Bern University of Applied Sciences
Business

The Performance of Pairs Trading in Switzerland

Bachelor Thesis

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Management Summary

Although filled with uncertainties and risks, the stock market attracts many traders and investors who try to exploit it using different approaches. While many see potential for profit in forecasting if a certain stock goes up or down, a team at Morgan Stanley pioneered a way to profit from the financial markets without betting on the direction of the stock in the mid-1980s. Belonging to the category of statistical arbitrage and mostly used by hedge funds, this strategy is called pairs trading. The returns of pairs trading have been long documented in the United States, with data going back to the 1960s. However, little information is available on returns after 2015 and even less on returns in Switzerland. The question therefore arises:

Is it possible to profit from pairs trading on the Swiss Stock Exchange?

The approach taken in this thesis, called the distance method, is based on two periods, the formation and trading period. Lasting one year, the formation period is when the pairs of stocks that meet a certain criterion are selected and eventually traded in the half-year long trading period given a pre-defined rule to enter and exit a trade. Drawing on 20 years of daily data from all Swiss Performance Index stocks, the above-stated question is answered by back-testing the strategy. In the first iteration, a naïve approach to the method was taken without any restrictions. With this approach unable to achieve a positive return, a second version was developed that introduced a volume filter. All stocks are now subject to a minimum standard of volume during the formation period in order to be selected for trading. However, despite its innovations, this version was also unable to generate a positive return. This underperformance was due to a weak relationship between the chosen pairs which could be traced back to a lack of a fundamental relationship between the stocks themselves. As a solution, a new approach was developed. This version implemented a rule that only stocks operating in the same sector could be matched. Although this solution managed to achieve statistically significant returns of over zero, this profit disappeared when trading costs were subtracted, leaving the strategy mostly negative again. In response, a final version was developed that expanded on the idea of matching related companies – perhaps to an extreme – by pairing stocks representing the same company. It did so by pre-selecting all pairs that will be traded over the whole back-testing period. Although very profitable over the 20 years tested, this strategy was unable to sustain its high returns, eventually losing the edge it seemed to have in 2013.

In sum, the implementation of the distance method using swiss stocks exclusively was able to generate a statistically significant return before trading costs but was unable to do so after.

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1 Introduction

Moving from one extreme to another, the stock market is leaving everyone with a lot of uncertainty. In 2020, after the market was trending with seemingly infinite returns, optimism was abruptly crushed as the market crashed due to the spread of the COVID-19 virus and its ripple effects. With investors seeking certainty and lower volatility, a statistical arbitrage strategy called “pairs trading”, which offers returns in all market situations seems like a perfect fit.

1.1 Pairs trading

There are many different approaches to investing and trading. However, what most of these have in common is that they require a directional trade, where investments are made based on a prediction whether the stock goes up or down. Offering a different approach towards trading, an alternative strategy called statistical arbitrage does not rely on picking stocks but rather exploiting inefficiencies in the markets to generate a profit. Although there are many ways of statistical arbitrage, among the most prominent of these is pairs trading.

Pairs trading is a market neutral strategy that involves taking a long position in one security and a short position in another with the goal of profiting from mispricing in two correlated securities. To make it equity and therefore market neutral, the long and short position should completely offset each other.
The strategy itself has been researched often and used since the 1980s when it was first developed by technical researchers at Morgan Stanley under the lead of Wall Street quant Nunzio Tartaglia. A team of physicists, mathematicians, and computer scientists looked at the equities markets with the goal of finding market inefficiencies and automating them. They eventually found pairs of equities that tended to move together and traded them successfully. Although the group disbanded after two unprofitable years, the strategy remained and is still actively used by individual and institutional investors. (Vidyamurthy, 2004)

One must keep in mind that the market has drastically changed since the strategy was first introduced and traded. According to JPMorgan, currently only about 10 % of US Equity trades are being done by humans (Wigglesworth, 2019). This claim is backed up by Deutsche Bank, according to which 90 % of equity futures and 80 % of cash equity trades are done algorithmically with no human interaction (Kambayashi, 2019).
Since traditional mutual funds are not able to sell stocks short, a fund using this strategy would need to be a hedge fund. In looking at their results, it seems impossible that such anomalies still exist. Hedge funds had a hard couple of years (Uhlfelder, 2019) during which

they underperformed the stock market by half. But not all Funds were bad. With the power of algorithms behind him, Jim Simons reached the peak of quant funds by returning 66 % per year before fees on average for over 30 years (Dewey & Moallemi, 2019). This astonishing number was due to strategies based on algorithms exclusively.

Based on this short detour into the world of quantitative funds, it seems that these anomalies exist to a certain degree but are hard to detect and profit from.

1.2 Why pairs trading?

As explained in the previous chapter, pairs trading allows the trader to profit without making directional decisions in one equity. In other words, the trader will profit whether the market goes up or down, if the relationship between his two chosen stocks stands, he will profit. Pairs trading is therefore a viable strategy for all markets, theoretically able to perform and generate a positive return in every situation.

1.3 Relevance of the topic

The relevancy of this thesis and trading based on a set of mathematical rules is justified by the elimination of emotional decisions. One market player already adapting this emotionless approach to trading are so-called Quant funds (Chen, Quant Fund, 2019). Quant funds are investment funds who base their decision solely on quantitative analysis. Instead of a big fund manager calling the shots by intuition, quant funds develops numerical models and uses them to determine investment decisions for the fund.

Quantitative investing or trading has been around for over a century. The first record of this investment style being used was in the paper “The Theory of Speculation” by Louis Bachelier released in 1900 where he studied the statistical behavior of stock prices. Since then, quantitative investing has developed a great deal with introductions such as the Modern Portfolio Theory by Harry Markowitz or the Capital Asset Pricing Model by William Sharpe. (Willy Ballmann, 2005)

Since the investment style of quant funds is often very different from that of traditional funds, they are classified as alternative investments and charge a higher management fee.

quant funds can be operated as both, either a hedge fund or a normal investment fund. The difference between the two is that hedge funds offer more flexibility to the manager because they are subject to less regulation. The goal of a quantitative hedge fund is to earn an absolute return using investment styles such as arbitrage, high frequency, and market-neutral investing. Quantitative funds operated as a normal fund use quantitative methods to screen for stocks and manage risk to find an edge for the investor.

1.4 Problem definition

The financial world can look back at a rich history of continuous changes. In the very process of writing this thesis, COVID-19 turned the world as we know it upside down. The stock market dropped and gave rise once again to hedgers who may have underperformed during the bull-run since 2010. All of this is evidence that a strategy offering equity neutral returns must be tested in the Swiss markets. The country is a financial powerhouse with political stability and stocks denominated in the Swiss Franc, which is itself stable and strong (Delfeld, 2019). Within these Swiss walls, there has to be a way to profit off a strategy like pairs trading, where one is not subject to market moves but rather neutral, with no net exposure.

1.5 Research Question

The aim of this bachelor’s thesis is to find out whether it is still possible to turn a profit using pairs trading. The market has matured a lot since the early days of this strategy and is arguably more efficient with the rise of algorithmic trading as explained in Chapter 1.1. In addition, the strategy goes against the weak form of the efficient-market theory suggested by EF Fama (Fama, 1969), trying to prove instead that the market is inefficient and that there is money to be made from these inefficiencies.

All of this leads to the following question:

Is it possible to profit from pairs trading on the Swiss Stock Exchange?
And if so, will the costs of this strategy overweigh the return?

1.6 Hypotheses

Out of the research question and the follow-up question, we deduct the following hypotheses.

Hypothesis one: It is possible to achieve a positive mean return using a pairs trading strategy in the Swiss Stock Exchange.	
Null-Hypothesis (H_0)	The mean return $\bar{\mu}$ of the strategy is equal to or less than 0. $$H_0 : \bar{\mu} \leq 0$$
Alternative-Hypothesis (H_1)	The mean return μ is greater than 0. $$H_1 : \bar{\mu} > 0$$

Table 1 Source: First hypothesis which will be tested (own representation)

If the null hypothesis is rejected, a second hypothesis will be tested. Given that the raw results in the first hypothesis do not account for trading costs and the assumptions of the author as well as related research states (Do & Faff, 2012) that those costs will have a significant impact on profits and even eliminate them, a second hypothesis will be tested.

Hypothesis two: It is possible to achieve a positive mean return using a pairs trading strategy on the Swiss Stock Exchange after deducting trading costs.	
Null-Hypothesis (H_0)	The mean return after fees $\bar{\mu}_f$ of the strategy is equal or less than 0. $$H_0 : \bar{\mu}_f \leq 0$$
Alternative-Hypothesis (H_1)	The mean return after fees is greater than 0. $$H_1 : \bar{\mu}_f > 0$$

Table 2 Source: Second hypothesis which will be tested (own representation)

A t-test will then be conducted to test whether the returns of the strategy are significantly different. A p-value below 5 % is required to reject the null hypothesis making the significance level α = 0.05 (5 %), which is the state of the art in related literature (Statistics Solutions, 2020).

1.7 Overview of the structure

This Chapter introduced the topic of pairs trading and asked the question, if it is possible to profit on the Swiss Stock Exchange using pairs trading. After explaining the theory and literature of pairs trading in Chapter 2, Chapter 3 will focus on the methods used to answer the research question. The results are then presented in Chapter 4 and finally, discussed in Chapter 5.

2 Theory

This chapter will go into the literature of pairs trading and explain the theory behind the concepts used to understand the strategy.

2.1 Literature review

Pairs trading has been the subject of much analysis. Two important papers that open doors to further readings on the topic are "Statistical arbitrage pairs trading strategies: Review and outlook" by Christopher Krauss (2017) and "The profitability of pairs trading strategies: distance, cointegration, and copula methods" by Hossein Rad, Rand Kwong Yew Low and Robert Faff (2015). Both highlight different approaches to pairs trading and compare them using data from the US equity market.
These papers explain many different methods, both traditional and newer with newer strategies relying heavily on advanced mathematics. To prevent this thesis from straying beyond its scope, one approach named the distance method by Gatev, Goetzmann and Rouwenhorst (2006) be explained and tested later.

2.1.1 Distance Method

The distance method is an approach to pairs trading first devised in a Yale ICF Working Paper (Gatev, Goetzmann, & Rouwenhorst, 2006). Due to its simplicity and clarity, it is the most extensively covered pairs trading method. It has also proven profitable over multiple markets, asset classes and time frames. However, whereas the method showed good returns before 2002, it was largely unprofitable after that accounting for trading costs (Do & Faff, 2012).

2.1.2 Cointegration approach

Recent research has focused on developing advanced mathematical methods while continuing to analyze historical prices. One of the most notable additions to the literature was the introduction of the cointegration approach. This approach was first introduced by Vidyamurthy, 2004, who used the Engle and Granger (1987) error correction model representation to trade pairs.

2.1.3 Other approaches

Diving even further into the mathematical side of pairs trading means engaging with approaches such as time series, stochastic, PCA, coupla, and Machine Learning. The authors of frameworks such as the time series approach take different views from the previously mentioned literature. They ignore the formation period and expect the reader to already have a set of pairs in mind to trade and focus fully on the execution and optimization of the trades (Elliot, Van Der Hoek, & Malcom, 2005).

2.2 Short Selling

To understand this trading strategy fully, we must know what short selling is. A financial transaction that allows the speculator or investor to profit from the decline of a stock, it is a tool for speculating on stocks that are highly probable to fall but also for hedging against downside risk.

Here is a rundown for how it works. The financial institution or professional goes to their broker or bank and asks, for 10 stocks of company X. They receive the stocks and immediately sell them on the open market for a certain amount of money. Given that they owe these 10 stocks, they must eventually buy them back on the open market and return them to the financial institution. Their goal is to sell the stocks at a high price and buy back the same amount of stocks at a lower price to return them again. The difference in price is their profit. (The Montley Fool, 2019)

2.3 Volume of trade

Volume is the quantity of shares traded during a given period. In this thesis, it is the number of shares that switched hands from buyer to seller on a daily basis for a given stock (Chen, Volume of Trade, 2020). For trades to execute immediately without moving the price, this value should be reasonably high. If there are not enough people selling or buying the share or doing so at a price different than would be expected, it would be bad for our strategy. We rely on trading the chosen stocks at the time and price the trading signal was generated. Of course, as later explained in Chapter 3.2.4 on trading costs, some slippage is expected, but low liquidity / volume stocks could make trading them impossible.

2.4 Chapter conclusion

Explaining multiple approaches in literature towards pairs trading, the distance method introduced by Gatev, Goetzmann & Rouwenhorst in 2006 will be used to answer the question if it is possible to profit in swiss stock markets using this strategy. The concepts of short selling as well as volume of trade have been introduced, which will be important to know in the next Chapter.

3 Methodology

This thesis is structured as an empirical test (The Business Professor, 2020) in which the final three steps will be repeated multiple times.

It begins by identifying the problem which the thesis seeks to solve that pairs trading has never been tested in Switzerland before and the question if returns, as shown in related literature, are still achievable today. More explanation of the observations can be found in Chapter 1 where the topic and main problem are discussed.

The next step, induction, involves the development of a hypothesis based on the observations made. Likewise found in Chapter 1, this hypothesis suggests that a trader can profit from an assumed relationship between the stocks in the Swiss Performance Index.

After the two initial steps are done, the testing design, testing itself, and evaluation begins. These steps will be iterated x-times since new results lead to new approaches to the strategy itself.

The loop starts with the third step in the overall structure, deduction. In this step, the test is defined and created with the aim of checking the hypothesis and can be found in Chapter 3.2 on back-testing.

The actual testing starts right after designing the test. Testing does not constitute its own chapter but is rather the execution of the deduction phase.

The last step, evaluation, is taken up in Chapter 4, which explains the results and makes observations. The evaluation phase produces new insights that must be tested in the future starting a new iteration by deducting a new test design. The process is one of trial and error: seeing if the designed back-test works as expected, analyzing the results, judging if they make sense, and then developing additional rules for the strategy based on further literature. Overall, four versions of the strategy will be tested and therefore four iterations $(x = 4)$ will be completed.

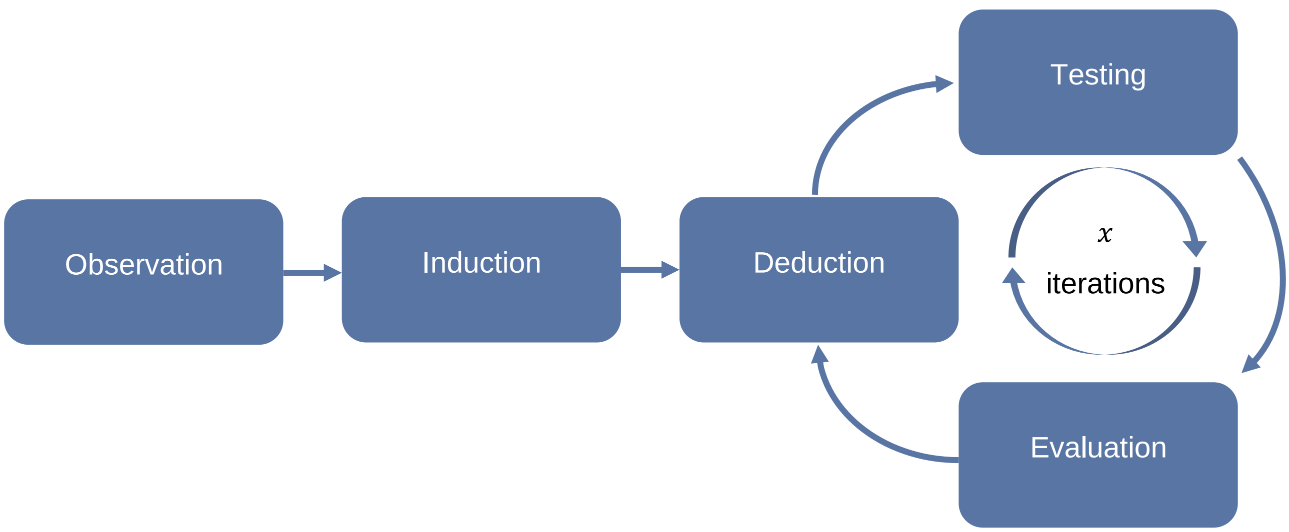

Figure 1 Source: Process of empirical research (own representation in the style of The Business Professor (2020))

3.1 The trading strategy

The approach to pairs trading used in this thesis is the distance method. Developed by Evan Gatev, William N. Goetzmann, and K. Geert Rouwenhorst in 1998, it is divided into the formation period and the trading period. The formation period lasts for 12 months and is used to form the pairs that will be traded in the next period. The trading period, which follows the formation period, lasts for 6 months and involves trading those pairs on the market according to a set of rules that will be explained in chapter 3.1.2. The time of both periods are chosen arbitrarily and are taken from the original strategy (Do & Faff, 2012). A visual representation of the process over 20 years of back-testing can be found in Table 3. Since the whole strategy progresses semiannual, there will not be any gaps in trading as trading is done continuously over the 38 periods.

	Year 1		Year 2		Year 3		…	Year 20	
Period 1	Formation		Trading				…		
Period 2		Formation		Trading			…		
Period 3			Formation		Trading		…		
Period 4				Formation		Trading	…		
Period 5					Formation		…		
…	…	…	…	…	…	…	…	…	…
Period 38							Formation		Trading

Table 3 Source: Timeline of the back-test representing formation and trading periods (own representation)

3.1.1 Formation period

The goal of the formation period is to find pairs to trade during the trading period. The stock universe used in this thesis is the Swiss Performance Index. At the times of writing, this universe includes 215 equities which are primarily listed on the SIX Swiss Exchange. To be included in the SPI, all primarily listed equities are further filtered by only taking stocks with a free float of over 20 % and excluding investment companies. (SIX Swiss Exchange Ltd, 2020)

Using these 215 stocks within the SPI for this strategy may not seem like an ambitious undertaking, but once all stocks are paired with each other the number of pairs that can be traded quickly grows. To calculate the number of possible pairs, we can use the binominal coefficient.

$$\binom{n}{k} = \frac{n!}{k!\,(n-k)!} \tag{1}$$

Where

n = total number of stocks in the dataset

k = amount to choose from in the dataset

According to this formula, there is a total universe of 23’005 unique pairs to trade.

Out of all these possible pairs, only a few will be considered for the trading period. Using the same approach as Gatev et al. (2006), the goal of this step is to find pairs that “move together.” The first approach tested will be an unrestricted one: pure decision making upon the pairs moving together in the past year. Later, a volume filter will be introduced to cut off stocks with barely any trading volume.

Just like in the original paper, an additional method is used where only stocks within the same sector are paired together. This additional filter assumes that companies that operate in the same sector are subject to similar influences and therefore “move together.”

In the last test, the pairs will be handpicked and then traded according to the same rules as the strategies before. Pairs are built by identifying companies which offer multiple share types such as preference and ordinary shares and pairing them. Since they represent a stake in the same company but with different rights, they are without a doubt related.

a) Unrestricted baseline strategy

The first step of the formation period is to create pairs. In this step, every stock within the SPI will be paired with all the others, producing a total of 23’005 possible pairs.

From this list of possible pairs, a chosen number are selected for trading during the trading period – preferably two stocks that appear to have similar price movements during the formation period.

We continue by normalizing each pair, by starting both stocks with a value of one, tracking percentage changes throughout the period. After subtracting one stock from the other, we are left with the spread between the two. This spread is then used to find out, which pairs are the most suitable to trade with the Sum of Squared Deviations SSD (Gatev, Goetzmann, & Rouwenhorst, 2006). SSD is a regression analysis which determines the dispersion of data points. To find the SSD for one pair, the mean of the spread during the formation period $\bar{s}$ gets subtracted from the daily spread between two specific stocks s_t and eventually squared. The SSD is then found by adding together the before calculated values over n days, where n is equal to the amount of trading days during a given formation period.

$$SSD = \sum_{t=1}^{n} (s_t - \bar{s})^2 \qquad \textbf{(2)}$$

The pairs with the lowest Sum of Squared Deviations during the 12-months formation period get traded in the following 6-months trading period. The number of pairs chosen will be 2, 5 and 10, to see if more pairs add more security and therefore less drawdown to the strategy.

b) Baseline strategy with a volume filter

To ensure all our trades get executed, we include a volume filter in this version of the strategy. The volume of trade outlined in the theory chapter of this thesis is an important factor in picking pairs of suitable stocks to trade. If a stock is barely traded, a simple market buy order can cut through the thin order book and change the price of the stock. This development would greatly damage the strategy because the prices get distorted which the SSD calculations are solely based on. To work around that problem, this sub-chapter introduces a filter for volume traded, excluding stocks with insufficient volume.

The first step in finding a rule was to make volume comparable. Given that volume of trade simply measures how many shares are traded each day, stocks with a lower value are traded more often than others. The stock of Chocoladefabriken Lindt & Sprüngli AG (LISN) is trading at a value of over CHF 60’000.- a share since 2017 and therefore cannot be directly compared to a stock like Nestle SA (NESN), which was trading at around CHF 80.- in 2017. Of course, the simple volume of shares traded will be far higher for NESN than for LISN. In order to find a comparable number, the volume of every stock is modified daily to find to find the adjusted Volume AV_t by,

$$AV_t = \left(\frac{O_t + H_t + L_t + C_t}{4}\right) \cdot V_t \qquad \textbf{(3)}$$

Where:
O_t = price at which the stock opened on day t
H_t = highest price on day t
L_t = lowest price on day t
C_t = price of the last share traded on day t
V_t = number of shares traded during day t

The first part of the equation is used to derive the daily average price of the stock. It is then multiplied by the number of shares traded during the day to produce a share price adjusted volume that can be directly compared to other stocks.

It is still difficult to find an appropriate cut-off value because the minimum number of shares traded is 0 and the distribution exhibits a heavy positive skew and fat tails with a kurtosis of 62.98, meaning it is heavily leptokurtic. Measuring standard deviation is no use because the distribution varies too much from a normal one to be suitable.

Analyzing the boxplot of the daily mean volume of all stocks provides some valuable insight into the distribution of volume. The high skew and kurtosis can be seen in Figure 2. It indicates clearly, that a different approach than standard deviation must be found.

Figure 2 Source: Distribution of daily mean volume (own representation)

Given that too much volume is not a problem, we will only focus on defining a low value. A stock must have a higher mean value during the formation period than the value defined, in order to be analyzed further. The chosen cut-off value is the lower end of the 1st quartile. This cuts off the lowest 25% of volumes and effectively means that in order to be traded, the stock must have an average daily adjusted volume of higher than that. The quartile is calculated at the beginning of every trading period based on the data provided during the formation period.

c) Sector restricted pairing

After testing the baseline approach and adding an additional volume filter to it, we try to determine whether it is possible to add value to the strategy by pairing stocks from the same sector with each other exclusively.
Because we still want a sizeable dataset for each sector, we will focus only on Switzerland's four main ones: Health Care, Consumer Goods, Financials, and Industrials.

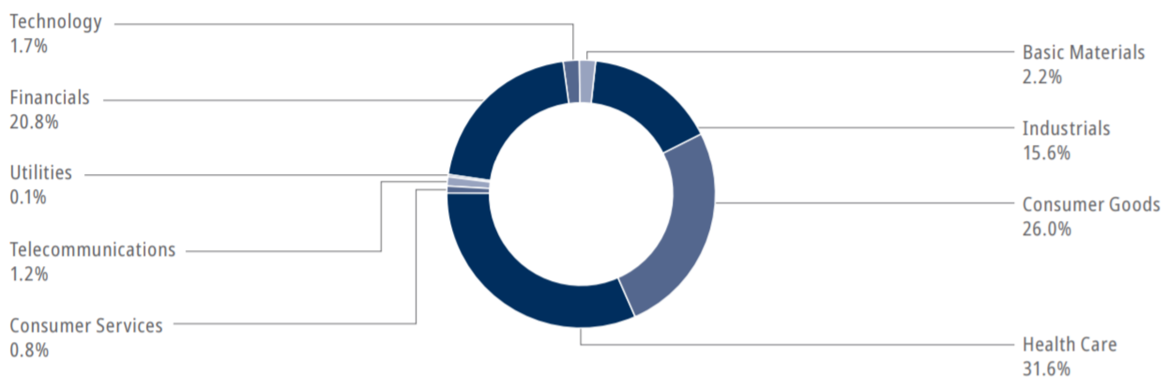

Figure 3 Source: SPI Sector overview **(SIX, 2017)**

Within each sector, the same baseline process with a volume filter, as outlined in Chapter 3.1.1.c, will be used to determine which pairs of stocks will be traded during the trading period. As seen in Figure 4, the pairs will be divided at first into the chosen sectors before being further filtered to build a final portfolio.

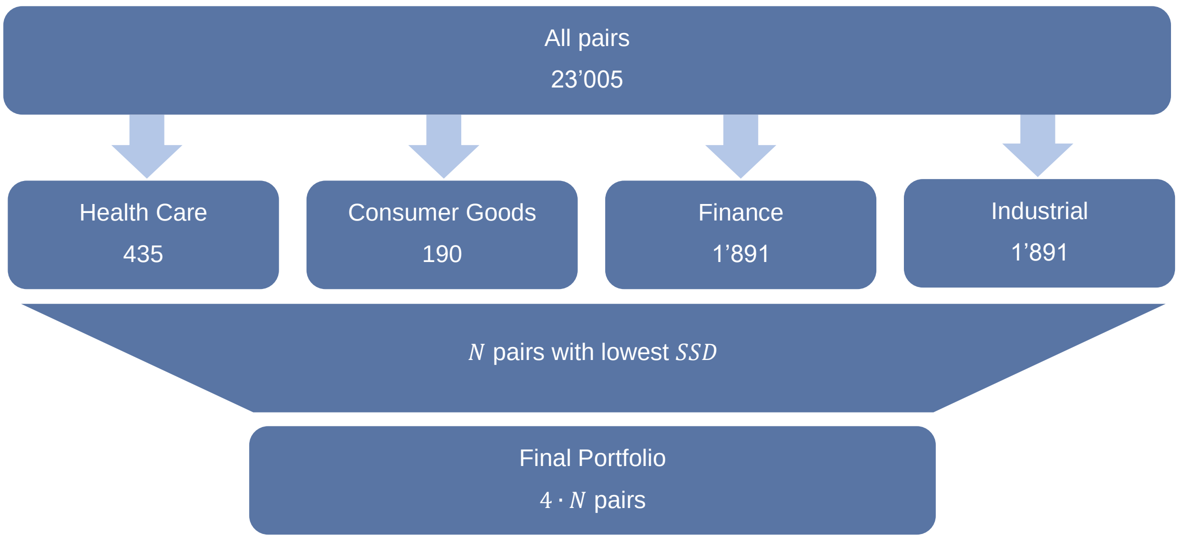

Figure 4 Source: Process of finding tradable stock pairs (own representation)

The amount of stocks, N, chosen after filtering out low volume ones will be 2, 5 and 10. In the example of the top 10, this would lead to 40 stock pairs available for trading during the trading period. The idea behind this version of the strategy is that companies operating in the same sector are subject to similar influences. Finance companies are all bound together by the state of the economy, the condition of the real estate market in their active-business, new financial laws, and so on. Because they are influenced by the same factors, they face reduced risk aside from that of the micro economical kind.

d) Pre-selection of stocks with multiple listings

Although this last type of adaption could lead to a selection bias, the strategy is typically used with stock that are fundamentally the same. One such example explored in related literature is GOOG and GOOGL. Although both are shares of Alphabet Inc., GOOGL represents class A shares with voting rights and GOOG represents class C shares without such rights (Wu, 2015). Because both classes have the same underlying company fundamentals, the main reason for price differences is the value of the voting rights. With a stock pair like this one, a trader does not need a formation period as discussed before but only the trading period.
In the SPI, there are a few similar tradable relationships that might be exploitable with the pairs trading strategy. The ones chosen to be traded during the whole 20-year back-testing period are listed below.

LISN & LISP

This is the first obvious pair of stocks that will be traded by this strategy. Both represent shares of Chocoladenfabriken Lindt & Sprüngli AG, but with different rights. Whereas LISN shares do have voting rights, the LISP participation certificates do not (Lindt & Sprüngli, 2020). Because both shares are actively traded on the Swiss Stock Exchange while backing the exact same company, they are a perfect pair for pairs trading.

UHR & UHRN

Almost exclusively funded by equity, the Swatch Group offers two different share options: UHR, which is their bearer share; and UHRN, which represents the ticker of their registered shares.
The bearer share is listed in the Swiss Market Index, making it the more obvious choice for people wanting to invest in the Swatch Group, and likely the reason why it continues to be traded at a premium compared to the registered share (Züger, 2018). Although the two share types trade at different prices and historically seem divergent, they share the same underlying company. The fact that every half year the prices are once again normalized could make up for the divergence over the long duration.

SCHN & SCHP

The two stocks represent the registered share and participation certificate of Schindler (Schindler Holding Ltd., 2020). As with Chocoladenfabriken Lindt & Sprüngli AG, they are both traded on the SIX Swiss Exchange with participation certificate holders unable to vote or attend the Annual General Meeting.

RO & ROG

Divided up in bearer shares and participation certificates, Roche Holding AG is likewise similar to the stock pairs listed before. While holders of the participation certificate are not able to vote, the bearer shareholders are (Roche Holding AG, 2020).

3.1.2 Trading Period

Once all suitable pairs have been found, trading begins immediately for a period of 6 months. All trading rules are pre-specified. The first step here is normalizing the prices of both stocks again in the same way explained in Chapter 3.1.1.a.

The whole process of buying and selling is then based on cross-overs and cross-unders. If the spread s_t of the normalized prices crosses above a certain threshold, which is below the mean $\bar{s}$, the spread will be bought. If it crosses below the threshold, above the mean $\bar{s}$, the spread will be sold.

The threshold is defined as a multiple of the sample standard deviation during the formation period (Gimeno, 2020).

$$\sigma_s = \sqrt{\frac{\sum_{t=1}^{t}(s_t - \bar{s})^2}{n-1}} \qquad \textbf{(4)}$$

Where:

n = the number of observations in the given formation period

s_t = return on day t

$\bar{s}$ = the mean value of the returns during the formation period

To get robust results, four multiples have been chosen to generate four different versions of each strategy. These multiples define how narrow or wide the entry thresholds will be with 0.5 representing half the standard deviation σ_s and 2.0 double the standard deviation σ_s above and below the mean. Incrementing equally, this leads to multiples of 0.5, 1.0, 1.5 and 2.0. Once the spread of the two chosen stocks crosses into a multiple of standard deviation above and below the mean, a trade will be opened with the goal that the spread will revert to the historical mean. In other words, the opened trades will be closed with profit once they cross the mean. If the observed relationship breaks and the spread crosses back into the zone between the thresholds but ends up outside of it when the trading period closes, the trade is closed at a loss.

3.1.3 Example

This subchapter provides an example of a full cycle of the distance method, from selecting the two stocks to trading them. Two companies operating in the same industry have been chosen: UBS Group AG (UBSG) and Credit Suisse Group AG (CSGR).

If we look at the formation period in the year 2014, meaning from January 1, 2014 to December 31, 2014, and normalize the prices, one can already guess that there might be a relationship between the two, as seen in Figure 5. Their overall trends seem to be similar with local divergence.

Figure 5 Source: Formation period of UBSG and CSGR in 2014 (own representation)

To further analyze this relationship, the scatterplot in Figure 6 is helpful.

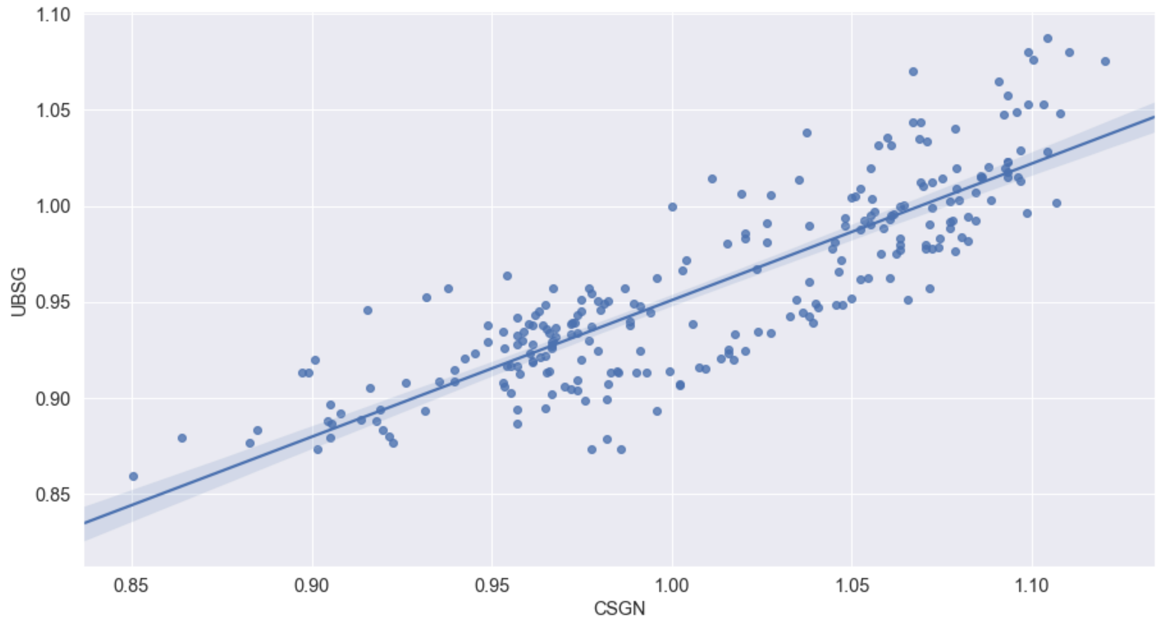

Figure 6 Source: Relationship between UBSG and CSGR in a scatter plot (own representation)

The scatterplot confirms what was speculated before: that Credit Suisse Group AG and UBS Group AG have a positive correlation. To quantify this relationship, we can calculate the sum of squares statistic SSD used to rank the different pairs during the formation period, which returns a value of 0.7507. A low value, like the one calculated, indicates that the difference between the normalized adjusted closing prices of Credit Suisse Group AG and UBS Group AG offer low variability in the observed time period, meaning they are a perfect target for this trading strategy.

Once the decision is made to trade this pair, the trading period commences. At the start of this period, we once again normalize the closing prices and calculate the standard deviation as well as the mean of the formation period.

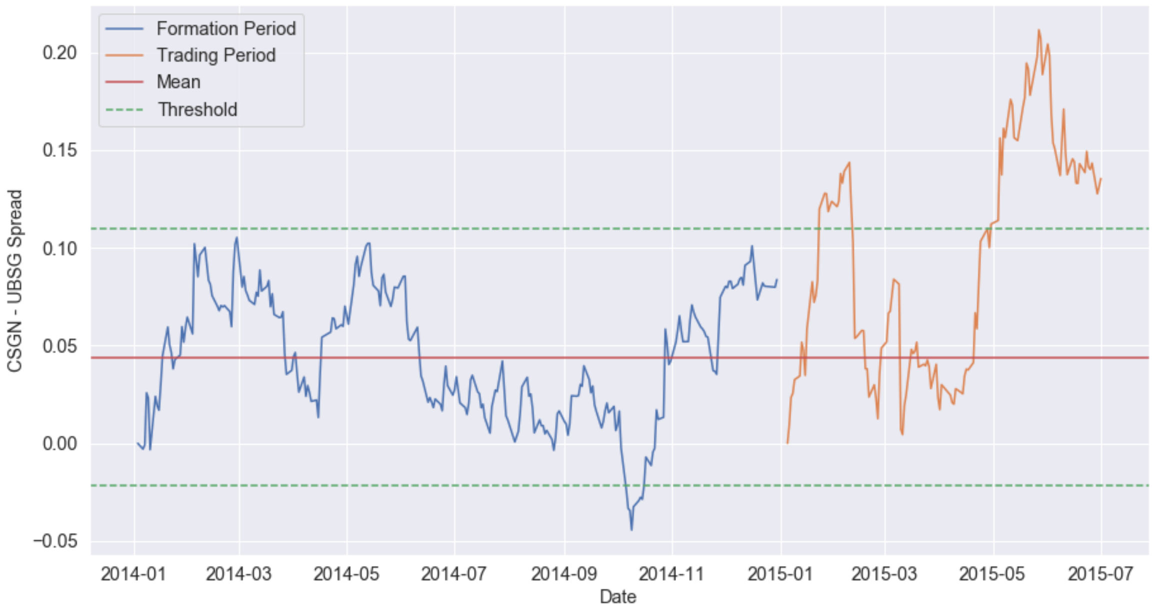

Figure 7 Source: Full representation of a trading cycle (own representation)

The threshold used in this example is two standard deviations from the mean calculated during the formation period. The process of normalizing the stock prices at the beginning of each period can be observed in Figure 7 with the value of the spread starting with zero both times. Given that a trade is only opened when the spread crosses the threshold, only two trades were made.

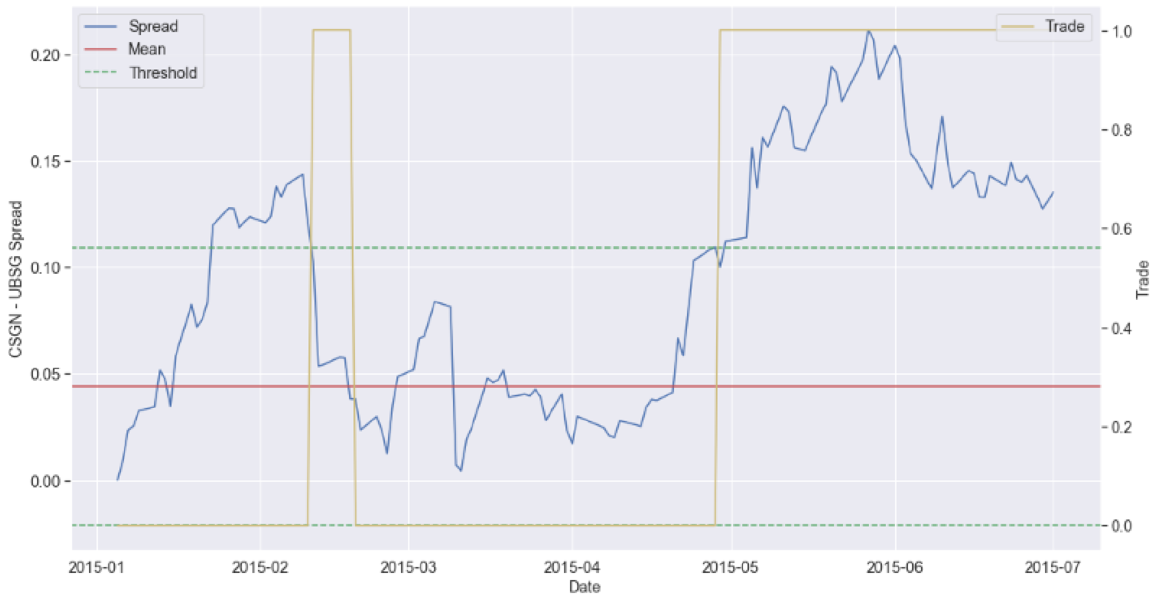

Figure 8 Source: Trade justification for a trading cycle (own representation)

The first trade happened in the middle of February 2015 and closed short after. With the spread converging back to the mean shortly after entering the trade, it managed to generate a nice return. This quick mean reversion is a perfect example of what a successful trade using the distance method looks like. An example of what an unsuccessful trade looks like happened at the end of April 2015. We opened the trade because of a short dip while the spread was trending up, and it did not revert to the mean until the end of the trading period, meaning we would have had to close this trade at a loss and move on to the next trading period.

Let's take a closer look at what happened with the first trade and what will happen once we enter it.

Figure 9 shows the spread at the beginning of the trading period, which is high with a value of 0.12, and increases to over 0.14 in the following days. This spread is calculated by subtracting the closing prizes of Credit Suisse Group AG from that of UBS Group AG, and therefore diverges more from zero if the difference between these two widens. The larger drop of UBSG propelled our system to enter a trade, buying CSGN shares and short-sell UBSG shares. In short, we make a profit if CSGN rises or if UBSN falls. Both stocks started rising in price while CSGN gained more than UBSG eventually lowering the spread between the two stocks to 0.04 and leaving us with a profit in the end.

Figure 9 Source: Return calculations of a single trade (own representation)

The two trades we entered were short selling UBSG and buying CSGN stock. The return of both trades before fees shows the idea behind this strategy: win more in one leg than you lose on the other.

Symbol	Direction	Adj. Price	Adj. Price	Return
CSGN	Long	15.46	17.99	+16.36 %
UBSG	Short	12.15	13.09	-7.18 %
Total				+9.18 %

Table 4 Source: Returns of a pairs trade (own representation)

In looking at overall performance of this trading period in Table 4, we can see how profitable the strategy can be even with the second trade ending in a loss. Taking the second trade into account, the pair generated 6.11 % total return over this 6-month period.

	Duration in months	Total Return	Max. Drawdown
Overall	6	6.11 %	-8.38 %

Table 5 Source: Return metrics of a pairs trade (own representation)

Through this example of one full formation and trading cycle, we showed the inner workings of the strategy and the way it generates returns. One must remember that during the formation period all SPI stocks get taken into consideration to be traded during the trading period. After a filtered list of preferred pairs of stocks have been created, they will all be traded using the methodology in the example.

3.2 Back-testing

What was explained in the example in Chapter 3.1.3 is called Back-testing, which is simply a process used to test trading rules on historical data. In our case, it involves looking at historical data to see how the strategy would have performed if all trading decision were made according to the pre-defined strategy. In this thesis, this process has been fully automated with the programing language Python. The code that was used can be found in the appendix.

3.2.1 Workflow

The workflow starts with data collection, for which a specialized tool provided by Thomson Reuters has been used. The data itself is further explained in Chapter 3.2.2.
Written in pseudo-code, the algorithm will go through the following steps for each cycle within a back-test:

Read the data
Normalize it for the formation period
Calculate SSD
Sort by smallest SSD value and extract the top n amount of pairs
Calculate the entry and exit points using the data from the formation period
Normalize the data for the trading period

At this point, the program has a data frame saved with all pairs that will be traded as well as the entry and exit values for each pair. This data will then be passed on to the back-tester, which will go through every day of trading data iteratively and store daily percentage returns on open trades. The percentage returns are calculated for both long and short positions separately. At the end of the trading period, we once again go through every day of trading data and take the daily mean return of all trades made over all pairs, which leaves us with the overall performance of the portfolio traded during this trading period. The whole process then begins again with finding pairs and testing them for the next trading period.

3.2.2 Data

The data is provided by Thomson Reuters DataLink on an End-of-Day basis. The values available are daily opening, low, high, and closing values as well as the volume traded that day. The earliest data point was recorded on January 5, 1987, but the back-testing of the strategy will start in January 2000. The reason behind starting in January 2000 being, that there is little information available and not many stocks have data that date to before 2000. Survivorship bias is not accounted for and should be investigated further in future research.

3.2.3 Benchmark

To compare the pairs trading strategy with something else, this sub-chapter chooses a benchmark. Given that this strategy allows for long and short positions, an appropriate benchmark should do so as well. In addition, given that the investment universe is based completely on Swiss equities, the benchmark should only reflect Swiss equities as well. These two requirements are hard to fulfill because a long-short fund only trading in Switzerland is difficult if not impossible to find.

Ultimately the long-only SPI Index was chosen as a benchmark. It is comparable to pairs-trading in Switzerland to a certain degree, since all equities used in this thesis are also held in the SPI Index itself. Given the decision to find a benchmark with which to compare the strategy to was made, the overall goal of the thesis is to be profitable, but not to beat the benchmark.

3.2.4 Trading costs

Even if the strategy should technically generate returns, the profits are often eaten away by trading costs. It is not only the cost of the transaction that must be considered, but also the market impact and short-selling costs.

Do & Faff did extensive research on the subject and came up with a definitive distinction between commissions, market impact, and short selling costs.

Whereas commissions and market impact can be calculated simply and deducted at the time of the trade, short selling depends on the length of the position and the ease with which the stock can be borrowed, making it hard to estimate.

With easier access to trading and more trades happening electronically, the costs were substantially slashed in recent years. Do & Faff (2012) found out that commissions were on average 34 bps for the period from 1963 to 2009, though with a clear trend toward lower costs. While they were above 20 bps until 1990, they lowered drastically in recent years, reaching their lowest of 7 bps in 2007. (Do & Faff, 2012)

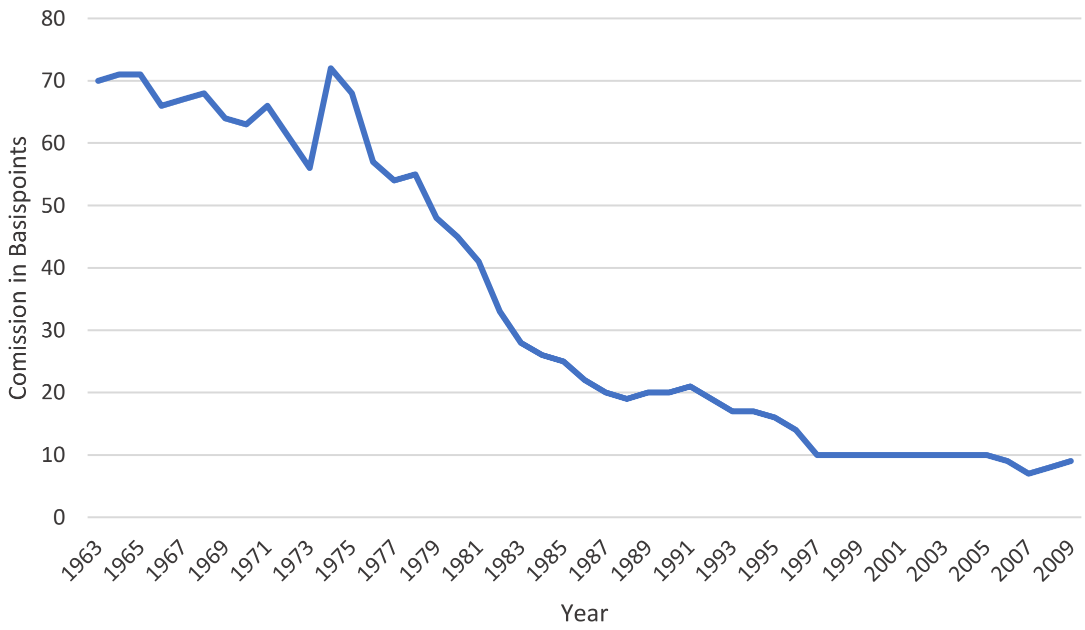

Figure 10 Source: Evolution of trading costs (Do & Faff, 2012)

Comparing those research results and the 2019Q4 cost review of Virtu Financial, one of the largest providers of financial services, it is safe to say the downtrend continued. The company reported an average trading commission of 4.7 bps in Europe excluding the UK in 2019 (Virtu Financial, 2020).

As mentioned before, we also must add market impact such as the bid – ask spread and the liquidity of the stock traded. In their research, Do & Faff found that between 1989 and 2009 the average market impact on a pairs trade was 20 bps (Do & Faff, 2012).

Adding the previous and more recent average of commission costs of 7 bps to the market impact of 20 bps amounts to a total one-way cost of 27 bps.

Short-selling costs are now added to the above estimation. For the sake of simplicity, we chose a constant fee of 0.6 % per year. This amount is based on the research by D'Avolio (2002) in which he figured out the average cost of borrowing in 2000-2001 was 0.6 %.

3.3 Chapter conclusion

This chapter introduced the overall methodology of this thesis and outlined the process by which the stated hypotheses will be tested. Specifically, it explained the strategy that we adopted, starting with the baseline approach then moving to a volume filter, a sector dependent approach and finishing with hand-picked pairs. To better understand the trading strategy's process, it then furnished an example by describing a whole round trip of the strategy, from the formation period to the actual trading of the chosen pair. Finally, it explained how the back-test of this strategy takes place, what kind of data is used, and how trading costs are calculated for the final comparison if the method is still profitable even after costs.

4 Results

This chapter goes over how the results were calculated, what they actually amounted to and explains the process of how the naïve approach evolved into different versions of the strategy.

4.1 Risk and return measurements

To calculate the returns in the back-test, we used the return on committed capital at the beginning of the trading period. Another method explained by Gatev, Goetzmann, & Rouwenhorst (2006) uses the return on actual employed capital, which would mean not committing any capital to pairs with no trades. For this method to work, we would need to be able to transfer capital between traded pairs instantly. While doing so might be possible for hedge funds with a fleshed-out infrastructure that are able to quickly de-invest capital from pairs and invest in new ones that are traded, this thesis will stick with committed capital. To calculate the daily portfolio returns r_p, the return of each pair r_i will be divided by the total amount of pairs chosen N to trade during that period. The daily portfolio returns are therefore calculated by,

$$r_p = \sum_{i=1}^{N} \frac{r_i}{N} \qquad \textbf{\textit{(5)}}$$

4.1.1 Annual return & volatility

The annual return r_a and volatility σ_a calculations are derived from the portfolio return r_p stated in formula ***(5)***. The daily portfolio returns r_p are annualized by,

$$r_a = \left(\frac{P_T}{P_0}\right)^{\frac{1}{Y}} - 1 \qquad \textbf{\textit{(6)}}$$

Where:
P_T = the final value of the portfolio
P_0 = the starting value of the portfolio
Y = years passed between P_0 und P_T

While the annual standard deviation σ_a is approximated by multiplying the sample daily standard deviation σ_s calculated by equation ***4*** by the square root of annual trading days T.

$$\sigma_a = \sigma_s \sqrt{T} \qquad \textbf{\textit{(7)}}$$

4.1.2 Maximum Drawdown

The maximum drawdown is a risk measure that gives the observer a sense of the worst loss that happened in the time tested. It is a calculation that measures the drop from peak to trough. The goal of our strategy would be to ensure this measure is as low as possible.

4.1.3 Sortino ratio

The Sortino ratio was developed by Frank A. Sortino to capture the return of an asset or portfolio compared to its downside risk. While the otherwise popular Sharpe ratio accounts for both upside and downside volatility, upside volatility is not looked at as a problem because it means the strategy is gaining money. To determine the Sortino ratio, the downside volatility σ_D must be calculated by (Gimeno, 2020),

$$\sigma_D = \sqrt{\sum_{i=1}^{T} \frac{\left[Min(\bar{\mu} - r_f,\ 0)\right]^2}{T}} \tag{8}$$

Where:
$\bar{\mu}$ = mean of daily returns
r_f = daily risk-free return

Once the downside volatility σ_D is known, it is inserted into the following calculation to get the Sortino ratio SR,

$$SR = \frac{\bar{\mu} - r_f}{\sigma_D} \tag{9}$$

The goal is to achieve a high ratio, meaning high returns over the risk-free rate of return compared to negative volatility. The risk free return r_f used in the calculations is based on a yearly 1.90 %, which is the mean yield of a Swiss government 10-year bond (Trading Economics, 2020) for the period from 2001 to 2020.

4.1.4 t-statistic

The last measurement is the one sample, one-tailed t-test. This t-test is used to determine whether there is a statistical difference between the mean of the strategy tested and zero. Given that it is a one-tailed test, it only evaluates effects in one direction. It is therefore also known as a directional test compared to the two-tailed t-test. The following calculation will be used to determine the t-statistic t (Kaufman, 2019).

$$t = \frac{\bar{\mu}}{\bar{\sigma}/\sqrt{T}} \tag{10}$$

Where:
$\bar{\mu}$ = mean of daily returns
$\bar{\sigma}$ = standard deviation of daily returns
T = amount of trading days

The higher the t-value t, the bigger the difference between the mean of the strategy and zero. With the degrees of freedom at 4'798 and the required significance level at $\alpha = 0.05$, it should also surpass 1.645 for the null hypothesis to be rejected.

After we determine the t-value t, we then can calculate the probability of observing the test statistic under the null hypothesis (Statistics Solutions, 2020) where t^* is the critical value of a t-distribution with $(n-1)$ degrees of freedom.

$$p = \mathrm{P}\,(t^* > t) \tag{11}$$

This test allows us to see whether any values fall in the upper tail of the normal distribution curve and if so, show how much higher than zero are the strategy returns. With the help of the p-value, the result gets validated and checked for statistical significance. The lower this probability value is, the more evidence there is that the null hypothesis can be rejected.
In this test, a p-value of lower than 5 % must be achieved to be considered statistically significant.

4.2 Unrestricted strategy results

The first test was made on the full data set of all SPI stocks without any restriction. The decision of which stocks to trade was made solely based on the sum of squared differences described in the distance method in Chapter 3.1.1.a.

s	SSD	r_a	σ_a	SR	MDD	t	p
0.5							
	Top 2	-2.51 %	10.56 %	-.35	-47.72 %	-.782	.434
	Top 5	-1.09 %	5.96 %	-.27	-27.58 %	-.666	.505
	Top 10	-0.16 %	5.58 %	-.17	-17.42 %	-.001	.499
1.0							
	Top 2	0.05 %	7.46 %	-.11	-32.02 %	.190	.999
	Top 5	0.76 %	5.27 %	-.05	-10.56 %	.740	.459
	Top 10	-0.29 %	4.65 %	-.19	-19.36 %	-.167	.868
1.5							
	Top 2	-1.36 %	6.68 %	-.29	-44.46 %	-.751	.453
	Top 5	-0.27 %	5.07 %	-.18	-22.26 %	-.119	.905
	Top 10	-0.41 %	5.17 %	-.20	-15.14 %	-.234	.815
2.0							
	Top 2	1.00 %	5.72 %	-.02	-19.43 %	.883	.377
	Top 5	0.43 %	4.80 %	-.10	-10.74 %	.498	.619
	Top 10	-0.35 %	4.58 %	-.20	-13.12 %	-.231	.817

Table 6 Source: Return metrics of the unrestricted strategy (own representation)

s = entry threshold, SSD = number of lowest SSD ranked chosen to trade, r_a *= annualized return,* σ_a *= annualized volatility, MDD = maximum drawdown, t = t-value, p = p-value*

It is clear that this strategy would have generated losses even before accounting for trading costs. With not a single Sortino Ratio above 0 and no p-value p below the significance level of 0.05, none of these should be traded in a live environment. The reason for this bad result becomes apparent through a closer look at one of the traded versions.

Figure 11 Source: Returns of the strategy with no restrictions traded where the 2 lowest SSD pairs and a threshold of 0.5 (own representation)

Analyzing the results of the strategy with an entry threshold of 0.5 and the 2 lowest SSD valued pairs chosen, only three events caused this strategy to dip so low into the negative. In 2002, 2011, and 2015 it lost over 30% at some points, though the question of why must be further analyzed.

In the trading period of the second half of 2002, the strategy lost over 30%, trading Arundel AG (ARON) against Graubündner Kantonalbank (GRKP) and Basellandschaftliche Kantonalbank (BLKB) against Basler Kantonalbank (BSKP).

The second pair seems to be fundamentally correlated in that they are cantonal banks in adjacent cantons. Their relationship proved to remain strong during the trading period, returning 1.47%. The problem is with the first chosen pair. Both operate in the financial sector, which would lead one to assume they are fundamentally similar as well. However, whereas GRKP is, as mentioned previously, a cantonal bank, ARON is a Global Financial Service Provider and Investor. Clearly, they are already different in terms of their geographical focus as well as their field of work within the financial industry.

Taking a closer look at their individual stocks, it is understandable why the strategy had such a big drawdown. ARON is a barely traded stock that managed to drop from CHF 2'500.- to around CHF 800.- in one day — a 70 % drop just after we had opened a long position on the stock. The big mistake was not to consider the volume during the formation period. During that time, stocks with no volume can produce misleading SSD results, showing correlation to stocks that did not have big moves but would not have been correlated at all from the perspective of the fundamentals. Selecting all stocks from the SPI makes space for a few outliners that are not heavily traded and can have these kinds of drops and changes without much money flowing in or out.

4.3 Volume filtered strategy results

Learning from past mistakes, we added a volume filter during the formation period of this test described in Chapter 3.1.1.b. This filter should keep low liquidity stocks out, which would be hard to trade in any case because barely anyone is trading them, and a trader would not be able to get rid or acquire the stocks.

The results are surprisingly not substantially different from the results without the volume filter. Overall, the strategy still performed badly before trading costs with no positive Sortino ratio and high maximum drawdowns.

s	SSD	r_a	σ_a	SR	MDD	t	p
0.5							
	2	-0.46 %	6.15 %	-.19	-34.62 %	-.195	.846
	5	0.00 %	4.78 %	-.15	-30.39 %	-.107	.915
	10	-0.13 %	4.49 %	-.17	-19.80 %	-.028	.978
1.0							
	2	-1.32 %	6.89 %	-.26	-30.65 %	-.692	.489
	5	-0.43 %	5.43 %	-.19	-25.15 %	-.230	.818
	10	-0.33 %	4.96 %	-.18	-22.61 %	-.182	.856
1.5							
	2	-2.98 %	6.67 %	-.46	-47.18 %	-1.829	.067
	5	-2.13 %	5.23 %	-.39	-38.20 %	-1.679	.093
	10	-0.99 %	4.96 %	-.27	-32.05 %	-.762	.446
2.0							
	2	0.69 %	5.07 %	-.07	-12.17 %	.697	.486
	5	-0.87 %	4.82 %	-.26	-18.93 %	-.681	.496
	10	-0.69 %	4.74 %	-.24	-23.45 %	-.528	.597

Table 7 Source: Return measurement of the volume filtered strategy (own representation)
s = entry threshold, SSD = number of lowest SSD ranked chosen to trade, r_a = annualized return,
σ_a = annualized volatility, SR = Sortino ratio, MDD = maximum drawdown, t = t-value, p = p-value

To understand why the performance is still not improving, one must investigate the specific trades that were conducted.

If trading costs would be considered, a strategy with a larger threshold should be less impacted by the costs than one with a small threshold. Additionally, the more pairs that are chosen to be traded, the more it should give stability to the strategy because the risk is spread out across all chosen pairs. That is why, the lowest 10 SSD-Ranked pairs with a historical standard deviation of 2.0 will be further analyzed.

To improve the strategy, a deeper analysis of the second half of 2010 was conducted. The strategy experienced big drawdowns and lost 6 % overall. The biggest contribution to the loss was made by Allreal Holding AG (ALLN), which was paired with Bachem Holding AG (BANB). The problem was that Bachem Holding AG dropped from CHF 65.99 on August 19, 2010 to just CHF 53.99 two trading days later, while Allreal Holding AG (ALLN) didn't move significantly during the same stretch.

This development completely broke the relationship between the two and ended up in a big loss for the strategy.

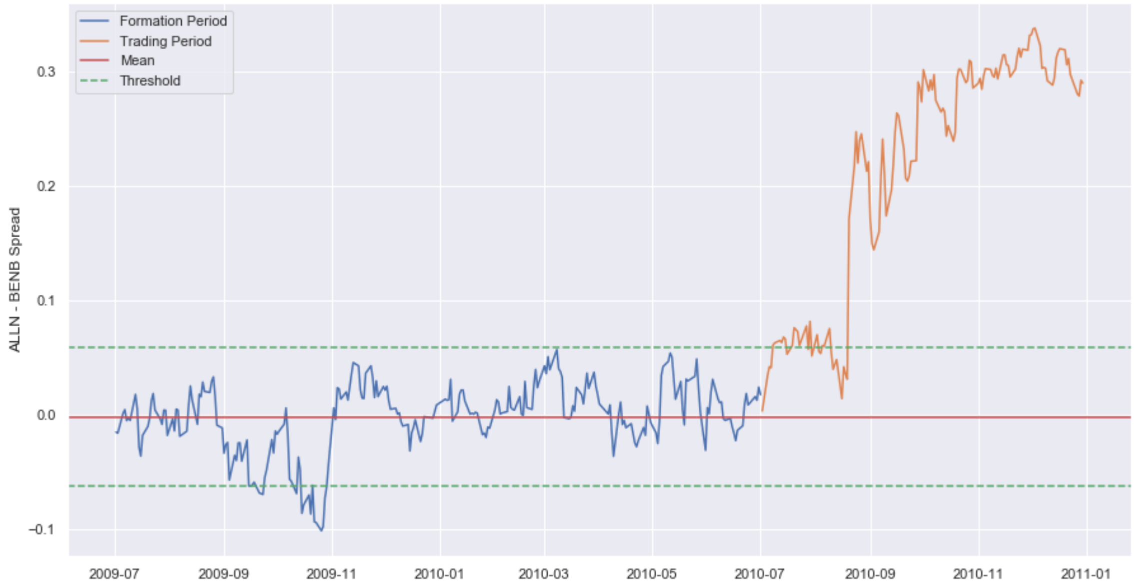

Figure 12 Source: Representation of the difference between ALLN and BENB during the formation and trading period starting from July 2009 until December 2010 (own representation)

The SSD check was not wrong to assume that they were related during the formation period because the spread between the two was mean reverting the whole time. As soon as the trading period started, the relationship broke, and the pair noted a loss of close to 30 %.

All the losses mentioned can be traced back to the fact that the only rule for filtering stocks and finding pairs is the sum of squared differences. Having only this one check in place can lead to a false assumption that two stocks can be correlated when in fact they simply moved in a similar fashion by causation. The example presented previously shows how this can happen. Allreal Holding AG (ALLN) is a real estate company (Allreal Holding AG, 2020) operating in the Financial sector of the SPI, while Bachem Holding AG (BANB) is a technology company active in the fields of chemistry, biochemistry, and pharmaceuticals, and therefore traded in the Health Care sector of the SPI (Bachem Holding AG, 2020). Two different sectors with vastly different influences.

For this reason, an extra rule was added to the next test. The fact that companies must operate in the same sector gives a concrete explanation why they move similarly and are not expected to break their relationship during the trading period.

4.4 Sector restricted strategy results

We further expand the baseline strategy with a volume filter, by only considering stock pairs if both companies in a pair are operating in the same sector. Every chosen sector gets back-tested separately while the mean of those returns will be considered as the portfolio return, as explained in Chapter 3.1.1.c.

s	SSD	r_a	σ_a	SR	MDD	t	p
0.5							
	2	0.62 %	6.68 %	-.050	-17.97 %	.552	.580
	5	2.75 %	4.93 %	.185	-7.67 %	2.506	.012
	10	2.99 %	3.75 %	.236	-6.30 %	3.508	>.001
1.0							
	2	0.81 %	7.46 %	-.024	-20.16 %	.631	.527
	5	1.62 %	5.33 %	.048	-14.56 %	1.424	.154
	10	1.96 %	4.25 %	.091	-12.86 %	2.083	.037
1.5							
	2	1.26 %	7.02 %	.018	-15.04 %	.927	.354
	5	2.50 %	5.19 %	.152	-9.62 %	2.181	.029
	10	1.95 %	4.11 %	.092	-8.56 %	2.131	.033
2.0							
	2	2.57 %	6.53 %	.160	-11.32 %	1.831	.067
	5	2.06 %	5.05 %	.103	-10.53 %	1.871	.061
	10	1.40 %	3.87 %	.020	-8.06 %	1.653	.098

Table 8 Source: Sector restricted strategy results measurements before trading costs (own representation)

s = entry threshold, SSD = number of lowest SSD ranked chosen to trade, r_a = annualized return, σ_a = annualized volatility, SR = Sortino ratio, MDD = maximum drawdown, t = t-value, p = p-value

This fundamental rule of matching companies with others in the same industry seems to work fine, with positive returns over all versions and drastically lower drawdowns compared to the versions covered before. One still must bear in mind, though, that no trading costs have been deducted yet.

The fundamental goal of pairs trading having low volatility and low drawdowns can now be achieved. The best performing version of this strategy was a short threshold strategy at 0.5 times the historical standard deviation and the top 10 pairs with the lowest SSDs were chosen per sector. With an annualized return r_a of 2.99 % and a maximum drawdown of -6.30 % over the whole 19-year period, this strategy was able to perform at times when the market could not.

To understand the forces behind these results, we will take a closer look at the results of the 10 SSD 0.5 entry threshold strategy and the performance of each sector by themselves.

Figure 13 Source: Comparison of the returns each sector produced to the total return of all combined over the 19-year back-testing period (own representation)

Visually, it is clear that the financial sector did not contribute anything to the overall strategy results. Although it had little volatility, it was only able to achieve a total return of 10.23 %. In comparison, the Industrial, Consumer Goods and Health Care sectors all returned around 3 % annually, though with a volatility of over 6 %.

Sector	r_a	σ_a	SR	MDD
Industrial	3.82 %	8.12 %	.270	-17.88 %
Financial	0.51 %	4.26 %	-.093	-20.94 %
Consumer Goods	3.93 %	7.37 %	.288	-14.47 %
Health Care	3.09 %	8.16 %	.200	-24.11 %
Overall	2.99 %	3.75 %	.236	-6.30 %

Table 9 Source: Comparison of sector measurements (own representation)

r_a = annualized return, σ_a = annualized volatility, SR = Sortino ratio, MDD = maximum drawdown

Combining all these sectors gives us a low annual volatility of 3.91 % and an incredible maximal drawdown of only -6.30 %.
In comparison, the SPI returned 7.89 % annually but with a yearly volatility of 18.86 % and a maximal drawdown of -53.54 %.

One big question that needs to be solved is why the financial sector underperformed by so much. Containing many regional banks as well as insurance and real estate companies, all having the fundamental relationship regarding the nature of their business.
Looking at the actual performance of the strategy in the financial sector, the losses are due to big and sharp drops in years such as 2005, 2008, and 2010. It is not hard to figure out what happened in 2008 to cause this big disruption. The financial crisis broke many relationships and therefore pushed the spreads away from the mean, leaving the strategy with a big loss. One example is the Allreal Holding AG (ALLN) and Mobimo Holding AG (MOBN) pair. During the formation period, it looked like they had a solid relationship, but once the second half of 2008 started, the relationship broke, creating a drawdown of up to -15 %.
But the other underperformances are harder to judge. A deeper analysis of the 2005 drop shows that more than half of the pairs chosen lost their relationship and had a negative return during the trading period.
The chosen benchmark, the SPI, had a fantastic year in 2005, with almost no volatility. Returning 33.8 %, it was already going to be hard for the pairs trading strategy to outperform it. Because of the nature of the strategy, it does not matter whether markets go up or down; they should just do so with enough volatility in order to produce profits.

The reasons why it underperformed and even crashed in 2005 can be illustrated through two chosen pairs: Swiss Life Holding AG (SLHN) and Swiss Re (SREN) as well as Swiss Life Holding AG (SLHN) and VP Bank AG (VPBN). The first pair seemed to be perfect because both are insurance companies. This relationship can also be seen clearly in Figure 14, which shows how their relationship held up and they continued to move in a similar fashion. But as SLHN performed increasingly well, its spread became bigger and bigger, leaving the strategy with a big loss in the end.

Figure 14 Source: Stock returns of SLHN and SREN during the trading period of July 2005 until December 2005 (own representation)

The second pair, SLHN and VPBN shown in Figure 15, justifies the loss created by the strategy. The overperformance of SLHN clearly was a problem, and it ended with a 15 % loss. This loss could have been far worse, if there would not have been a profitable beginning. Thanks to early returns during the time when their prices were still crossing each other, the fall of 25 % did not hurt as much as it should have.

Figure 15 Source: Stock returns of VBPN and SLHN over the trading period July 2005 until December 2005 (own representation)

Overall, this version of the distance method was the most successful one so far. However, there is still room for improvement. In the next chapter, we try implementing a new approach to the formation period and stock selection.

4.5 Selection of stocks with multiple listings

The next step is completely getting rid of the formation period and trusting stock pairs where both stocks represent the same company with different rights.

This version of the strategy performed well with all of them achieving a positive return with minimal drawdowns. Moreover, all but one strategy managed to have a p-value below the pre-determined significance level of 5 %, meaning that their returns are statistically significant to zero.

s	r_a	σ_a	SR	MDD	t	p
0.5	2.92 %	5.39 %	.213	-7.28 %	2.448	0.014
1.0	3.02 %	5.70 %	.217	-6.74 %	2.396	0.016
1.5	2.61 %	5.38 %	.174	-6.65 %	2.201	0.027
2.0	1.70 %	4.95 %	.063	-5.91 %	1.588	0.112

Table 10 Source: Results of the distance method on selected stock pairs from 2001 to 2019 (own representation)
s = entry threshold, r_a = annualized return, σ_a = annualized volatility, SR = Sortino ratio, MDD = maximum drawdown, t = t-value, p = p-value

Looking at the performance year by year paints another picture. While the performance was outstanding in the initial years, the profits completely stopped by 2013. With the before thought edge on the market completely gone, not able to generate returns and experiencing all maximal drawdowns during the last seven years, this strategy should not be traded anymore.

s	r_a	σ_a	SR	MDD	t	p
0.5	0.79 %	2.56 %	-.082	-7.28 %	.852	.197
1.0	0.64 %	2.98 %	-.095	-6.74 %	.609	.271
1.5	-0.11 %	2.91 %	-.212	-6.65 %	-0.65	.474
2.0	0.38 %	2.88 %	-.137	-5.91 %	.388	.349

Table 11 Source: Results of the distance method on selected stock pairs from 2013 to 2019 (own representation)
s = entry threshold, r_a = annualized return, σ_a = annualized volatility, SR = Sortino ratio, MDD = maximum drawdown, t = t-value, p = p-value

The null hypothesis could not be rejected for any of the strategies in the last seven years, making the effort to trade this version nowadays unviable.

Circling back to Chapter 1.1, the underperformance could be traced back to the rise of more algorithmic traders in the market and funds executing similar arbitrage strategies between these stocks, diminishing profits, and making the market more efficient. To further understand the reason for this strategy turning so bad, a closer look at the trading behavior is taken.

Looking at the trading returns for Schindler Holding AG (SCHN) and Schindler Holding AG Participation (SCHP) during 2006, they were wonderful, returning 3 % in 6 months with barely any drawdowns. This return can be attributed to the two stocks not diverging but rather moving back to their mean during both the formation and the trading period. This convergence made it easy for the distance method to enter many trades and profit from them. However, the returns of the same pair diminished by 2013. Looking at the relationship between them during the formation and trading period of 2017 in Figure 16 explains why. The spread between the two no longer reverted to the mean, but rather diverged away from it, with a clear downward trend. This shift in the spread made the rules of the distance method use a historical entry threshold and mean way beyond what the start point of the new trading period will be.

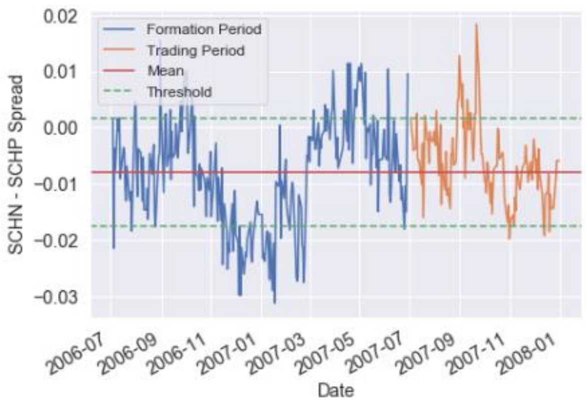

Figure 17 Source: Formation and Trading period of a successful, pre-selected pair (own representation)

Figure 16 Source: Formation and Trading period showing the breaking relationship between a pre-selected stock pair (own representation)

This issue may be fixed by selecting a shorter formation and trading period.

Overall, the sector restricted strategy explored in chapter 3.1.1.c will be used for further analysis due to its diversification and lack of bias towards certain stock-pairs. As indicated, the returns over the whole 19 years are inferior to the pre-selected pairs, but the returns do not diminish as much in the sector restricted adaption of the distance method.

4.6 Stress Test

To further analyze the sector restricted, lowest 10 SSD and 0.5 standard deviation strategy, a stress test was used to see in detail how it performed during certain times in financial history. The events in Table 12 are included in the test, providing a sense of how the strategy compared to a benchmark, in our case the Swiss Performance Index.

Stress Events	Start Date	End Date	SPI returns	Strategy returns	SPI MDD	Strategy MDD
Dot-com bubble	2001-01-01	2003-03-31	-48.56 %	11.62 %	-53.54 %	-3.86 %
Low Volatility Bull Market	2005-01-01	2007-05-31	78.88 %	3.34 %	-12.09 %	-5.51 %
2007-2008 Financial Crisis	2007-07-01	2008-12-31	-39.48 %	7.98 %	-43.99 %	-2.83 %
Recovery	2011-09-01	2015-07-31	95.52 %	9.77 %	-14.65 %	-3.05 %
2015-16 Stock Market selloff	2015-01-01	2016-12-31	2.38 %	7.71 %	-19.47 %	-1.72 %

Table 12 Source: Return comparison between the SPI and pairs trading during different stress events (own representation)

The first comparison takes place during the late 1990s dot-com bubble, when internet-based companies rallied exponentially, leaving investors wondering if they would always have it this good. Of course, everything was mostly fueled by speculative investors betting on new companies becoming profitable one day. Such was not the case for a lot of those start-ups, most of who's budget was put into marketing and getting in new money instead of developing cutting edge technology. The bubble finally burst in 2001, busting most dotcom companies and, in turn, making the downfall of the stock market even harder. (Hayes, 2019)

Figure 18 Source: Return comparison between the SPI and Pairs-Trading during the dot-com bubble (own representation)

Given that the pairs trading strategy does not bet on a single stock going in a certain direction, this situation did not affect the profits heavily. Quite the contrary, the strategy even profited 11.62 % over the chosen period of the bubble bursting with a maximal drawdown of only -3.86 %. The SPI did not take the crash so well, losing -48.56 % over the same period with a low point of -53.54 %.

The second test was conducted during a low volatility bull market. During this time, the market was in a phase of recovery, usually trending upward and ending our benchmark in a total return of 78.88 % and a maximal drawdown of only -12.09 %. This is exactly the time when the chosen approach to trading massively underperforms. While the markets did phenomenal, pairs trading would have only returned 3.34 % with a maximal drawdown of still -5.51 %.

Figure 19 Source: Return comparison between the SPI and pairs trading during a low volatility bull market (own representation)

A popular example is number three: the financial crisis of 2007-2008. As explained by Sandro Bächli in the IBF1 lecture about the crisis, it was described as a “once-in-a-century credit tsunami.” The world saw a huge rise in financial markets and grew more comfortable and therefore creative with financial innovation. Without going in to too much detail, the rise of subprime lending (the practice of giving high-risk loans to customers with poor credit histories) and the bundling of these loans into asset backed securities made the US housing market look like it was growing at an exponential pace and could never collapse. But the mortgage rates began to rise in 2004, causing more and more homeowners to default on their loans. Eventually, the market reacted with falling housing prices and a sharp decline in the value of the stock market. Once again, the time was ripe for the pairs trading strategy to shine. Although the returns within the strategy of the financial sector suffered some losses, the other sectors were doing what they were supposed to be doing, exploiting this volatility and generating returns. Resulting in Figure 20, a 7.89 % total return for pairs trading with the SPI losing 39.48 % over the same time period.

Figure 20 Source: Return comparison between the SPI and pairs trading during the financial crisis (own representation)

Once the financial crisis hit bottom, it was time to recover again from the massive losses. A strong bull-run soon began, leading the financial markets to new highs. In such a setting, pairs trading is not the most suitable strategy as can be seen in Figure 20. Though it had a total return of 9.77 %, this number is dwarfed by the 95.52 % that the SPI gained during the same stretch of time. The only upside was, like before, the low drawdown. While the market still experienced drops of maximal -14.65 %, the chosen strategy only lost -3.05 % from peak to valley.

Figure 21 Source: Return comparison between the SPI and Pairs-Trading during a recovery period (own representation)

Finally, we turn to a period which is different to the ones mentioned before. The 2015-2016 Stock Market selloff was due to the introduction of negative interest rates and the flattening of the U.S. Treasury yield curve. In addition, oil output rose with the use of fracking, causing energy and commodity prices to plummet. (Randall & Gaffen, 2016)

Although the market mostly held its ground, this period was filled with volatility and sharp fluctuations in the stock markets. The SPI still managed to come out ahead, returning 2.38% during this period but with a maximal drawdown of -19.47 %. In this scenario, the chosen pairs trading approach worked well as seen in Figure 21, managing to profit from this volatility without ever loosing much of its value. The result was a total return of 7.71 % and a maximal drawdown of only -1.72 %.

Figure 22 Source: Return comparison between the SPI and Pairs-Trading during a stock market selloff (own representation)

4.7 Performance after trading costs

Considering that the best performing, 0.5 historical standard deviation strategy is the narrowest one tested, it does a lot of trades. Therefore, it also generates high trading costs. If these costs are taken into account, the results will not look as bright as they did before.

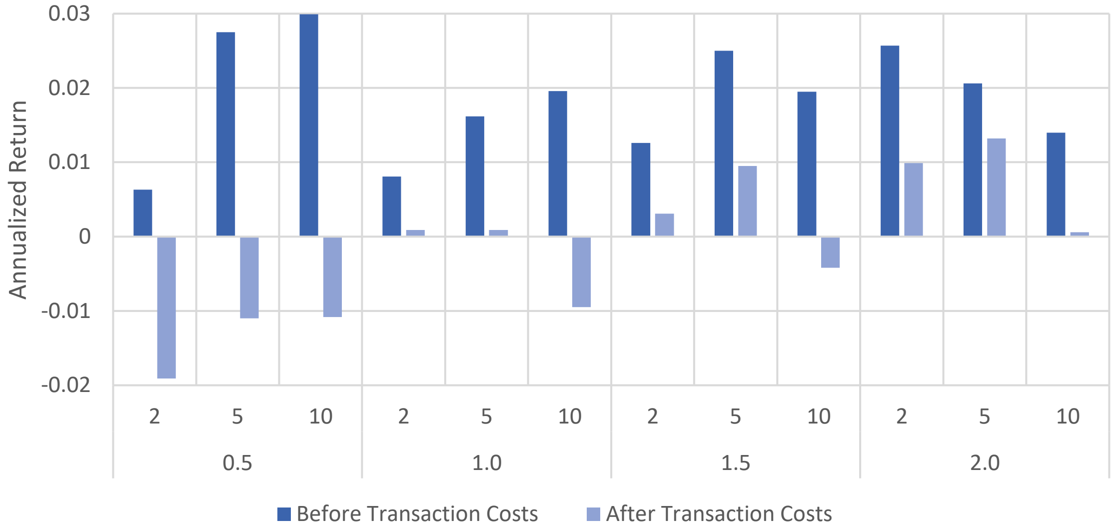

Figure 23 Source: Impact of trading costs on annual strategy returns (own representation)

While the favorite version with a standard deviation and SSD of 0.5 and 10, respectively, performed well, it is now among the worst, dropping to a total return of -18.59 %. The trend in the results is clear: higher entry threshold leads to less trades being executed, less trading costs generated, and consequently better returns. The difference between before and after adjusting for trading costs is not nearly as much for a 2.0 standard deviation, then it is for a 0.5 one. Moreover, the fewer stocks that are picked for each trading period the better, with the 10 top stocks now being the worst performing version of the strategy over all entry thresholds except 0.5.

The best strategy now would be the top 5 stocks with the lowest SSD traded at a 2.0 historical standard deviation. Although this strategy is still underperforming the market by far, it generated consistent positive returns ($r_a = 1.32\ \%$). Given that the volatility ($\sigma_a = 5.25\ \%$) was still very high for the returns calculated, the Sortino ratio was only barely able to get into positive territory at a value of 0.015.

4.8 Chapter conclusion

This chapter started off with explaining how returns are calculated and how the performance of the different strategies is measured. After realizing that a naïve approach towards pairs trading is not profitable, a volume filter is added and tested. Still not able to be profitable, a sector restriction is introduced which managed to generate profits before trading costs. Expanding on this fundamental relationship between stocks, pairs are finally pre-selected where only stocks with multiple listings are considered. This turned out to be a great idea, but the edge is lost in the last seven years making this version unprofitable to trade in todays day and age. Next, the before calculated returns of the sector restricted strategy are tested during certain stress events such as the financial crisis and the dot-com bubble proving, that it is an all-weather strategy able to generate returns in every market situation. Finally, trading costs are deducted and analyzed concluding that they manage to turn the strategy unprofitable in almost all cases.

5 Discussion

Putting the 0.5 threshold sector restricted strategy with the lowest 10 SSD pairs chosen to the test, this chapter will provide a thorough examination of whether the returns generated are coincidental and if they are statistically significant.

Hypothesis 1: It is possible to achieve a positive mean return using a pairs trading strategy in the Swiss Stock Exchange.

Analyzing the first null hypothesis, whether the mean returns is zero or less, a t-value of 3.5 indicates the answer is no. With a p-value of 0.00023, below the significance level of 0.05, it is clear that the returns generated are significantly more than zero and therefore the null hypothesis can be rejected.

Checking only the best-performing strategy for significance, the results are heavily optimized. All other versions of this volume restricted approach were ignored, making this conclusion biased to only the perfect execution of this strategy.
For this reason, all back-tested results of this strategy will be considered in order to see whether the result was due to extreme optimization or if one can indeed profit with sector restricted pairs trading.
As mentioned before, a t-value of over 1.645 means that the strategy produced returns different than zero. Analyzing all t-values generated by the strategy, 66 % are above this threshold. Meanwhile, 66 % of the p-values are below the significance level of 0.05. These figures lead to the conclusion that the null hypothesis can be rejected and that it is possible to achieve statistically significant returns using a pairs trading strategy on Swiss Stock Markets.

Hypothesis 2: It is possible to achieve a positive mean return using a pairs trading strategy on the Swiss Stock Exchange after deducting trading costs.

Accounting for trading costs paints a different picture. Not a single t-value can surpass the amount given to prove that its returns are different from zero. Moreover, no p-value was able to achieve a value below the significance level of 0.05 as can be seen in Table 11. Clearly, the second null hypothesis could not be rejected. Pairs trading, though still able to generate positive total returns for seven of the 12 strategies tested, cannot provide statistically significant returns after trading costs.

s	SSD	r_a	σ_a	SR	MDD	t	p
0.5							
	2	-1.91 %	7.03 %	-.309	-36.82 %	-1.044	.297
	5	-1.10 %	5.34 %	-.259	-26.91 %	-.786	.432
	10	-1.08 %	4.31 %	-.287	-26.99 %	-.998	.318
1.0							
	2	0.09 %	7.49 %	-.095	-27.02 %	.214	.831
	5	0.09 %	5.94 %	-.115	-19.35 %	.197	.844
	10	-0.95 %	4.79 %	-.258	-32.34 %	-.766	.443
1.5							
	2	0.31 %	7.46 %	-.074	-34.76 %	.341	.733
	5	0.95 %	5.42 %	-.026	-15.27 %	.876	.381
	10	-0.42 %	4.66 %	-.200	-24.00 %	-.293	.770
2.0							
	2	0.99 %	6.76 %	-.012	-24.70 %	.779	.436
	5	1.32 %	5.25 %	.015	-15.41 %	1.199	.231
	10	0.06 %	4.39 %	-.149	-21.20 %	.151	.880

Table 13 Source: Return measurements of the sector restricted strategy after trading costs (own representation)

s = entry threshold, SSD = number of lowest SSD ranked chosen to trade, r_a = annualized return, σ_a = annualized volatility, SR = Sortino ratio, MDD = maximum drawdown, t = t-value, p = p-value

Overall, this thesis proves that it is possible to generate a profit using the relationship between two stocks. Taking the trading costs into account, the distance approach attempted in this thesis would not have been profitable. Due to the recent no-cost revolution of trading through platforms such as Robinhood and Trading Republic (Ermey, 2019) and the fact that the provided strategy trades on a daily basis and not intraday, it might be possible for a private investor to realize these returns.

This discussion still leaves a lot of future research questions open. A next step would be to analyze how sensitive the amount of time the formation and trading periods take are and if it would be possible to realize returns which were recently lost with shorter time intervals such as hourly, every minute or second.

The strategy also needs to be tested further for robustness. What influences the returns and is there any actual alpha derived from the strategy or is it all up to other factors? To carry out such a test, one might use the Fama-French 3-Factor Model but doing so is well beyond the scope of this thesis. Not all factors of the Fama-French Model are researched enough within Switzerland which poses an interesting research question in itself.

In this thesis, the strategy was only tested on stocks registered in the Swiss Performance Index. In the future, it should be tested in different geographical markets and with different assets in order to see if this market inefficiency persists and is exploitable elsewhere.

Another factor that could be changed and should be documented is the weighting process. Although the approach of this thesis is based on equal weighting of the equities within the portfolio, there are many other weighting methods available as touched on in Chapter 4.1 about risk and return measurements.

Finally, different versions of pairs trading, some of which are explained in the literature review in Chapter 2.1, could also be tested and compared to decide whether it is at all possible to turn a profit after accounting for trading costs.

6 Critical reflection

Learning a lot in the process of writing this thesis, I am proud of the result and happy I can reflect on this time.

Being motivated and excited to research about this topic early on, I started reading related literature and testing concepts immediately. Although I stayed curious throughout the thesis, I ran into a lot of dead ends because of this over-enthusiasm. I should have stuck to the plan and not skip ahead to stay focused on one goal – answering the research question.

Additionally, I would approach the coding part of the thesis differently. Since I was used to handling financial data from personal projects before, I relied heavily on python packages doing part of the calculations for me. These are packages that I can import and call upon if I need their help. In the process of interpreting the results I got from my back-tester, I realized that some of those numbers are a bit off and that I would need to code my return measurements from scratch. On one hand, this ended up losing me a lot of time while on the other, it helped me develop my coding skills since I now make sure I know what is going on under the hood of these packages before importing them.

Finally, thanks to this thesis I managed to learn a lot about hypothesis testing in finance. In general, it was a good experience to apply a lot of theories learned in lectures which ended up giving me a deeper understanding of the subject.

7 Declaration

The length of this text, including chapter 1 heading and up to the declaration is 13’649 words.

I hereby certify that I have independently written this term paper. Any text passages which were not written by me are quoted as citations and specific references to their origins are made.

All used sources (including images, graphics, etc.) are included in the bibliography.

Thun, 11.05.2020

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Jan Daniel Gobeli

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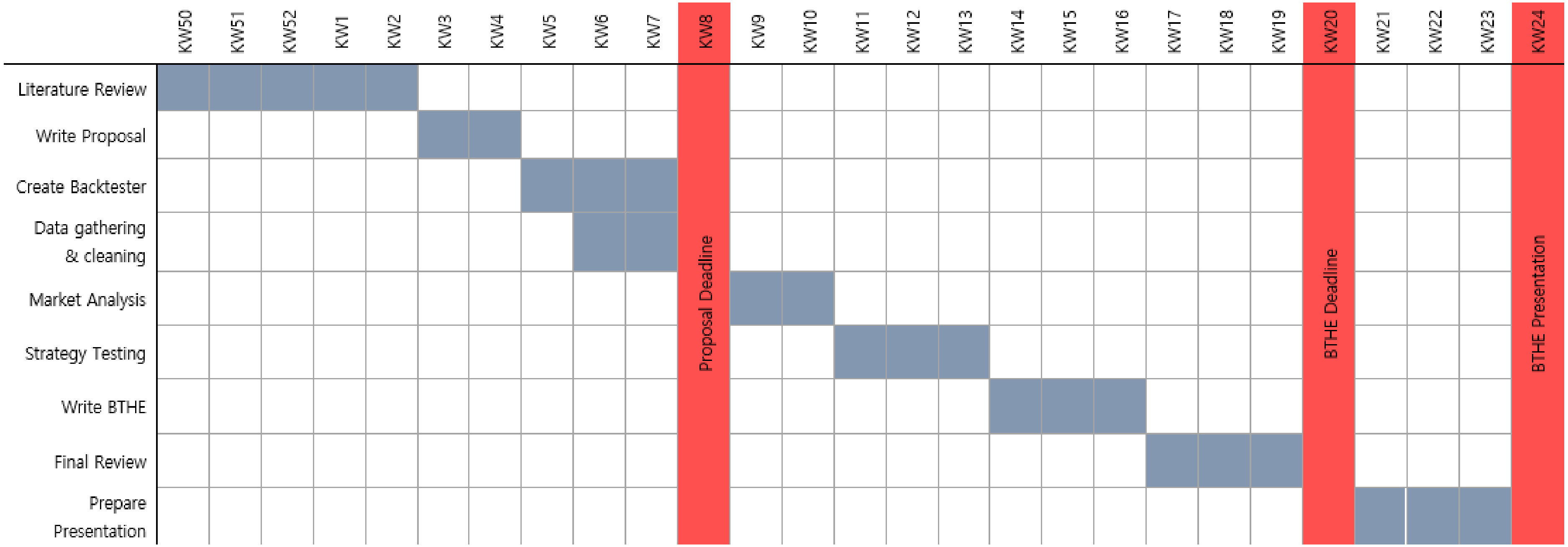
8.2 Figures

8.3 Tables

9 Appendix

9.1 Gantt chart – Schedule of thesis



9.2 Progress report

KW5

This week I started creating the back-testing framework used for later analysis. So far, everything is tested on yahoo finance data which will probably change later. To analyze the results, a python package named ffn is used.

KW6

Continuing the creation of the back-tester. I based it on iterations through a pandas data frame which sadly is computational not the best way to do it, but more readable for my level of coding knowledge.

KW7

Making some last touches to the back-tester and adjusting it for costs. Researching about how much should be deducted was difficult, since there isn't any up-to-date data. Still, thanks to Virtu Financial I got a sense of how commissions developed in recent years and to my surprise, they were low. Adding slippage and short-selling costs, it looks like its still a lot of bps I must deduct each round trip, confirming my hunch that it might not be profitable after it.

KW8

This week I finished writing the proposal and handed it in. I research about quant funds, pairs trading in general as well as hedge funds. I am very happy with how it turned out and cant wait to start testing and writing. Getting instant feedback from Prof. Dr. Sandor Bächli was very reassuring and a good exercise to explain what I'm trying to achieve.

KW9

Better data is needed to perform a representative analysis of this strategy. I emailed the SIX Group and explained my situation, asking for access to their SPI data. Looking for a suitable stock universe, I ended up going for the SPI. With 215 stocks in it, they offer a lot of variety and representation in the sectors that will be later tested.

KW10

I started the main document of the thesis and build the overall framework with what I want to do and write about. Doing a lot more research in how I could expand the strategy, I read through 3 more research papers taking away that barely any different thresholds have been tested as well as transaction costs were mostly neglected.

KW11

Sadly, no answer yet from the SIX Group. I emailed them again, asking for SPI data for my thesis. In the meantime, I started writing on the theory behind pairs trading and worked out an example in order to make it more understandable.

KW12

Still no answer from SIX Group about the data so I had to find alternative ways to get them. I tried many different services (Quandl, CQG, Alpha Vantage, and many more) but none of them seem to offer the kind of data I needed. Sadly, I couldn't go to university libraries anymore due to the recent lockdown of all schools. Finally, I found DataLink provided by Metastock. A service which is offered by Thomson Reuters and usually costs a lot to get. They offered all data provided by Reuters for only $30.- a month and since I was not able to access libraries with access to this service for free due to the coronavirus, I had to take it.

KW13

I started exploring the data and organizing it in a same manner, which I am used to by yahoo finance. This is due to the fact that all my code written was based on their structure of data.

KW14

This week started off with a bit of a struggle. I back-tested all different version of the strategy just to find out I made a single typo while changing the code up a bit.

KW15

I started off by completing the analysis of all results from the Baseline strategy. It came out, that low volume stocks skewed the results a lot, that's why the addition of a volume filter came into play. Adjusting the code and finding the right value to cut-off unwanted stocks was the main focus of a whole day. I made some additions to the literature review and overall fleshed out the thesis.

KW16

This week took one step further with introducing the sector version of the strategy. I already started coding for it over the weekend and conducted all the back-tests during the week. The results looked surprisingly good, except for the financial sector. That's exactly the things I was looking for, some insight in why the financial sector is bad to trade while the other chosen ones did amazing.

KW17

After finishing the sector version of the strategy, a dive into a selection of particular stocks was made. I was on the fence if I should continue with this approach or go for an analysis of the performance of the strategy during the current market situation. Since its more reasonable and would generate more insight, I chose the first one, selecting fundamentally similar stocks to trade. It wasn’t as successful as I expected, and I documented my findings. Since I wasn’t sure how to test trading returns for significance, I consulted a colleague working in the industry. David Fankhauser, Consultant for Academic Alpha helped me out in explaining their approach to developing and testing trading strategies.

KW18

This week started off with cleaning the structure of the thesis as well as some code. I found multiple wrong calculations in my code while generating the return measurements which I immediately changed and recalculated my results. Gladly they were only off a few bps and therefore I didn’t had to change any of my results written in the thesis. A friend of mine, Jan Eisenmann who studies Nanotechnology looked over the thesis and gave me some tipps and tricks on how I could change it up a bit. He helped me especially visually, since he is used to represent complex structures in charts for his own work.

KW19

In the final week, I read through the thesis repeatedly. I gave it to a friend so he can proofread it and adjusted it constantly. I thought I can finish on Sunday, the 10th of march but wasn’t quite able to do so. Having Monday the 11th of march off, helped me go over it one last time to make sure everything looks like I planned it before I finally handed it in.

9.3 Code examples

Backtester.py	
Backtest_all.py	
Backtest_volume.py	
Sector_test.ipynb	

9.3.1 Backtester.py

```
def backtest(temp, asset1, asset2):
    long = False
    short = False
    trades = 0
    last_price1 = None
    last_price2 = None
    ret = []

    for index, row in temp.iterrows():
        if row['longsignal'] and not long:
            trades += 1
            short = False
            long = True
            last_price1 = row[asset1]
            last_price2 = row[asset2]
            ret.append(0)
        elif row['shortsignal'] and not short :
            trades += 1
            long = False
            short = True
            last_price1 = row[asset1]
            last_price2 = row[asset2]
            ret.append(0)
        elif long and row['closelong']:
            short = False
            long = False
            long_ret = (row[asset1] / last_price1) - 1
            short_ret = (row[asset2] / -last_price2) + 1
            last_price1 = row[asset1]
            last_price2 = row[asset2]
            ret.append(long_ret+short_ret)
        elif short and row['closeshort']:
            short = False
            long = False
            long_ret = (row[asset2] / last_price2) - 1
            short_ret = (row[asset1] / -last_price1) + 1
            last_price1 = row[asset1]
            last_price2 = row[asset2]
            ret.append(long_ret+short_ret)
        elif long:
            long_ret = (row[asset1] / last_price1) - 1
            short_ret = (row[asset2] / -last_price2) + 1
            last_price1 = row[asset1]
            last_price2 = row[asset2]
            ret.append(long_ret+short_ret)
        elif short:
            long_ret = (row[asset2] / last_price2) - 1
            short_ret = (row[asset1] / -last_price1) + 1
            last_price1 = row[asset1]
            last_price2 = row[asset2]
            ret.append(long_ret+short_ret)
        else:
            last_price1 = row[asset1]
            last_price2 = row[asset2]
            ret.append(0)
    temp['returns'] = ret
    temp['cum_returns'] = temp.returns.cumsum() + 1
    return temp
```

9.3.2 Backtest_all.py

```python
def create_pairs(tickers):
        result = []
        for p1 in range(len(tickers)):
                for p2 in range(p1+1,len(tickers)):
                        result.append([tickers[p1],tickers[p2]])
        return result

def get_closing(temp, name):
    temp.DATE = pd.to_datetime(temp['DATE'].str[:10], dayfirst=True)
    temp = temp.set_index(temp.DATE)
    temp.columns = ['Date', 'Symbol', 'Interval', 'Open', 'High', 'Low', name, 'Volume'
]
    temp = temp[name]
    return temp

def find_ssd(df, pairs):
    ssd = {}
    for p in pairs:
        pair = p[0]+','+p[1]
        A = df[p[0]]
        B = df[p[1]]
        s = np.sum((A-B)**2)
        if s == 0.0:
            continue
        if len(A.dropna()) < 248 or len(B.dropna()) < 248:
            continue
        ssd[pair] = s
    return ssd

def find_tradeble_pairs(ssd, amount):
    sorted_lst = sorted(ssd, key=ssd.get)
    pair_lst = []
    if len(sorted_lst) < 1:
        return pair_lst
    for n in range(amount):
        pair_lst.append(sorted_lst[n].split(","))
    return pair_lst

def find_entry_exit(spread, n):
    mean = np.mean(spread)
    stdev = np.std(spread)
    upper = mean+(n*stdev)
    lower = mean-(n*stdev)
    return mean, upper, lower

def create_signal(df, pair, m, u, l):
    spread = df[pair[0]] - df[pair[1]]
    previous_spread = spread.shift(1)
    bt_df = pd.DataFrame()
    bt_df[pair[0]] = df[pair[0]]
    bt_df[pair[1]] = df[pair[1]]
    bt_df['shortsignal'] = ((spread < u) & (previous_spread > u))
    bt_df['longsignal'] = ((spread > l) & (previous_spread < l))
    bt_df['closelong'] = np.where(spread >= m, 1, 0)
    bt_df['closeshort'] = np.where(spread <= m, 1, 0)
    return bt_df
```

```
def trading(df_formation, df_trading, amount, n):
    returns = pd.DataFrame()
    ssd = find_ssd(df_formation, pairs)
    selected = find_tradeble_pairs(ssd, amount)
    for pair in selected:
        bt_name = pair[0]+pair[1]
        spread = df_formation[pair[0]] - df_formation[pair[1]]
        m, u, l = find_entry_exit(spread, n)
        bt_df = create_signal(df_trading, pair, m, u, l)
        ret = bt(bt_df, pair[0], pair[1])
        returns[bt_name] = ret.returns
    returns['mean'] = returns.mean(axis=1)
    returns = returns.set_index(df_trading.index)
    return returns['mean']

def backtest(df, amount, n):
    overall_ret = pd.DataFrame()
    start = pd.Timestamp('2000-01')
    mid = start + relativedelta(months=+12)
    end = start + relativedelta(months=+18)
    df_formation = (1 + df[start:mid].pct_change()).cumprod()
    df_trading = (1 + df[mid:end].pct_change()).cumprod()
    returns = trading(df_formation, df_trading, amount, n)
    overall_ret = returns
    for period in range(1, 38):
        start = start + relativedelta(months=+6)
        mid = start + relativedelta(months=+12)
        end = start + relativedelta(months=+18)
        df_formation = (1 + df[start:mid].pct_change()).cumprod()
        df_trading = (1 + df[mid:end].pct_change()).cumprod()
        returns = trading(df_formation, df_trading, amount, n)
        overall_ret = overall_ret.append(returns)
    return overall_ret

amounts = [2, 5, 10]
n = [0.5, 1.0 , 1.5, 2.0]
sectors = ['hc', 'cg', 'fin', 'ind', 'all']
for sector in sectors:
    UBS = pd.read_csv('…/csv/UBSG.csv', delimiter=";")
    UBS.DATE = pd.to_datetime(UBS['DATE'].str[:10], dayfirst=True)
    df = pd.DataFrame(UBS.CLOSE).set_index(UBS.DATE)
    df.columns = ['UBS']
    spreadsheet = pd.read_excel('…/BTHE/Sectors.xlsx', sheet_name=None)
    tickers = spreadsheet[sector].Ticker.tolist()
    pairs = create_pairs(tickers)
    for ticker in tickers:
        path = '…/csv/'+ticker+'.csv'
        df = df.join(get_closing(pd.read_csv(path, delimiter=";"), ticker)).ffill()
    df = df.drop(columns=['UBS'])
    save_name = 'results_'+sector+'.csv'
    master_lst = {}
    master_cum = {}
    for number in tqdm(n):
        for amount in amounts:
            name = '{}ssd{}std'.format(amount, number)
            ret = backtest(df, amount, number)
            master_lst[name] = ret
            master_cum[name] = (1 + ret).cumprod()
    master_df = pd.DataFrame(master_cum)
    master_df.to_csv(save_name)
```

9.3.3 Backtest_volume.py addition to backtest_all.py

```python
def find_ssd(df, vol, vol_thres, pairs):

    ssd = {}
    for p in pairs:
        pair = p[0]+','+p[1]
        if vol[p[0]].mean(axis=0) < vol_thres or vol[p[1]].mean(axis=0) < vol_thres:
            continue

        A = df[p[0]]
        B = df[p[1]]
        s = np.sum((A-B)**2)
        if s == 0.0:
            continue

        if len(A.dropna()) < 248 or len(B.dropna()) < 248:
            continue

        ssd[pair] = s
    return ssd

def trading(df_formation, df_trading, vol, amount, n):
    returns = pd.DataFrame()
    vol_thres = vol.mean().quantile(0.25)
    ssd = find_ssd(df_formation, vol, vol_thres, pairs)
    selected = find_tradeble_pairs(ssd, amount)
    for pair in selected:
        bt_name = pair[0]+pair[1]
        spread = df_formation[pair[0]] - df_formation[pair[1]]
        m, u, l = find_entry_exit(spread, n)
        bt_df = create_signal(df_trading, pair, m, u, l)
        ret = bt(bt_df, pair[0], pair[1])
        returns[bt_name] = ret.returns

    returns['mean'] = returns.mean(axis=1)
    returns = returns.set_index(df_trading.index)
    return returns['mean']

def backtest(df, vol, amount, n):
    overall_ret = pd.DataFrame()
    start = pd.Timestamp('2000-01')
    mid = start + relativedelta(months=+12)
    end = start + relativedelta(months=+18)

    df_formation = (1 + df[start:mid].pct_change()).cumprod()
    df_trading = (1 + df[mid:end].pct_change()).cumprod()
    vol_df = vol[start:mid]
    returns = trading(df_formation, df_trading, vol_df, amount, n)
    overall_ret = returns

    for period in range(1, 38):
        start = start + relativedelta(months=+6)
        mid = start + relativedelta(months=+12)
        end = start + relativedelta(months=+18)

        df_formation = (1 + df[start:mid].pct_change()).cumprod()
        df_trading = (1 + df[mid:end].pct_change()).cumprod()
        vol_df = vol[start:mid]
        returns = trading(df_formation, df_trading, vol_df, amount, n)
        overall_ret = overall_ret.append(returns)

    return overall_ret
```

9.3.4 Sector_test.py

```
def annual_return(returns):
    return (1+returns.pct_change().mean())**(len(returns)/19)-1

def cagr(returns):
    return (returns.iloc[-1])**(1/19)-1

def total_return(returns):
    return (returns.iloc[-1]-1)

def standard_deviation(returns):
    return returns.pct_change().std()*np.sqrt(252)

def mdd(returns):
    maximums = np.maximum.accumulate(returns)
    drawdowns = 1 - returns / maximums
    return np.max(drawdowns)

def downside_risk(returns, required_return=0):
    downside_diff = returns - required_return
    mask = downside_diff > 0
    downside_diff[mask] = 0.0
    squares = np.square(downside_diff)
    mean_squares = np.nanmean(squares, axis=0)
    return np.sqrt(mean_squares)

def sortino_ratio(returns, required_return=0):
    mu = np.nanmean(returns - required_return, axis=0)
    return mu / downside_risk(returns, required_return)

def sr(returns):
    ret = returns.pct_change()

    rf = (1.019)**(1/360) - 1
    TDD = np.sqrt(-np.where((ret-rf) < 0.0, (ret-rf), 0).mean())
    eff_ret = ret.mean() - rf

    return eff_ret/TDD

def ttest(returns):
    ret = returns.pct_change()
    ret[0] = 0.0
    tstat, pval = stats.ttest_1samp(ret.to_numpy(), 0.0)
    return tstat, pval

measurements = {}

for n in master_cum:
    measurements[n] = {}
    measurements[n]['annual_return'] = cagr(master_cum[n])*100
    measurements[n]['total_return'] = total_return(master_cum[n])
    measurements[n]['annual_volatility'] = standard_deviation(master_cum[n])*100
    measurements[n]['mdd'] = mdd(master_cum[n])*-100
    measurements[n]['sr'] = sr(master_cum[n])*100
    measurements[n]['tstat'], measurements[n]['pvalue'] = ttest(master_cum[n])
```

9.4 Data

Health Care

Company	Ticker	First Timestamp
ADDEX N	ADXN	22.05.2007
AEVIS N	AEVS	05.07.1999
ALCON N	ALC	09.04.2019
BACHEM N	BANB	18.06.1998
BASILEA N	BSLN	25.03.2004
BB BIOTECH N	BION	27.12.1993
CASSIOPEA N	SKIN	01.07.2015
COLTENE N	CLTN	23.06.2006
COSMO PHARM N	COPN	12.03.2007
EVOLVA N	EVE	06.05.2005
IDORSIA N	IDIA	16.06.2017
IVF HARTMANN N	VBSN	08.01.1987
KUROS N	KURN	29.10.2002
LONZA N	LONN	13.05.2002
MEDACTA GROUP N	MOVE	04.04.2009
MEDARTIS N	MED	23.03.2018
MOLECULAR PARTNERS N	MOLN	05.11.2014
NEWRON PHARMA N	NWRN	12.12.2006
NOVARTIS N	NOVN	09.05.2002
OBSEVA N	OBSN	13.03.2018
POLYPHOR N	POLN	15.05.2018
RELIEF THERAPEUTICS	RLF	26.08.2008
ROCHE	ROG	09.05.2002
SANTHERA N	SANN	03.11.2006
SIEGFRIED N	SFZN	05.01.1987
SONOVA N	SOON	01.12.1994
STRAUMANN N	STMN	02.06.1998
TECAN GROUP AG N	TECN	06.09.1989
VIFOR N	VIFN	25.02.2003
YPSOMED HLDG	YPSN	22.09.2004

Consumer Goods

Company	Ticker	First Timestamp
AIRESIS N	AIRE	06.09.1989
ARYZTA N	ARYN	22.08.2008
AUTONEUM N	AUTN	13.05.2011
BARRY CALLEBAUT N	BARN	15.06.1998
BELL FOOD GROUP N	BELL	28.09.1995
CALIDA N	CALN	17.06.1998
EMMI N	EMMN	06.12.2004
FORBO N	FORN	05.01.1987
GMSA N	GMI	31.05.1994

HOCHDORF N	HOCN	17.05.2011
LALIQUE GROUP N	LLQ	25.06.2018
LECLANCHE N	LECN	09.08.1996
LINDT N	LISN	05.01.1987
LINDT PS	LISP	05.01.1987
METALL ZUG AG	METN	15.07.1998
NESTLE N	NESN	13.05.2002
ORIOR N	ORON	22.04.2010
RICHEMONT N	CFR	13.05.2002
SWATCH GROUP I	UHR	09.05.2002
SWATCH GROUP N	UHRN	09.05.2002

Financials

Company	Ticker	First Timestamp
ALLREAL N	ALLN	03.03.2000
Arundel N	ARON	05.01.1987
BALOISE N	BALN	09.05.2002
BANQUE PROFIL DE GESTION N	BPDG	05.04.1994
BASELLAND KB PS	BLKB	08.01.1987
BASLER KB PS	BSKP	31.03.1994
BC GENEVE N	BCGE	31.03.1994
BC JURA N	BCJ	23.05.1991
BC VAUD N	BCVN	06.12.2002
BEKB / BCBE N	BEKN	02.08.2000
BELLEVUE GROUP N	BBN	16.11.1999
BFW LIEGENSCHAFTEN N	BLIN	12.06.2007
BK LINTH N	LINN	06.06.1988
CEMBRA MONEY BANK N	CMBN	30.10.2013
CI COM SA	CIE	18.07.1988
CIE FIN TR I	CFT	23.11.1998
CS GROUP N	CSGN	13.05.2002
EFG INTERNATIONAL N	EFGN	07.10.2005
Fundamenta Real Estate N	FREN	06.12.2018
GAM N	GAM	09.05.2002
GLARNER KB N	GLKBN	24.06.2014
GRAUB KB PS	GRKP	05.01.1987
HELVETIA HOLDING N	HELN	05.08.1996
HIAG IMMOBILIEN N	HIAG	16.05.2014
HYPO LENZB N	HBLN	25.03.1992
INTERSHOP N	ISN	05.01.1987
INVESTIS N	IREN	30.06.2016
JULIUS BAER N	BAER	01.10.2009
LEONTEQ N	LEON	19.10.2012
LIECHT LANDBK N	LLBN	03.06.1993
LUMX GROUP N	LUMX	06.11.2007
LUZERNER KB N	LUKN	12.03.2001
MOBIMO N	MOBN	23.06.2005

ORASCOM DEVELOPMENT HLD AG N	ODHN	14.05.2008
PARGESA I	PARG	05.01.1987
PARTNERS GROUP N	PGHN	23.03.2006
Peach Property N	PEAN	12.11.2010
PLAZZA N	PLAN	26.06.2015
PRIVATE EQUITY N	PEHN	18.01.1999
PSP N	PSPN	07.03.2000
SF Urban Properties N	SFPN	17.04.2012
SNB N	SNBN	12.01.1987
SPCE N	SPCE	13.10.1999
ST GALLER KB N	SGKN	02.04.2001
SWISS LIFE HOLDING AG N	SLHN	30.08.2002
SWISS PRIME SITE N	SPSN	05.04.2000
SWISS RE N	SREN	06.09.1989
SWISSQUOTE N	SQN	29.05.2000
THURGAUER KB PS	TKBP	07.04.2014
UBS GROUP N	UBSG	05.01.1987
VALARTIS GROUP N	VLRT	26.08.1991
VALIANT N	VATN	02.08.1996
VARIA US PROPERTIES N	VARN	08.12.2016
VAUDOISE ASSU N	VAHN	28.06.2005
VONTOBEL N	VONN	31.03.2000
VPB VADUZ N	VPBN	05.01.1987
VZ HOLDING N	VZN	23.03.2007
WARTECK N	WARN	12.04.1995
ZUEBLIN IMM N	ZUBN	12.02.1999
ZUG ESTATES HOLDING AG	ZUGN	02.07.2012
ZURICH INSURANCE N	ZURN	03.01.1994

Industrials

Company	Ticker	First Timestamp
ABB	ABBN	09.05.2002
ADECCO	ADEN	09.05.2002
ADVAL	ADVN	04.06.1998
ALUFLEXPACK	AFP	28.06.2019
ARBONIA	ARBN	20.06.1988
BELIMO	BEAN	20.11.1995
BOBST	BOBNN	12.11.2001
BOSSARD	BOSN	01.06.1987
BUCHER	BUCN	06.05.2005
BRUCKHARDT	BCHN	26.06.2006
BURKHALTER	BRKN	20.06.2008
BVZ HOL	BVZN	19.08.1999
CICOR TECH	CICN	24.04.1998
COMET	COTN	17.12.2002
CONZZETA	CONN	05.01.1999
DAETWYLER	DAE	05.01.1987

DKSH	DKSH	20.03.2012
DORMAKABA	DOKA	01.12.1995
ELMA ELECTRONIC	ELMN	09.01.1997
FEINTOOL	FTON	17.08.1998
FISCHER	FIN	05.01.1987
FLUGHAFEN ZUERICH	FHZN	06.01.1987
GAVAZZI	GAV	06.01.1987
GEBERIT	GEBN	22.06.1999
IMPLENIA	IMPN	06.03.2006
INFICON	IFCN	09.11.2000
INTERROLL	INRN	14.07.1997
KARDEX	KARN	01.04.1987
KLINGELNBERG	KLIN	20.06.2018
KOMAX	KOMN	11.06.1997
KUEHNE+NAGEL	KNIN	16.05.1994
LAFARGEHOLCIM	LHN	09.05.2002
LANDIS+GYR	LAND	21.07.2017
LEM	LEHN	06.07.1999
MCH GROUP	MCHN	29.06.2001
MEIER TOBLER	MTG	05.01.1987
MEYER BURGER	MBTN	23.11.2006
MIKRON	MIKN	06.01.1987
OC OERLIKON	OERL	09.05.2002
PERFECT	PRFN	18.10.1999
PERROT DUVAL	PEDU	10.11.1994
PHOENIX	PM	26.06.1989
POENINA HOLDING	PNHO	16.11.2017
RIETER	RIEN	05.01.1987
SCHAFFNER	SAHN	26.06.1998
SCHINDLER N	SCHN	05.01.1987
SCHINDLER PS	SCHP	2305.1991
SCHLATTER	STRN	12.07.1996
SCHWEITER	SWTQ	12.01.1987
SENSIRION	SENS	22.03.2018
SFS GROUP	SFSN	07.05.2014
SGS	SGSN	09.05.2002
SIG COMBIBLOC	SIGN	28.09.2018
SIKA	SIKA	05.01.1987
STADLER RAIL	SRAIL	12.04.2019
STARRAG GROUP	STGN	16.03.1998
SULZER	SUN	13.05.2002
TORNOS	TOHN	13.03.2001
VAT GROUP	VACN	14.04.2016
VETROPACK	VET	06.01.1987
VON ROLL	ROL	22.06.1987
ZEHNDER	ZEHN	05.01.1987