	0	3	4	0	0	1	1	1	2	15
90	2	1	1	4	1	2	0	2	3	6	0	0	3	2	0	27

Table B.7: Window size for the top 5 parameter sets of each stock of the HC sector.

	Stock															
P1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
1	1	2	2	4	3	2	4	4	2	1	1	0	2	1	1	30
2	2	1	0	0	2	2	2	5	2	1	3	2	3	0	2	27
3	5	3	5	5	4	2	3	1	3	4	4	3	1	1	4	48
4	2	4	3	1	1	4	1	0	3	4	2	5	4	8	3	45

Table B.8: Parameter P1 for the top 5 parameter sets of each stock of the HC sector.

	Stock															
P2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
4	3	4	2	3	0	1	2	3	1	3	0	4	5	4	2	37
5	2	1	2	2	4	3	3	3	2	2	3	1	3	3	2	36
6	2	2	3	4	1	1	2	2	4	1	2	4	2	2	2	34
7	3	3	3	1	5	5	3	2	3	4	5	1	0	1	4	43

Table B.9: Parameter P2 for the top 5 parameter sets of each stock of the HC sector.

	Stock															
Window Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
10	3	1	2	0	2	0	0	2	1	0	1	1	0	0	0	13
15	4	1	0	0	3	1	3	0	2	0	1	5	0	0	0	20
20	0	2	2	1	0	0	2	1	0	2	2	2	3	1	0	18
30	0	4	1	4	1	1	3	0	1	4	1	0	4	3	1	28
45	0	2	3	4	0	4	2	2	0	0	4	0	3	3	1	28
60	3	0	2	1	1	3	0	2	2	0	1	1	0	1	4	21
90	0	0	0	0	3	1	0	3	4	4	0	1	0	2	4	22

Table B.10: Window size for the top 4 parameter sets of each stock of the I&T sector.

	Stock															
P1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
1	0	1	3	1	1	1	0	3	1	1	3	1	0	2	0	18
2	2	0	2	2	2	1	1	1	4	2	1	2	1	3	3	27
3	4	3	1	4	2	2	6	3	3	4	1	4	4	3	0	44
4	4	6	4	3	5	6	3	3	2	3	5	3	5	2	7	61

Table B.11: Parameter P1 for the top 5 parameter sets of each stock of the I&T sector.

	Stock															
P2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	**TOTAL**
4	3	2	3	1	2	3	1	5	2	4	5	3	2	1	3	40
5	1	3	3	6	3	3	2	1	3	2	4	2	3	4	3	43
6	3	2	2	3	3	0	4	4	1	1	1	3	3	1	3	34
7	3	3	2	0	2	4	3	0	4	3	0	2	2	4	1	33

Table B.12: Parameter P1 for the top 5 parameter sets of each stock of the I&T sector.

Appendix B.3

S&P 500 INDEX										
position	Source	Wind	p1	p2	SP_S	SP_W	In S	In W	BH S	BH W
1		20	2	5	3.4	160.00	0.65	9.4	0.21	4
2	F. SECTOR	30	2	6	2.6	110.00	0.57	7.9	0.0071	0.62
3		20	1	6	2.2	100.00	0.65	9.4	0.21	4
4		10	1	5	1.7	120.00	0.61	9.6	0.31	5.5
5		10	4	4	1.6	120.00	0.61	9.6	0.31	5.5
6	HC. STOCKS	45	3	7	1.6	53.00	1.1	16	0.37	6.8
7		60	4	7	1.6	46.00	0.94	15	0.25	4.8
8		15	3	7	1.5	150.00	0.65	8.9	0.24	4.3
9		60	3	6	1.5	29.00	0.94	15	0.25	4.8
10		30	2	7	1.4	59.00	0.57	7.9	0.0071	0.62
11		20	1	5	1.3	39.00	0.65	9.4	0.21	4
12		60	4	5	1.3	33.00	0.94	15	0.25	4.8
13		15	2	4	1.2	41.00	0.65	8.9	0.24	4.3
14		20	2	6	1.1	53.00	0.65	9.4	0.21	4
15		30	3	7	1.1	47.00	0.57	7.9	0.0071	0.62
16		45	3	6	1.1	28.00	1.1	16	0.37	6.8
17		60	4	4	1.1	25.00	0.94	15	0.25	4.8
18		60	3	5	1.1	21.00	0.94	15	0.25	4.8
19		15	1	5	1	42.00	0.65	8.9	0.24	4.3
20		20	4	4	1	35.00	0.65	9.4	0.21	4
21		60	1	6	0.99	17.00	0.94	15	0.25	4.8
22		45	2	7	0.98	25.00	1.1	16	0.37	6.8
23		20	1	7	0.92	46.00	0.65	9.4	0.21	4
24		10	2	5	0.86	57.00	0.61	9.6	0.31	5.5
25		20	1	4	0.82	16.00	0.65	9.4	0.21	4
26		20	2	4	0.78	20.00	0.65	9.4	0.21	4
27		45	2	6	0.77	18.00	1.1	16	0.37	6.8
28		20	4	5	0.75	30.00	0.65	9.4	0.21	4
29		45	4	6	0.69	20.00	1.1	16	0.37	6.8
30		20	4	6	0.68	38.00	0.65	9.4	0.21	4
31		10	2	4	0.63	25.00	0.61	9.6	0.31	5.5
32		30	1	4	0.54	7.60	0.57	7.9	0.0071	0.62
33		45	4	7	0.43	13.00	1.1	16	0.37	6.8
34	F.&IT. STOCKS+G2	30	4	5	0.42	13.00	0.57	7.9	0.0071	0.62
35		60	2	5	0.38	6.80	0.94	15	0.25	4.8
36	IT. STOCKS+G2	45	4	5	0.35	11.00	1.1	16	0.37	6.8
37		15	2	6	0.32	15.00	0.65	8.9	0.24	4.3
38		30	3	6	0.31	9.20	0.57	7.9	0.0071	0.62
39		30	1	5	0.29	4.70	0.57	7.9	0.0071	0.62

40		60	2	4	0.21	3.00	0.94	15	0.25	4.8
41	IT. SECTOR+G2	45	4	4	0.17	4.60	1.1	16	0.37	6.8
42	GROUP 2	45	3	4	0.16	3.10	1.1	16	0.37	6.8
43		20	2	7	0.1	4.80	0.65	9.4	0.21	4
44		10	2	7	0.096	10.00	0.61	9.6	0.31	5.5
45	GROUP 2	30	4	4	0.083	1.90	0.57	7.9	0.0071	0.62
46	FORMER	30	2	5	0.079	1.80	0.57	7.9	0.0071	0.62
47		15	4	7	0.072	5.00	0.65	8.9	0.24	4.3
48		15	2	5	0.056	2.30	0.65	8.9	0.24	4.3
49		60	3	7	0.053	1.20	0.94	15	0.25	4.8
50		15	1	6	0.041	1.80	0.65	8.9	0.24	4.3
51		60	1	4	0.0096	0.08	0.94	15	0.25	4.8
52		45	1	7	-0.004	-0.10	1.1	16	0.37	6.8
53		20	3	6	-0.046	-1.90	0.65	9.4	0.21	4
54		15	3	6	-0.05	-2.40	0.65	8.9	0.24	4.3
55		90	4	7	-0.051	-1.10	0.35	3.6	-0.5	-7.8
56	GROUP 2	30	3	4	-0.063	-1.40	0.57	7.9	0.0071	0.62
57	GROUP 2	45	3	5	-0.082	-1.70	1.1	16	0.37	6.8
58		60	4	6	-0.082	-1.80	0.94	15	0.25	4.8
59		15	3	5	-0.12	-5.40	0.65	8.9	0.24	4.3
60		30	1	6	-0.15	-3.50	0.57	7.9	0.0071	0.62
61		30	1	7	-0.16	-4.80	0.57	7.9	0.0071	0.62
62		15	4	4	-0.18	-7.10	0.65	8.9	0.24	4.3
63		30	2	4	-0.2	-3.30	0.57	7.9	0.0071	0.62
64		10	3	7	-0.21	-21.00	0.61	9.6	0.31	5.5
65		20	3	4	-0.23	-6.00	0.65	9.4	0.21	4
66		45	1	5	-0.3	-4.30	1.1	16	0.37	6.8
67		10	4	7	-0.33	-29.00	0.61	9.6	0.31	5.5
68		60	2	7	-0.34	-6.90	0.94	15	0.25	4.8
69		90	3	7	-0.35	-7.60	0.35	3.6	-0.5	-7.8
70		15	1	4	-0.39	-8.50	0.65	8.9	0.24	4.3
71		15	4	6	-0.39	-17.00	0.65	8.9	0.24	4.3
72		60	2	6	-0.4	-6.70	0.94	15	0.25	4.8
73	HC. SECTOR	30	4	7	-0.41	-15.00	0.57	7.9	0.0071	0.62
74		10	4	6	-0.48	-33.00	0.61	9.6	0.31	5.5
75		45	1	6	-0.51	-8.50	1.1	16	0.37	6.8
76		15	3	4	-0.52	-16.00	0.65	8.9	0.24	4.3
77		60	3	4	-0.53	-8.60	0.94	15	0.25	4.8
78		90	1	7	-0.55	-9.10	0.35	3.6	-0.5	-7.8
79		10	1	4	-0.55	-17.00	0.61	9.6	0.31	5.5
80	FORMER	45	2	5	-0.57	-9.80	1.1	16	0.37	6.8
81		10	1	7	-0.6	-49.00	0.61	9.6	0.31	5.5
82		20	3	5	-0.7	-20.00	0.65	9.4	0.21	4
83		30	4	6	-0.73	-21.00	0.57	7.9	0.0071	0.62
84	GROUP 2	30	3	5	-0.75	-17.00	0.57	7.9	0.0071	0.62

85		90	2	4	-0.76	-8.20	0.35	3.6	-0.5	-7.8
86		90	3	6	-0.76	-13.00	0.35	3.6	-0.5	-7.8
87		90	4	5	-0.78	-15.00	0.35	3.6	-0.5	-7.8
88		90	4	4	-0.79	-13.00	0.35	3.6	-0.5	-7.8
89		90	4	6	-0.8	-15.00	0.35	3.6	-0.5	-7.8
90		10	3	4	-0.8	-32.00	0.61	9.6	0.31	5.5
91		10	3	5	-0.83	-45.00	0.61	9.6	0.31	5.5
92		60	1	7	-0.91	-16.00	0.94	15	0.25	4.8
93		15	4	5	-0.92	-36.00	0.65	8.9	0.24	4.3
94		45	2	4	-0.96	-13.00	1.1	16	0.37	6.8
95		20	3	7	-1	-48.00	0.65	9.4	0.21	4
96		60	1	5	-1.1	-14.00	0.94	15	0.25	4.8
97		90	2	5	-1.1	-14.00	0.35	3.6	-0.5	-7.8
98		90	2	6	-1.1	-18.00	0.35	3.6	-0.5	-7.8
99		10	3	6	-1.1	-62.00	0.61	9.6	0.31	5.5
100		90	1	6	-1.2	-17.00	0.35	3.6	-0.5	-7.8
101		10	1	6	-1.2	-63.00	0.61	9.6	0.31	5.5
102		15	1	7	-1.3	-63.00	0.65	8.9	0.24	4.3
103		10	4	5	-1.3	-65.00	0.61	9.6	0.31	5.5
104		90	1	4	-1.4	-5.30	0.35	3.6	-0.5	-7.8
105		90	2	7	-1.4	-22.00	0.35	3.6	-0.5	-7.8
106		15	2	7	-1.4	-65.00	0.65	8.9	0.24	4.3
107		90	1	5	-1.5	-15.00	0.35	3.6	-0.5	-7.8
108		20	4	7	-1.5	-63.00	0.65	9.4	0.21	4
109		45	1	4	-1.8	-18.00	1.1	16	0.37	6.8
110		90	3	4	-2	-26.00	0.35	3.6	-0.5	-7.8
111		10	2	6	-2	-81.00	0.61	9.6	0.31	5.5
112		90	3	5	-2.6	-36.00	0.35	3.6	-0.5	-7.8

Table B.13: Complete table of parameter sets belonging to the parameter space studied for the out-of-sample period and on the whole S&P 500 Index.