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Strategic Finance

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**PAIRS TRADING PROFITABILITY IN THE FINNISH STOCK MARKET:
A COMPARISON BETWEEN THREE METHODS**

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ABSTRACT

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| Title: | Pairs trading profitability in the Finnish stock market: A comparison between three methods |
| Faculty: | School of Business |
| Major: | Strategic Finance |
| Year: | 2016 |
| Examiners: | Professor Eero Pätäri Post-Doctoral Researcher Timo Leivo |
| Master's Thesis: | LUT School of Business 70 pages, 12 figures, 10 tables, 2 appendices |
| Key words: | Pairs trading, statistical arbitrage, copulas, cointegration, Finland, Nasdaq OMX, Helsinki Stock Exchange |

Pairs trading is an algorithmic trading strategy that is based on the historical co-movement of two separate assets and trades are executed on the basis of degree of relative mispricing. The purpose of this study is to explore one new and alternative copula-based method for pairs trading. The objective is to find out whether the copula method generates more trading opportunities and higher profits than the more traditional distance and cointegration methods applied extensively in previous empirical studies.

Methods are compared by selecting top five pairs from stocks of the large and medium-sized companies in the Finnish stock market. The research period includes years 2006-2015. All the methods are proven to be profitable and the Finnish stock market suitable for pairs trading. However, copula method doesn't generate more trading opportunities or higher profits than the other methods. It seems that the limitations of the more traditional methods are not too restrictive for this particular sample data.

TIIVISTELMÄ

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|-----------------------------|--|
| Tekijä: | Jens Harju |
| Tutkielman nimi: | Parikaupankäynnin kannattavuus Suomen osakemarkkinoilla: Kolmen menetelmän vertailu |
| Tiedekunta: | Kauppateieteellinen tiedekunta |
| Pääaine: | Strategic Finance |
| Vuosi: | 2016 |
| Tarkastajat: | Professori Eero Pätäri Tutkijatohtori Timo Leivo |
| Pro Gradu-tutkielma: | Lappeenrannan teknillinen yliopisto 70 sivua, 12 kuvaa, 10 taulukkoa, 2 liitettä |
| Hakusanat: | Parikaupankäynti, tilastollinen arbitraasi, kopulat, yhteisintegroituvuus, Suomi, Nasdaq OMX, Helsingin pörssi |

Parikaupankäynti on algoritminen kaupankäyntistrategia, joka perustuu historiallisesti hinnoiltaan samankaltaisesti käyttäytyviin arvopapereihin. Kauppaa käydään, kun tapahtuu suhteellinen virhehinnoittelu. Tämän tutkimuksen tarkoitus on tutkia uutta ja vaihtoehtoista kopula-pohjaista parikaupankäynnin menetelmää. Tavoitteena on selvittää, saavutetaanko kopula-pohjaisella menetelmällä enemmän kaupankäyntimahdollisuuksia ja paremmat tuotot kuin perinteisemmällä hintaeroon ja yhteisintegroituvuuteen perustuvilla menetelmillä, joita on laajasti käytetty aiemmissa empiirisissä tutkimuksissa.

Menetelmiä verrataan valikoimalla parhaat viisi paria Suomen osakemarkkinoiden suurten ja keskisuurten yritysten osakkeiden joukosta. Tutkimusperiodi kattaa vuodet 2006-2015. Kaikkien menetelmien todetaan tutkimuksessa tuottavan voittoa ja Suomen osakemarkkinat soveltuu hyvin parikaupankäyntiin. Kopula-pohjainen menetelmä ei tuota enemmän kaupankäyntimahdollisuuksia tai suurempia voittoja. Vaikuttaa siltä, että perinteisempiä menetelmiä koskevat tiukemmat rajoitteet eivät ole liian rajoittavia ainakaan tässä tutkimuksessa käytetyn aineiston osalta.

ACKNOWLEDGEMENTS

This master's thesis could be seen as the pinnacle of a lengthy personal plan. First of all, I would like to thank Professor Eero Pätäri for his guidance and patience during the whole thesis project.

I am relieved and satisfied that I didn't lose the sense of motivation and the urge to push myself through adversities throughout this whole project. I am also grateful to all the kind and caring people that I'm luckily surrounded by. You, I cannot even thank you enough.

In Pori 12th of May 2016

Jens Harju

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1 INTRODUCTION

1.1 Background and motivation

Computational intelligence has enabled a transformation in the trading markets and automatized algorithmic trading has become really popular and replaced manual work previously done by investors and traders. As an evidence of its popularity, according to Hendershott et al. (2011) algorithmic trading is now responsible for over 70 percent of trading actions in the US trading markets. Algorithmic trading is based on discovering certain algorithms that can explain trading patterns, capitalize on those patterns and therefore enable systematically profitable trading in the markets.

Pairs trading is one popular algorithmic trading strategy that has around 20-year history within the hedge funds and investment banks on Wall Street. The idea is to find a pair of assets whose prices have historically moved together. There is a spread calculated between the quoted prices of these two assets. When the spread widens, investor buys the undervalued asset and simultaneously shorts the overvalued asset. Based on the history of the pair, the prices are believed to converge back to their mean and then the pairs trading strategy will create profits. (Gatev et al. 2006)

Pairs trading is essentially a market-neutral strategy. In market-neutral strategy the investor expects that the long positions outperform the short positions in rising bull markets and that the short positions outperform the long positions in declining bear markets. This would create a profitable environment despite the existing market situation. (Ehrman 2006, 4) According to Ehrman (2006, 1), today's market uncertainties, global unrest and weak economic landscape has led investors to seek shelter. One option has been increased exploitation of market-neutral strategies. Pairs trading has been one long-lasting strategy that has proven to remain profitable throughout its existence.

Copulas are tools for modelling the dependence between random variables and copula theory has recently increased its popularity in statistics and finance. Copulas have much less rigorous assumptions on the data than some other theories and therefore copulas have been increasingly applied to financial modelling and asset pricing. (Ferreira 2008) Specifically for a pairs trading strategy, copulas present a new method in discovering trading signals.

1.2 Objectives of the study

Pairs trading is a trading strategy that has been widely researched in several different contexts. There is evidence of its profitability in different timeframes all the way from 1960s and it has been researched in several different financial markets and concerning different sectors and financial instruments. According to more recent research (Do & Faff 2010), the profitability of pairs trading has been diminishing as of late.

Pairs trading opportunities are traditionally recognized with distance or cointegration methods. Both of these methods rely on the idea that spread is an indication of mispricing, use cointegration analysis or maximum correlation criteria as the measures of dependence and assume that the assets have a linear association. This essentially means that these traditional methods would be viable if the data is normally distributed.

However, according to Ling (2006) and Ang & Chen (2002), actual financial data like stock returns mostly aren't normally distributed. Actually, returns of most assets and asset classes tend to indicate negative skewness or excess kurtosis (Kat 2003). So, using these traditional methods can cause pairs trading signals to be inaccurate. If there were methods with no such limitations of the data, these methods should theoretically perform better in indicating optimal trading signals at least in data that is not normally distributed.

Copula theory is a relatively new method to implement on pairs trading and interesting due to the fact that it doesn't have as strict assumptions as the more traditional methods. Currently there is some empirical evidence on the potential of copula-based pairs trading compared to the more traditional pairs trading methods. However, there is only minor amount of previous research and the main contribution of this study to the existing literature is to present more evidence on the potential of copula-based pairs trading.

Secondly, this study contributes to the existing research on pairs trading in the Finnish stock markets done by Kupiainen (2008), Rinne & Suominen (2011) and Broussard & Vaihekoski (2012). All of these studies were conducted using traditional distance method and documented pairs trading to be a profitable investment strategy in Finland.

Therefore, the aim of this study is to test the following hypothesis: pairs trading with copula method leads to more trading opportunities and higher profits compared to the distance and cointegration methods. This hypothesis is two-part and the study includes comparison of trading opportunities and generated returns between distance, cointegration and copula method using similar trading strategy.

According to Caldas et al. (2014), the literature lacks comprehensive studies regarding the performance of different methods across developed and emerging markets. Also, most studies use different trading periods or trading criteria and therefore, make cross-study comparisons challenging. (Caldas et al. 2014)

There are a few limitations regarding this study. This study revolves around the research on securities and this study is only focused on stock instruments in Finnish stock market (Helsinki Stock Exchange, OMXH). According to Ehrman (2006, 2), pairs trading can likewise be exploited on derivatives or options but these are out of the focus of this work. Pairs trading generally relies on statistical arbitrage pairs and their relative pricing.

According to Vidyamurthy (2004, 1), there also exists risk arbitrage pairs but those are in the context of mergers between companies and for that reason, outside of the scope of this study.

Finnish stock market also fulfills the requirements regarding diversity and uniformity. In order to make pairs trading strategy viable, the selected environment should give the trader a reasonably large amount of choices (Ehrman 2006, 147). During the last 20 years Finnish stock market has consistently had over 100 different listed companies.

1.3 Research methodology

This is essentially a quantitative research based on time-series analysis. The main objective of this study is to test certain hypothesis regarding pairs trading. The data for this study is numeric stock market data and three pairs trading execution models are tested. The results of applying these models are calculated and compared to each other in order to find evidence of their performance. Based on previous literature and empirical evidence, the hypothesis is that a copula-based method for pairs trading would generate higher returns and more trading opportunities than the more traditional distance and cointegration methods.

The implementation of this study requires certain methods regarding data collection, data modeling and data analysis. The raw stock market data is collected from Nasdaq OMX Nordic database and dataset is screened and prepared for modeling. Data modeling consist of constructing three comparable pairs trading models with distance, cointegration and copula methods. These models are created with an objective of ensuring their comparability to each other and with previous empirical research. Therefore, these models are not optimized in order to ensure their best performance in the Finnish stock market. Data preparation, modeling and analysis is done with two separate tools: R programming language and its libraries for statistical computing and SPSS statistical software.

Data analysis is done by using an identical method for return calculations for each method. Pairs trading research can also focus on mirroring actual, real-life scenarios of trading by taking into account certain factors, such as transaction costs of trading, liquidity of stocks, trading restrictions and policies or trader's risk management methods. Most of these factors reduce the actual profits that a pairs trader could theoretically get and therefore, they are important to remember when implementing real-life pairs trading algorithms. However, this study is comparative and therefore, these factors don't have a critical impact on the results or the validity of this study. The details of the research methodology are discussed in the 3rd section.

1.4 Structure of the study

The rest of this study is arranged in a following way: The 2nd section includes the theoretical framework and focuses on explaining more specifically what pairs trading actually is, how it works and how different pairs trading methods are applied. In the 3rd section, research methodology is explained in detail from data collection to data modeling. Section 4 presents empirical results and data analysis concerning the research hypothesis. Results are shown for each individual asset pair and methods are thereafter compared. Section 5 concludes the study.

2 THEORETICAL FRAMEWORK

2.1 History of pairs trading and its underlying theories

Pairs trading is essentially a market-neutral strategy. Market-neutral strategy means that returns are derived from relative performance and not from the absolute performance like in traditional investment portfolios. This means that the performance is a function of the return differential between assets with long positions and assets with short positions. (Ehrman 2006, 4) The returns of market-neutral strategy are uncorrelated with the market returns and hence market-neutral strategies can be profitable regardless of ups and downs in the trading market. (Vidyamurthy 2004, 5)

Market-neutral strategies and pairs trading are not new phenomena. However, market-neutral strategies became mainstream tools for investors and traders after the exploded popularity of hedge funds. After that, investors and traders started to use advanced tools and methods to implement trading strategies and make a collection of computer-driven systems with immense calculation power and speed. In 1990, there were only around 200 hedge funds while by 2005 the amount had risen to around 8000. Market-neutral strategies have become a compelling option because they offer diversification benefits and performance despite the economic situation. (Ehrman 2006, 20-21) Especially today's market uncertainties, global unrest and weak economic landscape has led investors to seek shelter. One valid option has been increased exploitation of market-neutral strategies and pairs trading has been one long-lasting successful strategy. (Ehrman 2006, 1)

Regarding history, famous trader Jesse Livermore is considered as the first one to use pairs trading principles in his trading actions in the early 1900s. By monitoring the so-called sister stocks, that operate in the same industry, he assumed that there was an existing trend if the sister stocks moved in tandem. Livermore was famed of using this tandem, spotting long-term

trends and generating significant profits from it. So, pairs trading essentially has almost a hundred years of history. (Ehrman 2006, 21-22)

However, the first proficient, algorithmic applications of pairs trading strategies were used by Nunzio Tartaglia's team of mathematicians, physicists and computer scientists in Wall Street in the mid-1980s. Their team tried to take advantage of quantitative arbitrage strategies with the use of automated computer-based trading system that was based on strict filter rules in trading behaviour. Pairs trading was one of their team's approaches and it was used with great success during the year 1987. Afterwards the idea of pairs trading started to spread and pairs trading strategies became common in many investment banks and hedge funds. (Vidyamurthy 2004, 73-74)

Pairs trading is a simple trading strategy that relies on statistical arbitrage pairs and their relative pricing. Relative pricing means that assets with similar characteristics should be priced in a similar fashion and the spread between the prices is a measure of mispricing. One can take advantage of the moments when these assets are not in equilibrium. So in essence, when the spread is increasing the mispricing is also of greater magnitude and there are bigger chances to gain profits. (Vidyamurthy 2004, 8)

Figures 1 and 2 show two series of stock prices. One can statistically discover that these stocks share a dependency and do not drift apart from each other that much. Distance between the two stocks at any point of time is called spread.

The proportion of the spread gives indication on trading signals. In pairs trading these signals have certain thresholds and as shown in the picture, trading is done in moments when these thresholds are met. Trades are closed when the prices converge and spread is zero. (Hoel 2013) There are several different methods to model the spread and this study focuses on three popular methods that are presented in later sections.

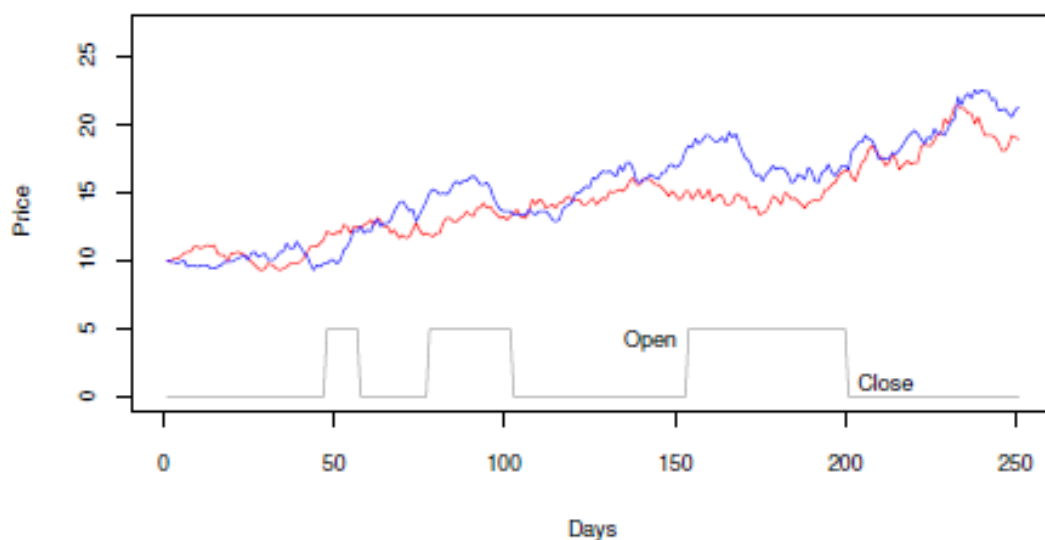


Figure 1. Two generic series of stock prices (Hoel 2013)

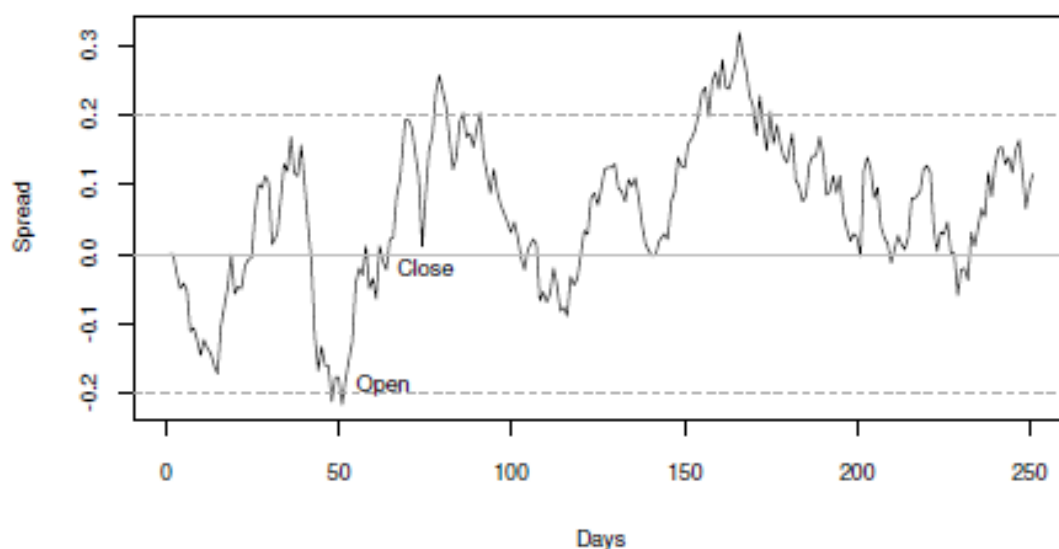


Figure 2. Spread of two generic stock prices (Hoel 2013)

Statistical arbitrage strategies like pairs trading are by nature contrary to fundamental investment strategies that explore the association between economic forces and asset prices. (Caldas et al. 2014) Simple arbitrage means that there are exploitable inefficiencies in the market but this hasn't been possible in the modern age due to increased information and computational intelligence. Arbitrage today is almost entirely based on perceived pricing flaws and not on actual and real pricing flaws created by slow or lacking information. In pairs trading the relative pricing arbitrage is

created by a temporary distortion of the prices of a pair of assets. Therefore, the most important aspect of arbitrage is that the distortion is only temporary and prices fluctuate back to their expected values over time. (Ehrman 2006, 5)

Pairs trading is contrarian by nature and thus shouldn't be profitable in truly efficient financial markets. Gatev et al. (2006) contemplated that pairs trading has psychological explanations for its success. Humans tend to want to buy rising assets and not declining ones. Disciplined pairs traders are capable of taking advantage of this behaviour and pairs trading profits could partly be due to over-reaction to news and shocks rather than due to fluctuation of common factors. (Gatev et al. 2006)

2.2 Profitability of pairs trading

Pairs trading is a strategy that has proven to be profitable in several different markets and timeframes: Gatev et al. (1999) originally documented excess returns in the U.S. financial markets during 1962-1997 and updated their research (2006) to show persistent returns even up to year 2002. However, with their simple pairs trading method they remarked declining returns in the most recent years. This research by Gatev et al. (2006) has been one of the most cited research paper in the area of pairs trading. Perlin (2009) showed that pairs trading was not specific to the U.S. market by documenting profitability in the Brazilian financial markets. Also several others have extended the research to various financial markets worldwide and several different instruments or sectors (e.g. Andrade et al. 2005, Broussard & Vaihekoski 2012, Engelberg et al. 2009).

Within time, the profitability of pairs trading has been questioned. According to Do and Faff (2010), arbitrage-based strategies commonly encounter increased competition between arbitrageurs who are attempting to exploit even marginal arbitrage opportunities. This will ultimately lead to smaller profits. Based on their research, pairs trading in the U.S. equity markets has had a declining trend in excess returns starting from the beginning of 1990s.

After that, negative return months have been clearly more frequent. Although, one interesting finding was that pairs trading generated increased profits during market downturns like the 2000-2002 dot-com bubble and the 2007-2009 global financial crisis. (Do & Faff 2010)

There is also more evidence on the effects of increased competition between arbitrageurs. Bowen et al. (2010) researched intra-day data over 12-month period in the year 2007 and discovered that returns of a pairs trading strategy are really sensitive to the speed of execution and the magnitude of transaction costs. Computerized pairs trading systems that are able to grasp trading signals quicker than competing arbitrage-based systems would essentially bring greater profits. However, transaction costs are generally more relevant factor in decreasing excess returns in the case of very frequent trading actions. (Bowen et al. 2010)

Regarding profitability and pairs trading opportunities, Andrade et al. (2005) linked uninformed news shocks to the profitability of pairs trading in their research. They discovered that initial price divergence is highly correlated to uninformed news shocks and pair trading opportunities open more quickly when one stock experiences large uninformed buying. (Andrade et al. 2005)

Papadakis and Wysocki (2007) discovered that around 10 percent of pair openings are activated by accounting event information. They also documented trades activated through accounting events to perform worse than events without significant triggering accounting information. They claim that accounting event information is increasing and thus decreasing pairs trading profitability. (Papadakis & Wysocki 2007)

Engelberg et al. (2009) also explored the news effects. Two kinds of accounting information are important: idiosyncratic (company-level) news and common (industry-level) news. Idiosyncratic news might benefit pairs trading if investors overreact to those kind of news but if information diffuses slowly into prices, permanent price divergence might happen and pairs

trading would be unprofitable. Regarding common news, the most important factor is the relative underreaction or overreaction. If the price of one of the stocks reacts faster than the other, beneficial price divergence for pairs trading is likely to occur. (Engelberg et al. 2009)

Jacobs and Weber (2015) researched pairs trading in U.S. stock markets between 1960 and 2008 and found evidence that relative profitability is not stable over time but affected by several factors like news announcements or investor attention. They found out that firm-specific news were negatively related to profitability. Also pair openings on days with dividend announcements and news stories made lower returns than other pairs. However, pair openings on days with macroeconomic news were mildly more profitable. Holiday effect was also proven to be significant as pair openings on the last trading days before holidays were indeed more profitable than in other days of the year. They also discovered that less visible pairs proved to be more profitable in pairs trading. Proxies for pair visibility included average newswire coverage and analysts coverage adjusted to firm size. (Jacobs & Weber 2015)

Pizzutilo (2013) constructed a simple pairs trading model that includes factors regarding implementation for individual investor. Transaction costs, initial margins, interest costs, cash guarantees and limitations to short selling were proven to be significant restrictions for pairs trading and its profitability. In Italian stock markets, profits still existed but only in the case of smaller portfolios of 5-10 pairs. (Pizzutilo 2013)

Do and Faff (2010) stated that there are certain characteristics separating bad pairs from good pairs. Initially good candidates would be those that not only have relatively good co-movement but also exhibit frequent crossings between their prices. These are called zero crossings and defined as how many times the normalized spread crosses the value zero. (Do & Faff 2010)

Pairs trading pairs are discovered to generate more profits within the utilities and financials industry. In utility companies there is greater homogeneity in the form of stable demand, low product differentiation and usually tighter regulation. In financial firms there are several macroeconomic factors that heavily impact their asset prices and therefore, co-movements are more likely to occur. (Do & Faff 2010)

Kim (2011) has found out that non-cyclical demand driven industries like distribution, household products, automobiles & components showed relatively higher returns. Industries with fast-paced technological development and international demand, such as technology hardware, software and services, performed worse. Pairs in these industries were less likely to maintain consistent cointegration relationship. (Kim 2011)

Pairs trading in Finnish stock market has been studied by Kupiainen (2008), Rinne and Suominen (2011) and Broussard and Vaihekoski (2012). Kupiainen (2008) discovered 5 pairs in Finnish equity markets between the years 2004-2007 and by using simple technical analysis and distance method was able to prove pairs trading strategy viable and profitable. Rinne and Suominen (2011) researched only one pair between the years 1987 and 2003. This pair was two of the largest companies in Finland and competing forest industry companies UPM-Kymmene and Stora-Enso. This pair generated 1.46 % - 2.37 % of returns per transaction with pairs trading limits of 0.5 % -1 %. Pairs trading with this particular pair was proven to be profitable even allowing for transactions costs. However Rinne and Suominen (2011) also discovered decreasing profitability towards the end of research period.

Broussard and Vaihekoski (2012) researched the period between 1987 and 2008 and by using distance method discovered that pairs trading could be used as a profitable investment strategy even in low liquidity environment such as Finland. Finnish stock market has a multiple share class environment and four out of their five recognized pairs were in fact multiple

share classes of the same company. Using comparable methods to earlier research done by Gatev et al. (2006) Broussard and Vaihekoski documented slightly higher returns (annualized returns of 12.53 % compared to Gatev et al.'s 9.31 %).

Regarding Finland's equity markets and their illiquidity, Engelberg et al. (2009) has documented that less liquid stocks are more likely to diverge for non-information reasons. Also, low levels of liquidity may drive arbitrageurs away, which could contribute to longer periods of price divergence.

2.3 Fundamentals of pairs trading

Pairs trading is an investment strategy that is market-neutral and based on statistical arbitrage and relative pricing. Hence, technical analysis plays an important role in conducting pairs trading and it is much more important than fundamental analysis. As defined by Ehrman (2006, 99) technical analysis is used in order to model past market activity and test trading algorithms that rely on the assumption that past market behaviour will continue in the future. However, market behaviour is quite unlikely to remain constant in the future and this is one of the main risks that pairs traders will face, the so-called model risk.

Pairs trading fundamentally requires selection of the pairs as the first step and trading as the second step. According to Liew and Wu (2013) there are several different methods and techniques to carry out pair selection and execute trades. The two most common ones are distance method and cointegration method. (Liew & Wu 2013)

If one uses statistical techniques like stationarity tests or cointegration, their usage in initial pair selection would become really time-consuming as the total amount of possible pairs in generally all security markets is so vast these days. So, before the pair selection step, there is usually a screening step where possible pairs are limited to a smaller amount.

Huck and Afabuwo (2015) documented that this has been done by picking only pairs whose returns in predetermined selection period differs less than 10 percent. Also basic correlation measures have been used as initial screening methods. Miao (2014) has done screening for pairs to have a correlation coefficient of over 0.9.

After the pair selection the trading step follows. Trading algorithm essentially involve rules to determine when to enter (open position) and exit (close position) pair trades. Entering rule is commonly determined by difference between normalized prices diverging by more than predetermined threshold within selected trading period. Exiting occurs usually when normalized prices converge or the trading period ends. (Pizzutilo 2013)

Non-convergence is the biggest risk in the execution of pairs trading. The pairs trader has the assumption that the prices will converge back within time and non-convergence takes place when the prices won't converge back. In trading strategy this basically means that either the duration of the trade lasts longer than the predetermined time period in which the pairs trader believes convergence to happen or the divergence reaches a stop-loss limit where the prices aren't believed to converge again and therefore, the trade is closed. Stop-loss is the most important risk management measure for the pairs trader. Stop-loss limit should be tight enough to not allow considerable losses to occur but also loose enough to not miss too many delayed converges after stop-loss. Stop-loss limit is usually different from manager to other and varies over time. However, specific stop-loss level can be calculated as follows:

$$(W \times W_m) - (L \times L_m) = P$$

where P is the expected profit from the strategy, W is the percentage of profitable trades, W_m is magnitude of profitable trades, L is percentage of losing trades and L_m is magnitude of losing trades. (Ehrman 2006, 83-85)

In pair selection one has to determine a certain formation period. In each formation period, all possible pairs are considered and suitable pairs are selected based on certain method. The length of formation period has varied significantly between different studies ranging from 60 days to several years. Formation period is followed by trading period where trading algorithm is applied to selected pairs and potential trades are executed. (Clegg 2014) After the trading period ends, open positions are naturally closed.

One of the most notable research papers on pairs trading is written by Gatev et al. (2006). They have used a formation period of 12 months and trading period of 6 months with daily data. Enter and exit thresholds were set based on price divergence increasing to over 2 standard deviations. These time periods, rules and thresholds have been used by other studies that have extended to the study of Gatev et al. Naturally, if enter and exit thresholds are increased, less trading opportunities and trades occur. (Huck & Afabuwo 2015)

According to Huck (2013), the results of pairs trading are highly sensitive to the choice of formation period, trading period and trading thresholds. Clegg (2014) found evidence that pair identification is highly sensitive to the initial time period. Pairs that are recognized as having historical co-movement during certain period of time don't necessarily have co-movement during other periods of time. Therefore, it is also important to have a method to identify when identified pair ceases to exist. (Clegg 2014)

2.4 Distance method

Distance method has been widely used after Gatev et al. (2006) made their research on pairs trading in the U.S. markets based on distance method. Initially in the distance method, measure of closeness is defined. Pairs are selected by minimizing the sum of squared differences (SSD) in the normalized asset prices that include reinvested dividends. Normalized prices of both assets are set to value 1 at the beginning of first trading day

in the formation period. The normalized price are calculated in a following way:

$$P_t^i = \prod_{\tau=1,t} (1 + r_\tau^i)$$

where P_t^i is the normalized asset price of asset i at the end of trading day t and the r_τ^i is the daily return with dividends for asset i on trading day τ . (Papadakis & Wysocki 2007)

Then for every pair a measure of the distance, the sum of squared normalized price deviations ($SSD_{i,j}$), is calculated:

$$SSD_{i,j} = \sum_{t=1}^T (P_t^i - P_t^j)^2$$

with P_t^i and P_t^j the normalized prices for assets i and j on time t , and T the number of trading days in the formation periods. When the distance measure for all asset pairs have been calculated, one generally ranks pairs based on the minimum distance and certain number of pairs with the smallest values of distance are selected for pairs trading portfolio.

Trading period commonly starts on the next day after formation period has ended. At the beginning of trading period asset prices are again set to value 1. During the trading period, long and short positions are entered as normalized price difference or spread divergences are bigger than the threshold limit. This threshold is usually a multiple of standard deviation, 2 standard deviations being the norm, from the historical spread over the formation period:

$$Threshold^{i,j} = \pm 2 \times stdev(P_t^i - P_t^j)$$

Positions are exited after prices cross or at the end of the trading period. According to Gatev et al. (2006), when working with daily closing prices it is preferred to use additional one-day waiting rule before entering and exiting

the positions. Calculated excess returns might be biased upwards due to bid-ask bounces, in other words, as one is implicitly buying at bid price and selling at ask price. Therefore, it is advisable to wait one day before executing trades. (Papadakis & Wysocki 2007) Formation and trading is usually repeated within specified time. Formation period usually has a fixed length like one or two years. (Huck & Afabuwo 2015)

Distance method is basically a model-free method that is not prone to errors in model specification or estimation. However, distance method makes an assumption that returns of the pair of assets are in parity. Also, the distance method is parameter free and therefore, there are no forecasting possibilities. (Do et al. 2006) According to Huck and Afabuwo (2015), there is also evidence that distance method has had relatively weak performance in the most recent years in the U.S. markets.

2.5 Cointegration method

Cointegration has been increasingly applied to financial econometrics and it has proven to be really effective statistical technique. (Alexander & Dimitriu 2005) Cointegration is based on the idea of mean reversion and it attempts to find long-term relationship between asset prices. (Huck & Afabuwo 2015)

In other words, cointegration states that, despite two non-stationary time series, a specific linear combination of the two time series is in fact stationary. A stationary process is essentially a stochastic process in which joint probability distribution doesn't change over time. (Miao 2014)

The most well-known cointegration test has been developed by Engle and Granger (1987). There is also a more advanced cointegration test developed by Johansen (1988) but in this study the more traditional Engle and Granger test is applied.

The first step in their method requires regression based on the log prices of the first asset P_t^i against the second asset P_t^j at time t

$$P_t^i - \beta P_t^j = \mu + \varepsilon_t$$

where β is the cointegration coefficient, μ is the constant term and $\varepsilon_t \sim I(0)$, i.e. ε_t is integrated of order 1. If the spread is stationary by nature, it will fluctuate around the long-run equilibrium μ . Regression parameters β and μ are in most cases estimated using the Ordinary Least Squares (OLS) method. (Huck & Afabuwo 2015)

Second step is done by using stationarity test to the residuals ε_t to verify the cointegration. There are several stationarity tests available but Augmented Dickey-Fuller (1987) test is generally the most used in the case of cointegration. Augmented Dickey-Fuller test is fitting because it is necessary to capture the full dynamic nature of the process and include sufficient lag terms. Augmented Dickey-Fuller test models for the presence of unit root in the residuals ε_t with the following formula:

$$\Delta Z_t = a + \beta_t + \gamma Z_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta Z_{t-1} + u_t$$

where a is a constant, β is the coefficient over time, p is lag order of the autoregressive process and u_t is the error term. If $a = 0$ and $\beta = 0$, equation models random walk and if they are not zero, equation models a random walk with a drift. Lag order of the process p is usually unknown and therefore, it is commonly estimated by using information criteria like Akaike information criteria (AIC) (Akaike 1992), Schwartz information criteria (SIC) (Schwartz 1978) or Hannan-Quinn criteria (HQC) (Hannan & Quinn 1979), final prediction error (FPE) (Akaike 1969) or Bayesian information criteria (BIC) (Akaike 1979). Estimation of the lag order of the process is determined by minimizing one of these criteria:

$$AIC = \ln(\hat{\sigma}_p^2) + \frac{2p}{T}$$

$$\begin{aligned}
SIC &= \ln(\hat{\sigma}_p^2) + \frac{p \ln(T)}{T} \\
HQC &= \ln(\hat{\sigma}_p^2) + \frac{2p \ln[\ln(T)]}{T} \\
FPE &= \hat{\sigma}_p^2 (T - p)^{-1} (T + p) \\
BIC &= (T - p) \ln\left(\frac{T \hat{\sigma}_p^2}{T - p}\right) + T[1 + \ln(\sqrt{2\pi})] + p \ln\left[\frac{\sum_{t=1}^T (\Delta Z_t)^2 - T \hat{\sigma}_p^2}{p}\right]
\end{aligned}$$

where T is the sample size and the estimation of the error variance $\hat{\sigma}_p^2$ is determined by

$$\hat{\sigma}_p^2 = \frac{\sum_{t=p}^T u_t^2}{T - p - 1}$$

Augmented Dickey Fuller test is done under the null hypothesis $H_0: \gamma = 0$ against the alternative hypothesis $H_1: \gamma < 0$. ADF test statistic is determined by a formula:

$$ADF = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$$

where $\hat{\gamma}$ is the cointegration coefficient and $SE(\hat{\gamma})$ are the standard errors of the OLS estimate. Standard errors are calculated by

$$SE(\hat{\gamma}) = \sqrt{\frac{\sum_{i=1}^n (\Delta Z_{ti} - \Delta \bar{Z}_t)^2}{(n - 2) \sum_{i=1}^n (Z_{t-1} - \bar{Z}_{(t-1)l})^2}}$$

If the Augmented Dickey-Fuller test statistic value is less than the critical value, null hypothesis is rejected and thus there is no unit root. This essentially means that regression residuals are stationary and the pair of assets are cointegrated. (Miao 2014)

Generally, pairs are ranked based on the test statistic. The smaller the cointegration test statistic, the higher the rank of the pair. Only highest ranked pairs or pairs that are over the acceptable cointegration criteria level

are picked on trading portfolios. For example, 95 % confidence level for the test statistic has been used as an inclusion criterion. (Miao 2014)

For the trading period, a threshold of certain amount of standard deviations of the spread during the formation period is used for opening positions. Positions are closed when the spread converges to the value of zero. (Liew & Wu 2013) Stop-loss limit is also generally bound to the amount of standard deviations, for example, 2 standard deviations, as in the case of Miao's research (2014).

Caldas et al. (2014) compared pair selection strategies and discovered that pairs formed with cointegration method have generally performed better on average than pairs formed with traditional distance method. For Brazil and main European stock markets from 1996 to 2012, the cointegration method had statistically significant higher average annual return with higher Sharpe ratio and generally a significantly lower volatility. (Caldas et al. 2014)

Cointegration is also quite similar in its nature as the distance method. Pairs that are formed based on the closeness measure are also most likely cointegrated as the spread is fluctuating around equilibrium.

There are certain factors that could create bias in the results of using cointegration method. Log returns of asset prices are not normally distributed, which is troublesome. For two assets to be cointegrated, the factor loadings of one asset must be exact multiple of the factor loadings of the other one. In addition to that, idiosyncratic risk components of the two assets must be free of unit roots. This essentially means that all firm-specific news must have only temporary effects on the price of this firm's asset. (Clegg 2014)

2.6 Copula method

Copula is a statistical measurement that stands for multivariate uniform distribution and it is used to research the dependence between random

variables. (Nayak et al. 2014) The most common methods for pairs trading, distance method and cointegration method, place restricting assumptions on the marginal distributions and their joint movement. This can cause inaccurate trading signals or missed profit opportunities for a pairs trader. Copulas separate marginal distributions from dependence structures and therefore, appropriate copula is able to grasp the dependence and co-movement features of the pair of assets.

Unlike the more common methods, copula method results in richer set of information regarding the shape and nature of the dependency between the asset prices. Two assets are not examined through a single number but two cumulative distributions and a joining surface of copula. So, returns of assets are linked probabilistically and viewed through two cumulative distributions with ranges of $[0,1]$. (Ferreira 2008)

Therefore, copulas provide more flexibility than the more traditional modeling techniques like for example multivariate generalized autoregressive conditional heteroscedasticity (GARCH) models. Copula models are generally applied in the field of portfolio management and more specifically related to risk management issues. (Berger & Missong 2014) However, there is one serious limitation for copula method in finance. Copulas are suitable for bivariate cases but multivariate cases with copulas of dimensions larger than 2 are not easy to optimize with current softwares (Mendes & Accioly 2013)

There are many parametric families of copula but generally two well-known ones are Elliptical copula and Archimedean copula. Elliptical copulas are related to elliptical distributions and they follow linear dependency structure. They are calculated from multivariate distribution functions based on Sklar's theorem. The traditional elliptical copulas are Gaussian and Student-t.

Archimedean copulas have non-elliptical distribution and they follow non-linear dependence structure. Common Archimedean copulas are Clayton,

Gumbel and Frank. (Nayak et al. 2014) In this study, the possible copulas are limited to Gaussian, Student-t, Gumbel, Frank and Clayton. Similar limitations have been used in previous academic literature too (Liew & Wu 2013)

Copula method is generally used in pairs trading to recognize trading opportunities. However, pair selection is a key part of pairs trading and a mandatory step before trading. With copula method, pairs are generally selected with distance method or cointegration method. (Xie & Wu 2013)

In a copula-based pairs trading method the objective is to choose an optimal copula function between the two stock returns and to identify the relative positions between the stocks by choosing a corresponding estimation procedure (Hu 2003). Copula method is unique because it splits the modelling of the dependence structure into two parts.

First, the best fitting marginal distribution is picked from the log returns of each asset in the formation period and by using a standard statistical software, relevant estimated parameters for each asset returns are applied and cumulative distribution function values in the range of $[0,1]$ are acquired. The cumulative distribution function values can be acquired with a parametric or non-parametric approach. In parametric approach an analytical software is used to fit a known statistical distribution like maximum likelihood estimation to the pair. In a non-parametric approach the empirical cumulative distribution function is estimated from the pair with statistical software. (Stander et al. 2012) In this study, the empirical cumulative distribution function is used.

To evaluate the dependence structure more clearly, a graphical representation of asset returns, like scatter plot, is very useful in order to assess e.g. tail dependence and certain outliers. This helps in picking the most fitting copula that take e.g. tail dependence into account. In this study,

statistical software's copula fitting function is applied in order to find the optimal copula and its parameters.

The copula fitting is executed so that all available copulas are fitted first by using maximum likelihood estimation. Then the criteria are computed and the copula with the minimum value is chosen. In this study a criteria of Akaike Information Criteria (AIC) is used. After that, a fitting copula is applied and calibrated to the data to create the dependence structure.

Then, one has to calculate the cumulative distribution function values for the trading period. This is done in a similar way to the formation period data. Then the selected optimal copula and its parameters are used in combination with the cumulative distribution functions values from the trading period. With a statistical software, one can calculate the conditional probability function values for each stock. These work as the indicators for overvaluation and undervaluation.

The conditional probabilities for stocks u and v are calculated by taking partial derivatives of the copula function:

$$V = P(U \leq u | V = v) = \frac{\partial C(u, v)}{\partial v}$$

$$U = P(V \leq v | U = u) = \frac{\partial C(u, v)}{\partial u}$$

The stocks are generally considered undervalued if the conditional probability is under 0.5 and relatively overvalued if over 0.5. If $V < 0.5$ then U is undervalued relative to V and if $V > 0.5$ then U is overvalued relative to V . Trades should be made when one of the conditional probabilities is close to one. (Ferreira 2008)

Regarding pairs trading strategy, Liew and Wu (2013) and Stander et al. (2012) used upper bound of 0.95 and lower bound of 0.05 as trading triggers for conditional probabilities. So, positions are opened when one of the two stocks is above the upper bound and simultaneously one is below the lower

bound or vice versa. Positions are closed when conditional probabilities cross the 0.5 boundary. (Liew & Wu 2013)

According to Ferreira (2008), copulas are a flexible and a relatively easy method to implement on pairs trading strategy. Due to its relative short history in finance, there is also much further development and research in the area. (Ferreira 2008) Some criticism has also been voiced out about copulas and their applications in finance. However criticism is a natural reaction to the wide array of applications that copulas actually have. Copulas cannot be seen as the only right solution for problems with stochastic dependence. (Jaworski et al. 2010, 5-6)

3 DATA AND RESEARCH METHODOLOGY

3.1 Data and screening criteria

Initial data for this study is from Finnish stock market (Helsinki Stock Exchange, OMXH) and it is collected from the Nasdaq OMX Nordic database. Database holds stock data for 137 different stocks starting from the beginning of year 1997. The average amount of instruments has varied between 55 and 134 during that time period (Figure 3). However, the amount of stocks is not equivalent to the amount of listed companies. Finnish stock market is atypical as there is a large amount of multiple share classes of the same company.

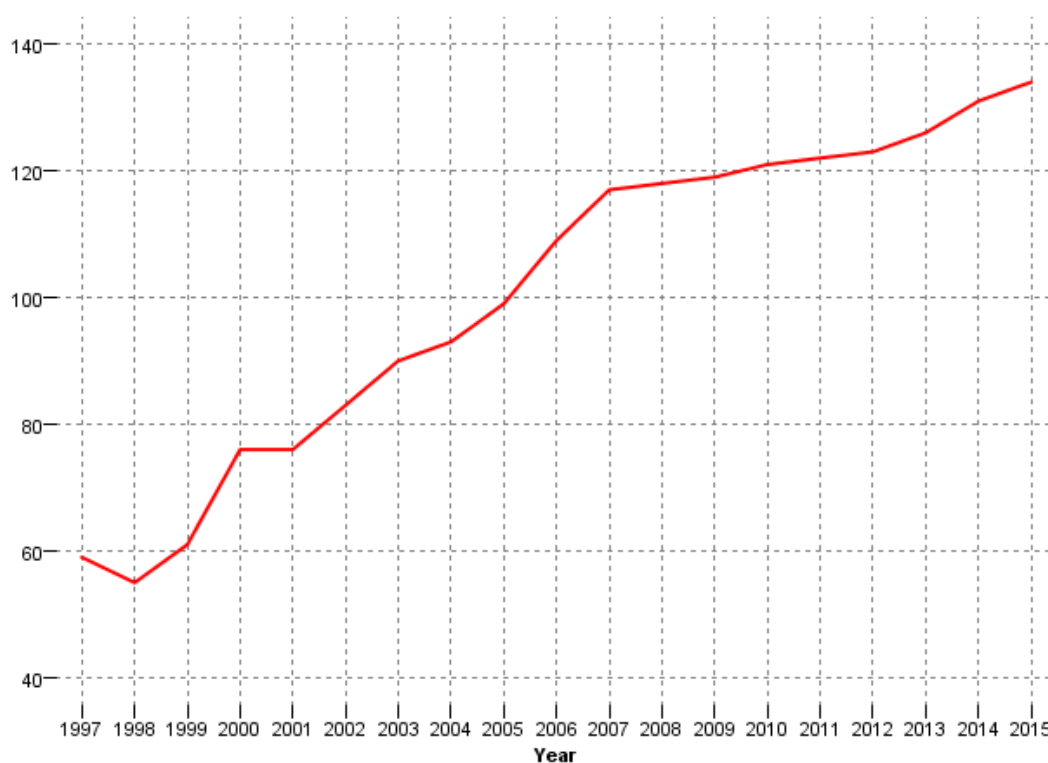


Figure 3. The amount of instruments by year in the database

In this study a 10-year time span from the beginning of 2006 to the end of 2015 is included. This 10-year time span and dataset is recent and large enough because the main objective of this study is to compare methods with same dataset and not to prove long-term profitability of pairs trading, which

has been one of the main objectives in previous studies, such as Gatev et al (2006). The 10-year time span also ensures that the formation and trading periods are subsequent and long enough to analyse both pair dependence structures and to reach clear differences in profitability between the methods.

During that time span there has been daily stock data for 2 514 trading days per stock. There have been 98 stocks that have stock data for the whole formation period. 29 percent of those stocks belong to large companies, 30 percent to mid-sized companies and 41 percent to small companies. Below there are statistics about the distribution of companies by industry and descriptive statistics of the research data.

Table 1. Distribution of companies in the formation period by industry

| Industry | Number of companies | % of total |
|--------------------|----------------------------|-------------------|
| Industrials | 32 | 26 % |
| Technology | 17 | 14 % |
| Consumer Goods | 14 | 11 % |
| Financials | 10 | 8.1 % |
| Consumer Services | 10 | 8.1 % |
| Basic Materials | 8 | 6.5 % |
| Health Care | 3 | 2.4 % |
| Telecommunications | 2 | 1.6 % |
| Utilities | 1 | 0.8 % |
| Oil & Gas | 1 | 0.8 % |
| Overall | 123 | 100 % |

Table 2. Descriptive statistics of the formation period data

| Industry | Daily trade amount |
|--------------------|---------------------------|
| n | 302 056 |
| Mean | 470 |
| Standard deviation | 1 476 |
| Median | 18 |
| Mode | 0 |
| Maximum | 135 579 |
| Minimum | 0 |

Stock data in this study consists of daily closing prices that are adjusted for dividends, issues and splits. Most of the previous research in pairs trading has used daily closing prices in their dataset. According to Kim (2011), daily closing prices have a few practical limitations. Trading is allowed only during the trading hours and there is a possibility that trading thresholds are met when market is closed. Also some security markets, like Korean stock market, prohibit shorting stocks at closing prices. (Kim 2011)

Usually pairs trading research involves initial screening of available data. Screening is done in order to eliminate large amount of assets that would not be good candidates for pairs trading portfolio. According to Ehrman (2006, 44), there are several criteria for screening. Some pairs traders might even exclude certain industries or sectors due to limited knowledge. Screening essentially allows the pairs trader to limit the number of assets and to save time in analysing selected pairs.

Usually assets should be liquid so that trading would be possible with the prevailing market price and at any point when the market is open. Trading with illiquid assets results in higher bid-ask spreads and larger transaction costs. Illiquid assets also become much harder to sell during market declines. (Ehrman 2006, 44)

Pairs trading involves shorting assets, and hence, it should be possible to short sell the available assets. This is not always possible due to some restrictions. For example countries like Spain, Italy, France, Greece, Belgium, Turkey, South Korea and the Securities and Exchange Commission in the United States have placed temporary bans or restrictions on short selling during recent years. (Eichler 2011)

It is also really risky to include assets in a pairs trading portfolio that could be involved in some sort of corporate actions, such as mergers, acquisitions, secondary public offerings or stock repurchases. These actions generally cause price fluctuations that are not otherwise even possible. (Ehrman 2006, 44-45)

In pairs trading sector neutrality is also taken into account. Sector neutrality means that the companies for a selected pair must be in the same sector. Usually there is even further requirement that both instruments have to be in the same industry. This is done because certain sector or industry swings might have major impact on the selected pair, their co-movement and performance. Pairs from different industries are significantly riskier. (Ehrman 2006, 65)

Finnish stock market has a fairly low level of liquidity and thin trading. Stocks have therefore low trading volumes and high bid-ask spreads. Short selling doesn't have major restrictions in Finland but it doesn't have a long history either as it was only officially made possible starting from the year 1995. (Broussard & Vaihekoski 2012)

In Finnish stock market there is so limited amount of stocks to select for pairs trading and therefore, no assets are excluded due to industry or short selling restrictions and corporate actions. Previous research on pairs trading in Finland's stock markets (Broussard & Vaihekoski 2012, Kupiainen 2008) haven't had such restrictions either. However, stocks that belong to small

companies are neglected because their trading volumes, price variance and liquidity is so low that actual pairs trading would be distorted.

Only stocks that have been listed for the whole formation period are included in the research. This ensures a consistent and equal execution of pair formation for all possible pairs. Yet there is no guarantee that all the selected stocks are listed for the whole subsequent trading period.

Therefore, if this kind of pairs are selected, the trading period is only as long as both of the stocks remain listed. This policy also ensures that there is no look-ahead bias in this study. The formation period data is regarded as in-sample or historical data for the pairs trader for executing the pair selection. The following trading period is out-of-sample data and essentially it might be that the pair is even no longer co-moving in the trading period.

3.2 Pair formation

After screening out assets, dataset includes assets that are suitable for pairs trading. Then there needs to be a certain pair formation methodology for predetermined time periods. Previous literature has mainly used comparable formation periods and trading periods for pairs trading. Widely-cited research papers in the pairs trading, such as Gatev et al. (2006), Andrade et al. (2005), Papadakis and Wysocki (2007), Engelberg et al. (2009), Do and Faff (2010), Broussard and Vaihekoski (2012), used equivalent formation periods of 12 months and 6-month trading periods after formation. This has alleviated data snooping biases and enabled to generate complementary out-of-sample results.

In previous research regarding pairs trading with copula method, varying lengths of time periods have been used. Liew and Wu (2013) used a longer formation period of 24 months and trading period of 12 months. Ferreira (2008) and Xie and Wu (2013) used a regular 12-month formation period, likewise Xie et al. (2014) used the same formation period with 6-month subsequent trading period.

One key difference in the research on pairs trading with traditional methods and copula methods is that researchers have used rolling time periods when using more traditional methods. Usually trading periods roll one month forward with trading periods following up. This way, the research covers multiple different trading periods where selected pairs generate trading opportunities and the pairs are formed separately for each period. However, copula method is a significantly more complex method. There is even not much empirical research on copula methods and those studies have been conducted with a single formation period and a single subsequent trading period. In order to keep this study extensive but not too large by scope, similar approach with single time periods is therefore used.

According to Liew and Wu (2013), there is no fixed guideline to the length of formation and trading period. Longer time periods ensure that the dependency structures are grasped properly and that meaningful results from the trading period can actually be generated. Short formation period would increase the risk of accidentally fitting certain pair of assets. It is critical not to mix random fit of assets to a longer-lasting dependency. In this study, a 3-year formation period is chosen and the following seven years make up the trading period. Therefore, formation period consists of 754 trading days per stock and trading period 1 761 trading days per stock.

According to Vidyamurthy (2004, 86) pair formation is usually done with an approach that aims to order pairs based on the degree of co-movement. Each potential pair is given a score or distance measure. The higher the score, the greater co-movement. (Vidyamurthy 2004, 86) Usually top 5-20 candidates are selected for pairs trading portfolio.

There are two common methods to select pairs during the formation period. In distance method, pairs are selected by minimizing the sum of squared deviations between the two normalized price series. This method has been

used frequently and it is popular because it mimics the description of how actual traders form pairs. (Gatev et al. 2006)

Second option is to use cointegration method. Alexander and Dimitriu (2005) and Caldas et al. (2014) presented several benefits of using cointegration instead of correlation based techniques, like distance method. These include mean reverting tracking error, enhanced weights stability, ability to not lose valuable information regarding assets, long-term viability, lesser sensitivity to outliers and volatility clustering that can lead to faulty conclusions regarding long-running dependencies. (Alexander & Dimitriu 2005, Caldas et al. 2014) Based on its benefits, cointegration method has been selected for pair formation in this study. There is no need to test both pair formation methods because the aim in this study is to achieve comparability regarding pairs trading profitability. Pair formation methods could also be tested against each other and researcher could get valuable information but this is unjustified due to previous research done by e.g. Alexander and Dimitriu (2005).

Cointegration-based pair formation can essentially be done to both raw and transformed prices. However, Vidyamurthy (2004, 80) states that for the cointegration model to apply, logarithm of stock prices is required to be a nonstationary series. The assumption that logarithm of stock prices is a random walk (in other words basically non-stationary) is quite general and extensively used in option pricing models. The non-stationarity gives a good chance that the stocks would also be cointegrated. Therefore, it is preferable to use logarithm of stock prices. (Vidyamurthy (2004, 80)

To estimate the relationship between pairs is usually done with Engle and Granger method and Ordinary Least Squares (OLS) regression. OLS minimizes the squared residuals of the dependent variable in regression equation. Teetor (2011) states that by fitting two separate stocks with OLS regression, the OLS fit is not symmetrical because critical mathematical assumption behind the OLS algorithm. Therefore, it might be possible that

the cointegration coefficients are not identical and one relationship will be cointegrated while the other will not. This is problematic in pairs trading. Vidyamurthy (2004, 112) has suggested tackling the limitation by putting weight in the asset with lower volatility. However, an alternative to OLS is Total Least Squares or in other words orthogonal regression, where coefficients are treated symmetrically. Instead of minimizing the residuals for one, TLS minimizes the distance from each point between variables to the regression line and distances are actually vectors that are orthogonal to the regression line. (Teetor 2011) The orthogonal regression or TLS is used in this study.

The orthogonal regression formula and ADF test formula are following:

$$\ln(P_t^i) - \beta \ln(P_t^j) = \hat{\varepsilon}_t$$

$$\Delta \hat{\varepsilon}_t = a_1 \hat{\varepsilon}_{t-1} + a_2 \Delta \hat{\varepsilon}_{t-1} + \varepsilon_t$$

The lag has been set to one. Longer lag lengths could have been used to recognize stationary series when shorter lag lengths reject the stationarity condition. However, there is no need to test this phenomenon and in this study only series that are proven to be stationary even with shorter lag length are retained. Also intercept and a time trend have been omitted from the test formula. The residuals are from regression and should be stationary, so there is no purpose to include these terms.

Pair formation requires rigorous testing for cointegration between all screened assets in the Finnish stock market. After screening small companies, there is a total amount of 58 assets. The amount of possible pairs for pairs trading in this study is therefore calculated with a mathematical formula:

$$Pair_N = \binom{N}{2} = \frac{N!}{2!(N-2)!}$$

where N is total amount of all assets. This makes total amount of 1 653 possible pairs to be tested in this study. From this amount, only 5 pairs that

have the most stationary spread and lowest ADF test statistic during the formation period are selected for trading portfolio.

3.3 Trading strategy for each method

Trading strategy in this study needs to be systematic and stable so that the results of trading with all three different methods would be comparable. Trading strategy essentially includes setting criteria regarding the length of trading period and thresholds for entering positions and exiting positions and a limit in case of certain pair not reverting back to equilibrium. Trading period in this study is a 7-year period between 2009 and 2015 and it is subsequent to the formation period.

Traditionally thresholds have been determined as a static measure based on the historical standard deviation of the spread. Most of the research is done with enter threshold being 2 standard deviations and exit threshold being the mean reversion point. This traditional approach is also applied to this study.

With the traditional distance and cointegration methods, the 2 standard deviations of the pair's historical spread are used as the trading signals. If the spread in the trading period floats to under 2 standard deviations from the mean, then the first stock is estimated to be undervalued and the other one overvalued. Positions are naturally reversed if the spread floats to over 2 standard deviations from the mean. Long position is taken on the undervalued stock and short position on the overvalued one. With the distance method positions are closed when the spread in the trading period crosses the mean of historical spread. With the cointegration method positions are closed when the spread converges to the value of zero.

With the copula method, the cumulative distribution function values in the trading period are acquired and the optimal copula and its parameters are used to calculate the conditional probabilities for both stocks in the trading period. As a guideline, one stock is undervalued if its derivative of the copula

with respect to the other stock is less than 0.5 and it is overvalued if the derivative of the copula is over 0.5.

According to Stander et al. (2012), the confidence bands are used as a trading signal. A back-test analysis is commonly used in order to determine the sufficient confidence level. If the confidence level is too low, there are more trading opportunities but they in most cases lead to too low returns to cover the trading costs. With too high confidence level, there are too few trading opportunities and profitable trades might be missed unwittingly. (Stander et al. 2012)

In previous research (e.g. Liew & Wu 2013, Ferreira 2008), upper confidence bound of 0.95 and lower bound of 0.05 have been used and these boundaries are also applied in this study to ensure consistency and comparability. Positions are then opened when one of the stocks is above the upper bound and simultaneously the other one is below the lower bound. Positions are closed when the conditional probabilities cross the 0.5 mark.

3.4 Calculation of trades and excess returns

Trading opportunities are analysed and compared in this study based on the amount of trades in the whole trading period. One trade occurs when positions are opened and closed. Therefore, there can only be one active and opened trade per pair at any time. If the trigger for closing positions is not met before the end of the trading period, positions are closed and returns are calculated at the end of the trading period's last trading day.

Pairs open and close various times during the trading period, and hence, they can generate multiple positive or negative cash flows. Like in Gatev et al.'s (2006) study, the trading gains and losses are calculated over long-short positions of one unit of currency and the payoffs have the interpretation of excess returns. Excess returns are the reinvested payoffs during the trading interval.

In actual pairs trading, traders need to determine how many stocks they are going to buy and sell in each trade and how to rebalance the portfolio in order to have the equal monetary exposure. There are various techniques for that need, such as Sharpe ratio or Stander et al.'s drift ratio. (Stander et al. 2012) In this study the method applied by Gatev et al. (2006) is used and therefore portfolio is not rebalanced at any point.

In this study, the calculation of excess returns is simplified and based on the idea of Augustine (2014). For each trade one euro is invested in each stock when the positions are opened in the trading period. The return is calculated as a return of the long and short positions from the opening point to the closing point of the trade with following formula:

$$R_{trade} = P_{long}(t) - P_{short}(t)$$

where $P_{long}(t)$ is the value of the long position at the closing day of the trade and $P_{short}(t)$ is the value of the short position at the closing day of the trade. Returns from each trade are summed to acquire total cumulative excess returns over certain time.

In previous academic literature one-day waiting rule has been applied for pairs trading. This study is based on the use of daily closing prices and one-day waiting rule essentially means that the trading is done based on the quoted price 24 hours after the initial opening and closing signal. The trades and returns are calculated separately with zero-day waiting and one-day waiting. According to Nordby (2013), in real-life pairs trading scenarios the active pairs trader can assumedly act quicker, and therefore, the results with the zero-day waiting rule might be more realistic.

4 RESULTS

4.1 Selected pairs in Helsinki Stock Exchange

Based on the pair formation with cointegration-based method, four out of the five most cointegrated pairs are multiple share classes of same company. This is no surprise and in line with the previous research in Finnish stock market (Broussard & Vaihekoski 2012). However, interesting notion is that testing the distance-based pair formation suggests quite different pairs to be selected. This might be one area for further research but in this study pairs are only selected based on the cointegration-based analysis and these same pairs are compared with different trading methods.

The selected pairs in this study are following ones:

1. Stora Enso Oyj R & Stora Enso Oyj A
2. Raisio Oyj Vaihto-osake & Raisio Oyj K
3. Stockmann Oyj Abp B & Stockmann Oyj Abp A
4. Metsä Board Oyj B & Metsä Board Oyj A
5. Citycon Oyj & Sponda Oyj

The Augmented Dickey Fuller test with the Engle Granger method rejected the null hypothesis with generally low test statistic values between -16 and -5 for all the selected pairs. Based on MacKinnon (1991) and Enders (2010) the critical value for rejection of the null hypothesis for 5 % significance level is -3.35.

Stora Enso is a large international Swedish-Finnish company and provider of renewable solutions in packaging, biomaterials, wood and paper. Stora Enso operates globally in over 35 countries and their stocks are listed both in Finnish and Swedish stock markets. Stora Enso has two classes of stocks: R and A. A-stock has one vote per stock and R-stock has one vote per 10 stocks. Stock prices in the formation period are shown below. (Kauppalehti 2016a, Stora Enso 2016)

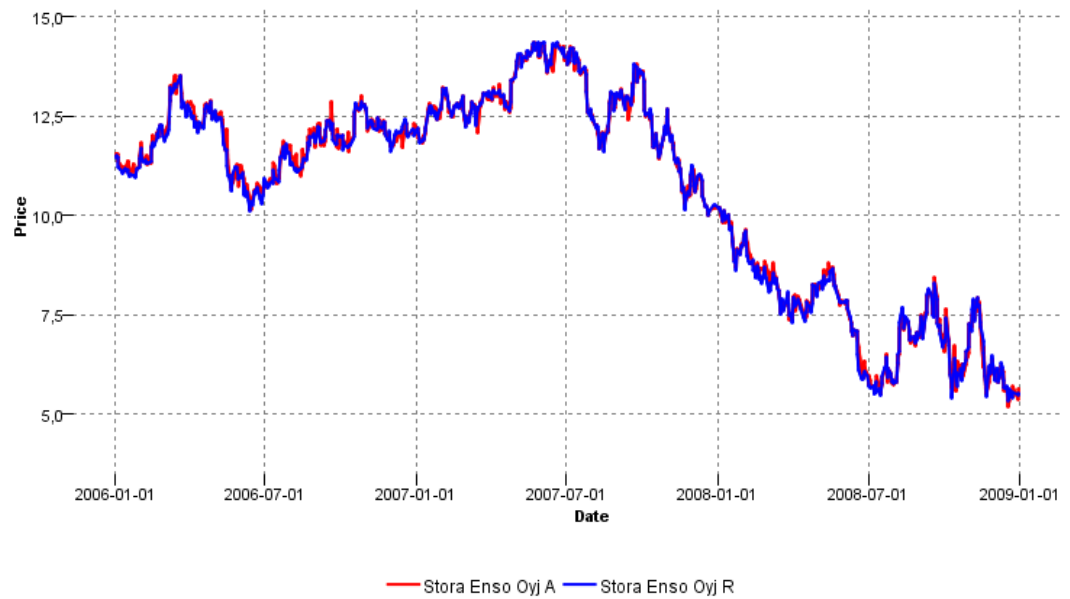


Figure 4. Stock prices for Stora Enso Oyj R and Stora Enso Oyj A during the formation period

Raisio is a food processing company and its main products are vegetable-based products, their healthy ingredients and fodder. Raisio operates globally and its main markets are in Finland, United Kingdom, Sweden, Russia, Ukraine, Poland and Baltic countries. Raisio has two classes of stocks: K-stocks and V-stocks. K-stock has 20 votes per stock and V-stock has one vote per stock. Stock prices in the formation period are shown below. (Kauppalehti 2016b, Raisio 2016)

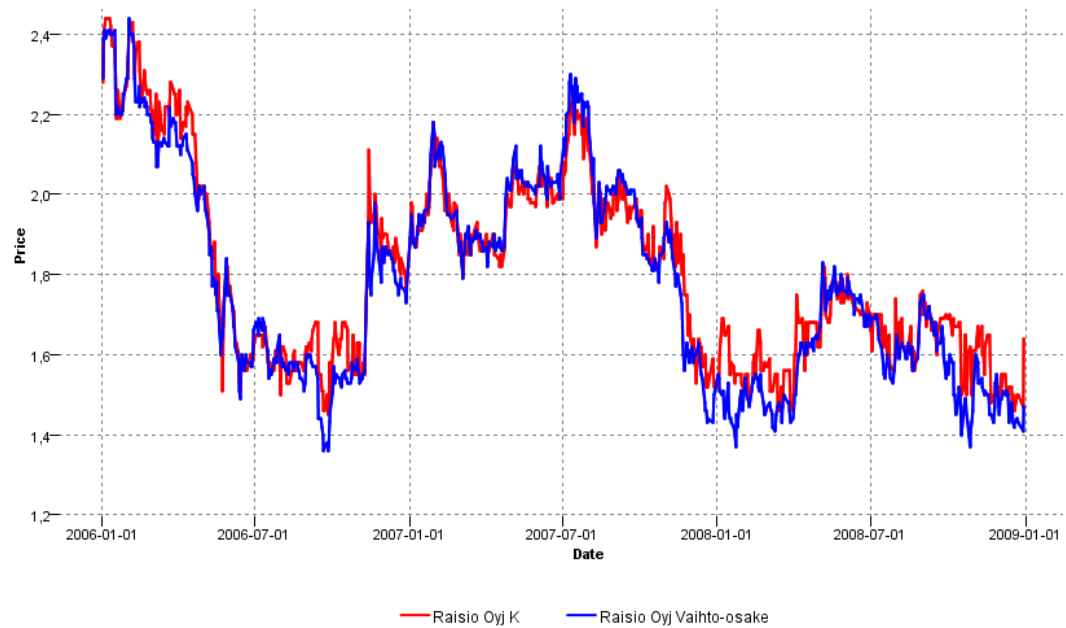


Figure 5. Stock prices for Raisio Oyj Vaihto-osake and Raisio Oyj K during the formation period

Stockmann operates in the department store trade and in the fashion industry with its separate Lindex chain. It also engages in the real estate business. Stockmann has two classes of stocks: A-stocks and B-stocks. A stocks have 10 votes per stock and B-stocks have one vote per stock. Stock prices in the formation period are shown below. (Kauppalehti 2016c, Stockmann 2016)

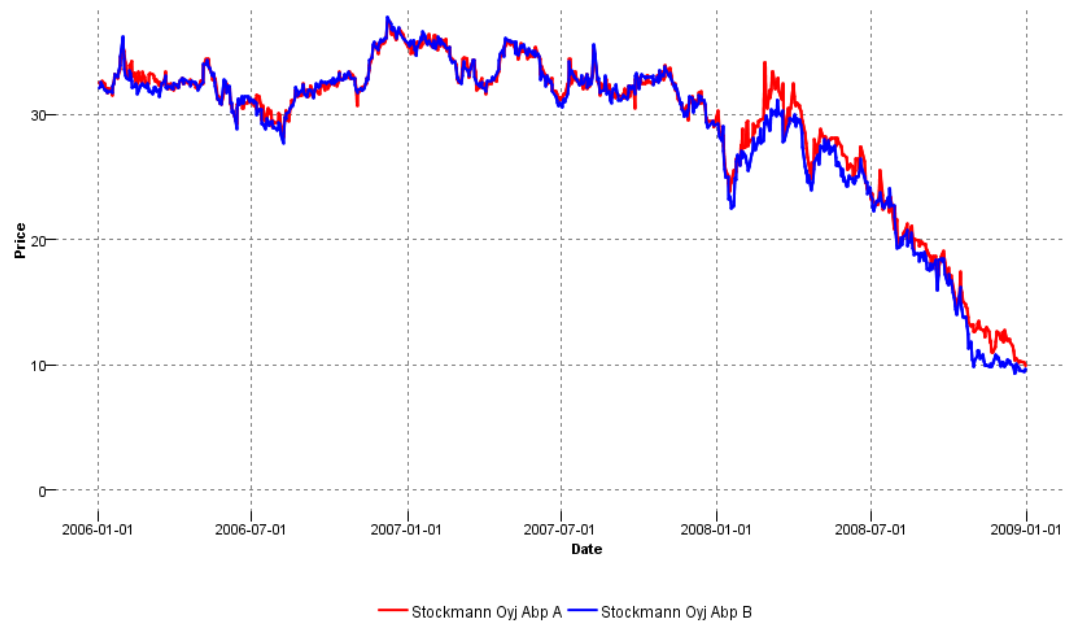


Figure 6. Stock prices for Stockmann Oyj Abp A and Stockmann Oyj Abp B during the formation period

Metsä Board is one of Europe's leading boxboard and linerboard manufacturers. It creates packaging, graphics and office end-use solutions. Metsä Board has two classes of stocks: A-stocks and B-stocks. A-stocks have 20 votes per stock and B-stocks have one vote per stock. Stock prices in the formation period are shown below. (Kauppalehti 2016d, Metsä Board 2016)

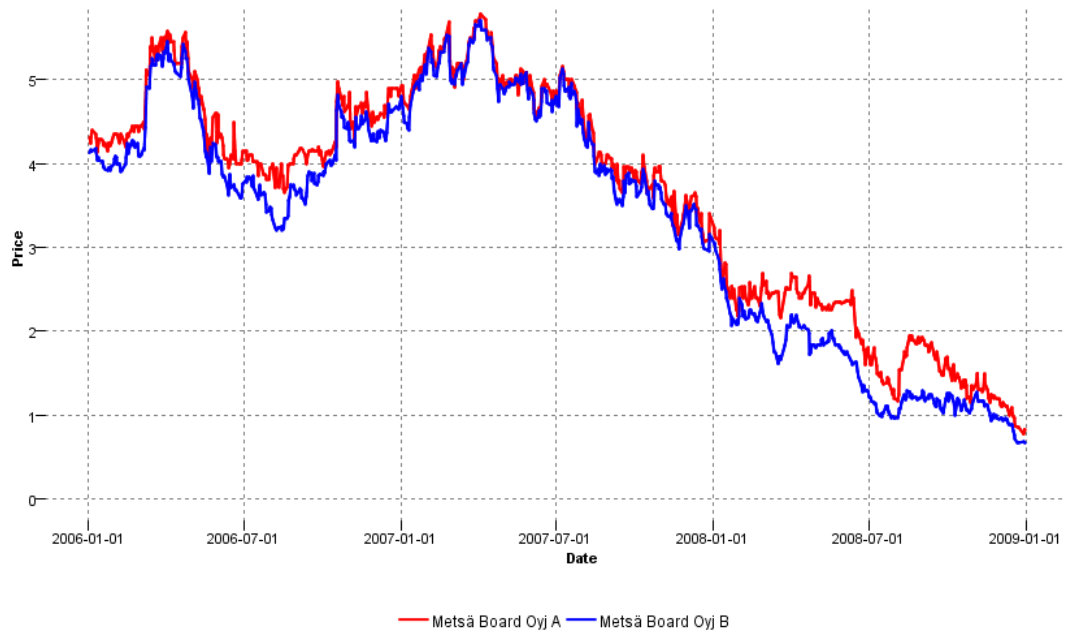


Figure 7. Stock prices for Metsä Board Oyj A and Metsä Board Oyj B during the formation period

Citycon is a real estate company and an owner, manager and developer of shopping centers in the Nordic and Baltic countries. It owns 36 shopping centers and 41 business estates. (Kauppalehti 2016e)

Sponda also operates in real estate business and it specializes in business premise rental, development and ownership. Sponda has facilities mainly in Finland and Russia. Stock prices in the formation period are shown below. (Kauppalehti 2016f)

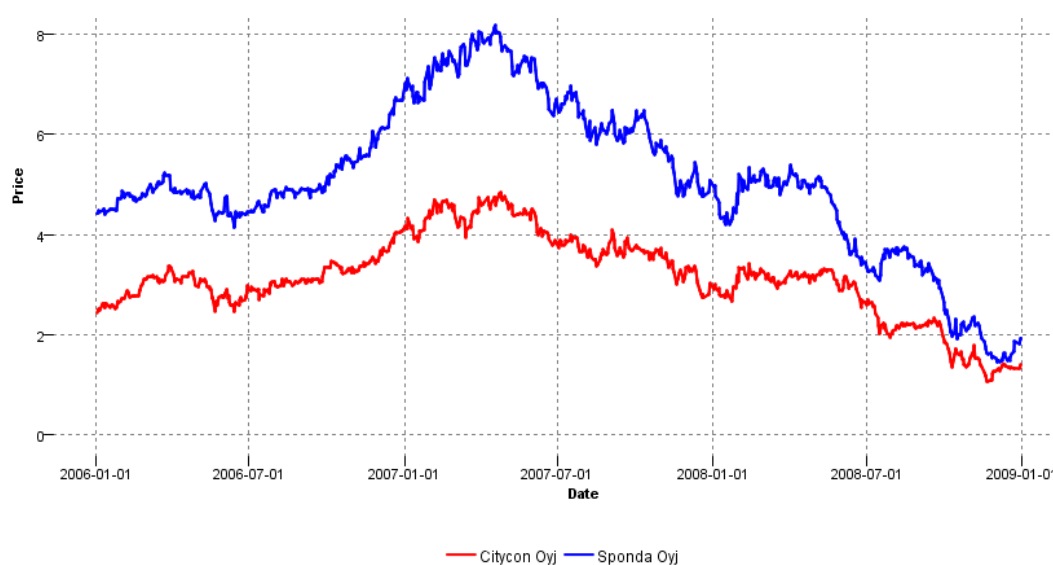


Figure 8. Stock prices for Citycon Oyj and Sponda Oyj during the formation period

4.2 Distance-based trading

Distance-based trading is based on the spread. This spread for the whole trading period and the underlying trade triggers for the first pair are shown in Figure 9 below. Other pairs are depicted in Appendix 1. The complete results of the trades for zero-day and one-day waiting are shown in Tables 3 and 4.

Distance method creates quite a lot of trading opportunities for all the pairs but those trades are only short-term by nature. However, this is quite characteristic behaviour for pairs trading. Both with zero-day waiting and one-day waiting rules the distance method is capable of generating profits. This is in line with the previous empirical evidence from the use of distance method.

From the spread curves one can see that trading opportunities for all the pairs are more common at the start of the trading period. This might be a consequence of using static thresholds for whole trading period.

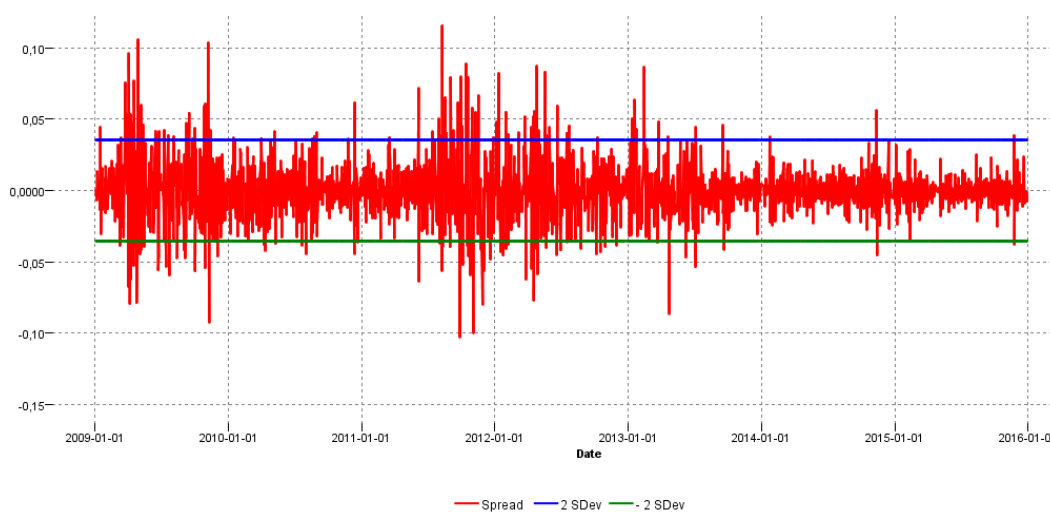


Figure 9. Spread and thresholds for Stora Enso Oyj R and Stora Enso Oyj A for distance-based trading

Table 3. No lag simple returns for distance-based trading

| | | Pair 1 | Pair 2 | Pair 3 | Pair 4 | Pair 5 |
|-----------------------------|----------------|--------------|----------|---------------|-------------|---------|
| | | Stora Enso A | Raisio V | Metsä Board A | Stockmann A | Citycon |
| | | Stora Enso R | Raisio K | Metsä Board B | Stockmann B | Sponda |
| Yearly excess returns | Average | 1.12 % | 10.8 % | 34.8 % | 14.1 % | 17.3 % |
| | Std. deviation | 11.3 % | 15.9 % | 55.2 % | 15.3 % | 40.1 % |
| | Minimum | -18.3 % | 0.00 % | 0.00 % | 0.00 % | -4.09 % |
| | Maximum | 16.5 % | 40.5 % | 156 % | 35.9 % | 109 % |
| Monthly excess returns | Average | 0.10 % | 0.90 % | 2.90 % | 1.18 % | 1.44 % |
| | Std. deviation | 2.73 % | 2.47 % | 11.5 % | 3.50 % | 12.2 % |
| | Minimum | -6.49 % | 0.00 % | -37.5 % | -6.27 % | -7.27 % |
| | Maximum | 11.7 % | 14.7 % | 80.2 % | 22.8 % | 110 % |
| Amount of trades per pair | | 110 | 28 | 59 | 44 | 27 |
| Avg. holding days per trade | | 1.6 d | 1.3 d | 1.6 d | 1.3 d | 2.0 d |
| % of time when pair is open | | 9.94 % | 2.10 % | 5.34 % | 3.35 % | 3.12 % |

Table 4. 1-day lag simple returns for distance-based trading

| | | Pair 1 | Pair 2 | Pair 3 | Pair 4 | Pair 5 |
|-----------------------------|----------------|--------------|----------|---------------|-------------|---------|
| | | Stora Enso A | Raisio V | Metsä Board A | Stockmann A | Citycon |
| | | Stora Enso R | Raisio K | Metsä Board B | Stockmann B | Sponda |
| Yearly excess returns | Average | 0.59 % | 6.09 % | 1.12 % | 7.41 % | 1.10 % |
| | Std. deviation | 12.6 % | 12.9 % | 9.99 % | 19.3 % | 5.46 % |
| | Minimum | -17.1 % | -0.29 % | -9.37 % | -7.44 % | -4.60 % |
| | Maximum | 24.8 % | 35.0 % | 19.2 % | 49.2 % | 12.8 % |
| Monthly excess returns | Average | 0.05 % | 0.51 % | 0.09 % | 0.62 % | 0.09 % |
| | Std. deviation | 2.72 % | 2.38 % | 3.90 % | 6.35 % | 1.17 % |
| | Minimum | -13.3 % | -8.27 % | -16.3 % | -11.4 % | -4.30 % |
| | Maximum | 10.8 % | 13.8 % | 18.2 % | 55.0 % | 5.00 % |
| Amount of trades per pair | | 110 | 28 | 59 | 44 | 27 |
| Avg. holding days per trade | | 1.6 d | 1.3 d | 1.6 d | 1.3 d | 2.0 d |
| % of time when open pairs | | 9.94 % | 2.10 % | 5.34 % | 3.35 % | 3.12 % |

4.3 Cointegration-based trading

Cointegration-based spread and the trading thresholds for the first pair are shown in Figure 10. Other pairs are depicted in Appendix 2. Results of trading are shown in Tables 5 and 6. Cointegration-based spread curves have a lot longer and stronger deviations from the mean. Therefore, trades are longer and there are not so many trades on average. Cointegration method is also capable of creating profits with both zero-day and one-day waiting rules.

The strong deviations are risky in real-life applications as there is no certainty that the deviations will gravitate back to the equilibrium. This is the main assumption that the pairs trading essentially relies on. In some cases the historical co-movement of the pair, that has been identified, can stop existing. If one examines the spread curve of Citycon Oyj and Sponda Oyj, one can see that the deviation becomes really large and it doesn't gravitate back to the equilibrium even at the end of the trading period. There is a strong possibility that the pair's co-movement doesn't exist anymore. In these cases, pairs trader must have some sort of risk management policies or stop-loss limits to ensure that the losses from these kind of pairs don't become too large.

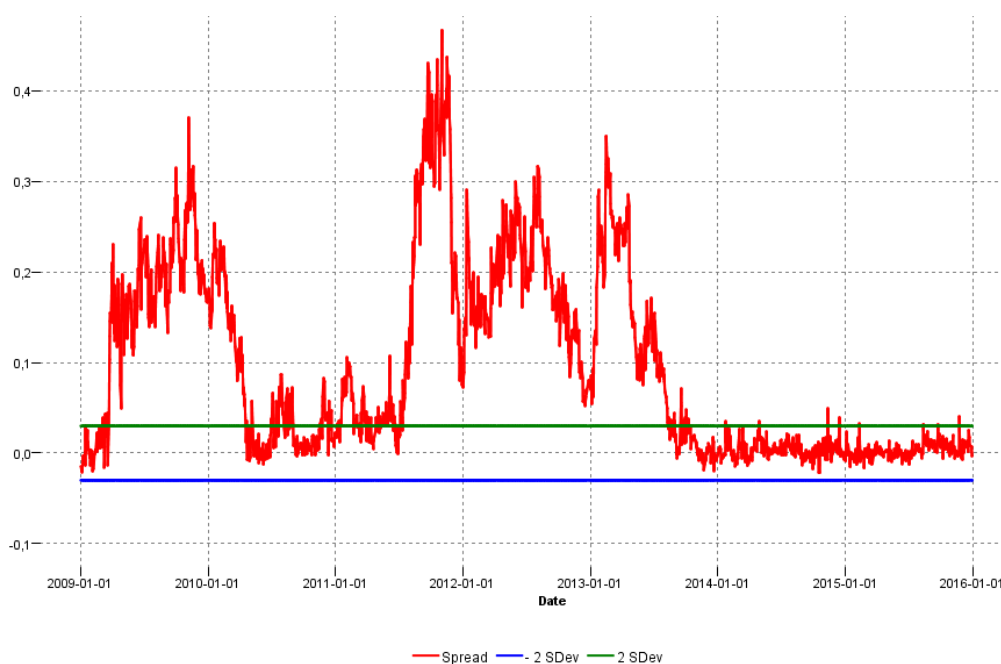


Figure 10. Spread and thresholds for Stora Enso Oyj R and Stora Enso Oyj A for cointegration-based trading

Table 5. No lag simple returns for cointegration-based trading

| | | Pair 1 | Pair 2 | Pair 3 | Pair 4 | Pair 5 |
|-----------------------------|----------------|--------------|----------|---------------|-------------|---------|
| | | Stora Enso A | Raisio V | Metsä Board A | Stockmann A | Citycon |
| | | Stora Enso R | Raisio K | Metsä Board B | Stockmann B | Sponda |
| Yearly excess returns | Average | 14.1 % | 14.4 % | 38.8 % | 29.2 % | 12.7 % |
| | Std. deviation | 12.3 % | 21.7 % | 53.3 % | 41.0 % | 33.7 % |
| | Minimum | 0.00 % | 0.00 % | 0.00 % | -3.59 % | 0.00 % |
| | Maximum | 38.7 % | 58.6 % | 152 % | 114 % | 89.1 % |
| Monthly excess returns | Average | 1.17 % | 1.20 % | 3.23 % | 2.43 % | 1.06 % |
| | Std. deviation | 3.30 % | 3.82 % | 15.3 % | 7.14 % | 9.72 % |
| | Minimum | 0.00 % | 0.00 % | 0.00 % | -3.59 % | 0.00 % |
| | Maximum | 24.5 % | 21.9 % | 133 % | 48.7 % | 89.1 % |
| Amount of trades per pair | | 17 | 11 | 9 | 20 | 1 |
| Avg. holding days per trade | | 67.5 d | 76.5 d | 111 d | 69.2 d | 1 271 d |
| % of time when pair is open | | 65.1 % | 47.8 % | 56.7 % | 78.5 % | 72.2 % |

Table 6. 1-day lag simple returns for cointegration-based trading

| | | Pair 1 | Pair 2 | Pair 3 | Pair 4 | Pair 5 |
|-----------------------------|----------------|--------------|----------|---------------|-------------|---------|
| | | Stora Enso A | Raisio V | Metsä Board A | Stockmann A | Citycon |
| | | Stora Enso R | Raisio K | Metsä Board B | Stockmann B | Sponda |
| Yearly excess returns | Average | 8.01 % | 3.35 % | 40.6 % | 11.6 % | -1.87 % |
| | Std. deviation | 11.4 % | 7.27 % | 65.5 % | 14.2 % | 4.96 % |
| | Minimum | 0.00 % | -4.72 % | 0.00 % | -3.58 % | -13.1 % |
| | Maximum | 32.6 % | 16.6 % | 187 % | 37.6 % | 0.00 % |
| Monthly excess returns | Average | 0.67 % | 0.28 % | 3.39 % | 0.96 % | -0.16 % |
| | Std. deviation | 3.30 % | 1.83 % | 19.0 % | 2.76 % | 1.43 % |
| | Minimum | -2.52 % | -4.72 % | -2.81 % | -3.58 % | -13.1 % |
| | Maximum | 28.8 % | 11.3 % | 170 % | 13.9 % | 0.00 % |
| Amount of trades per pair | | 17 | 11 | 9 | 20 | 1 |
| Avg. holding days per trade | | 67.5 d | 76.5 d | 111 d | 69.2 d | 1 271 d |
| % of time when pair is open | | 65.1 % | 47.8 % | 56.7 % | 78.5 % | 72.2 % |

4.4 Copula-based trading

Figure 11 shows the dependency structure of the first pair (Stora Enso's stocks) during the formation period. The upper left scatter plot illustrates the cumulative distribution functions values and the other five copula scatter plots show simulated data points made with statistical software and based on the optimal copula for the pair and its estimated parameters. As one can see, copulas have different dependency structures with e.g. varied tail dependencies or symmetry. The first pair has clearly symmetric tail dependency and it can even be seen from the scatter plots that it is best grasped with a Student-t copula.

Three other pairs are also best fitted to the Student-t copula. The pair with Citycon Oyj and Sponda Oyj is best fitted to the survival Gumbel copula. Survival copulas correspond to rotation by 180 degrees. Rotation of copulas is used in order to capture negative dependencies. (Brechmann 2013)

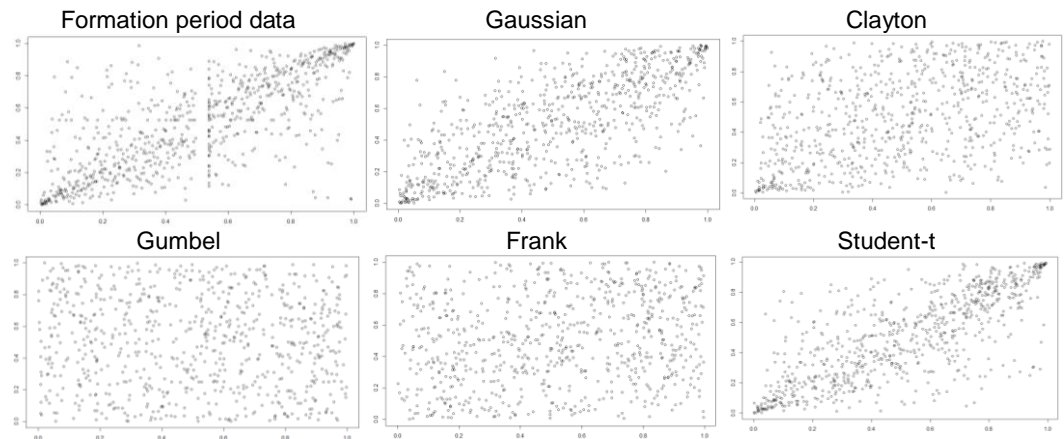


Figure 11. Formation period data as a scatter plot for cumulative marginals (Stora Enso Oyj R and Stora Enso Oyj A) and simulated data for fitted copulas

In Figure 12 there are the densities of the optimal copulas constructed for all the selected pairs from formation period data using Sklar's theorem. The contour plots illustrate the flexibility that the copula models can provide. (Anderson et al. 2009, 769-771) From the contour plots it can be seen that Stora Enso's stocks have clearer upper and lower tail dependence. Citycon & Sponda have clear lower tail dependence. Metsä Board stocks and Stockmann stocks are surprisingly similar.

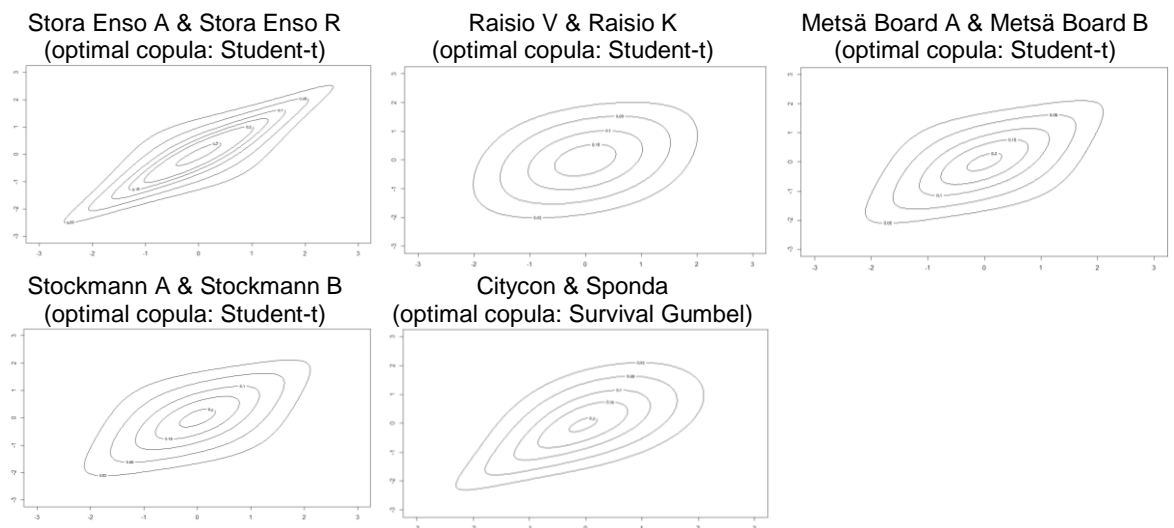


Figure 12. Contour plots for each pair

Based on Tables 7 and 8 copula method generates profits, but profits are quite low or even negative with the one-day waiting rule. Stora Enso's pair generates clearly more trading opportunities than the other pairs. Hence, Stora Enso's pair's dependency structure is quite successfully grasped with the Student-t copula itself.

Table 7. No lag simple returns for copula-based trading

| | | Pair 1 | Pair 2 | Pair 3 | Pair 4 | Pair 5 |
|-----------------------------|----------------|--------------|----------|---------------|-------------|---------|
| | | Stora Enso A | Raisio V | Metsä Board A | Stockmann A | Citycon |
| | | Stora Enso R | Raisio K | Metsä Board B | Stockmann B | Sponda |
| Yearly excess returns | Average | 14.4 % | 1.28 % | 16.4 % | 6.85 % | 3.90 % |
| | Std. deviation | 14.1 % | 2.53 % | 18.8 % | 6.20 % | 6.95 % |
| | Minimum | -3.63 % | 0.00 % | 0.00 % | 0.00 % | 0.00 % |
| | Maximum | 42.7 % | 6.70 % | 48.6 % | 19.4 % | 19.3 % |
| Monthly excess returns | Average | 1.20 % | 0.11 % | 1.37 % | 0.57 % | 0.32 % |
| | Std. deviation | 3.68 % | 0.73 % | 5.04 % | 1.78 % | 3.23 % |
| | Minimum | -15.3 % | -1.89 % | -10.3 % | -1.23 % | -7.27 % |
| | Maximum | 17.3 % | 4.49 % | 30.6 % | 11.4 % | 27.4 % |
| Amount of trades per pair | | 79 | 4 | 22 | 17 | 19 |
| Avg. holding days per trade | | 1.90 d | 3.25 d | 1.82 d | 1.41 d | 2.74 d |
| % of time when pair is open | | 8.52 % | 0.74 % | 2.27 % | 1.36 % | 2.95 % |

Table 8. 1-day lag simple returns for copula-based trading

| | | Pair 1 | Pair 2 | Pair 3 | Pair 4 | Pair 5 |
|-----------------------------|----------------|--------------|----------|---------------|-------------|---------|
| | | Stora Enso A | Raisio V | Metsä Board A | Stockmann A | Citycon |
| | | Stora Enso R | Raisio K | Metsä Board B | Stockmann B | Sponda |
| Yearly excess returns | Average | -0.68 % | -0.23 % | 1.46 % | -0.38 % | 1.45 % |
| | Std. deviation | 8.04 % | 0.70 % | 7.73 % | 4.02 % | 2.72 % |
| | Minimum | -16.8 % | -1.81 % | -11.1 % | -5.26 % | -1.34 % |
| | Maximum | 7.96 % | 0.22 % | 13.2 % | 6.15 % | 5.81 % |
| Monthly excess returns | Average | -0.06 % | -0.02 % | 0.12 % | -0.03 % | 0.12 % |
| | Std. deviation | 3.27 % | 0.55 % | 2.75 % | 1.74 % | 2.39 % |
| | Minimum | -19.9 % | -3.76 % | -10.1 % | -12.2 % | -9.81 % |
| | Maximum | 9.92 % | 2.30 % | 14.0 % | 4.33 % | 17.3 % |
| Amount of trades per pair | | 79 | 4 | 22 | 17 | 19 |
| Avg. holding days per trade | | 1.90 d | 3.25 d | 1.82 d | 1.41 d | 2.74 d |
| % of time when pair is open | | 8.52 % | 0.74 % | 2.27 % | 1.36 % | 2.95 % |

4.5 Comparison and summary of results

The averages for each method with the same five pairs are shown in Tables 9 and 10. By comparing trading opportunities, distance method turns out to generate most trades out of the methods. The difference is clear as the amount of trades is over double the amount with either cointegration or copula-based method. Copula method creates the second highest number

of trading signals. The number of trades could be significantly different with other thresholds. Now the thresholds for distance and cointegration methods are common limits and the confidence levels for copula method were also taken from previous empirical studies. Augustine (2014) used adjustable confidence limits that have generated more trading opportunities and higher returns than the unadjusted 0.95/0.05 confidence levels. Stander et al. (2012) showed that even 80 % confidence level can be used successfully with copula method and this could have led to greater amount of trades in this study.

The trade lengths are distinctly longest in the case of the cointegration method. It seems that the cointegration-based spreads deviate quite far away from the equilibrium and therefore, positions are open longer. Longer trade lengths naturally suggest higher risks for pairs trading. Distance and copula methods have shorter trade lengths and this would be good news for the investors that are seeking short holding periods.

Excess returns are highest for the cointegration method and lowest for the copula method. For the cointegration method, the pair of Metsä Board Oyj's stocks shows exceptionally high returns and is the main reason for high average returns. The standard deviation of the returns is also clearly highest for the same method. This suggest some instability regarding the cointegration method.

Copula method's returns seem to be the most stable ones. However, copula method generally doesn't fare well enough. The research aim was to test the hypothesis that pairs trading with copula method leads to more trading opportunities and higher returns compared to the distance and cointegration methods. With similar and comparable trading strategies, the hypothesis must be rejected as the more traditional methods generate more trades and higher returns than the copula method.

Table 9. No lag simple returns on average

| | | Distance | Cointegration | Copula |
|-----------------------------|----------------|----------|---------------|---------|
| Yearly excess returns | Average | 15.62 % | 21.84 % | 8.57 % |
| | Std. deviation | 27.56 % | 32.40 % | 9.72 % |
| | Minimum | -4.48 % | -0.72 % | -0.73 % |
| | Maximum | 71.58 % | 90.48 % | 27.34 % |
| Monthly excess returns | Average | 1.30 % | 1.82 % | 0.71 % |
| | Std. deviation | 6.48 % | 8.87 % | 2.89 % |
| | Minimum | -11.51 % | -0.72 % | -7.20 % |
| | Maximum | 47.88 % | 63.44 % | 18.24 % |
| Amount of trades per pair | | 53.6 | 11.6 | 28.2 |
| Avg. holding days per trade | | 1.56 | 319.04 | 2.224 |
| % of time when pair is open | | 4.77 % | 64.06 % | 3.17 % |

Table 10. 1-day lag simple returns on average

| | | Distance | Cointegration | Copula |
|-----------------------------|----------------|----------|---------------|----------|
| Yearly excess returns | Average | 3.26 % | 12.34 % | 0.32 % |
| | Std. deviation | 12.05 % | 20.67 % | 4.64 % |
| | Minimum | -7.76 % | -4.28 % | -7.26 % |
| | Maximum | 28.20 % | 54.76 % | 6.67 % |
| Monthly excess returns | Average | 0.27 % | 1.03 % | 0.03 % |
| | Std. deviation | 3.30 % | 5.66 % | 2.14 % |
| | Minimum | -10.71 % | -5.35 % | -11.15 % |
| | Maximum | 20.56 % | 44.80 % | 9.57 % |
| Amount of trades per pair | | 53.6 | 11.6 | 28.2 |
| Avg. holding days per trade | | 1.56 | 319.04 | 2.224 |
| % of time when pair is open | | 4.77 % | 64.06 % | 3.17 % |

This study gives contradictory research to the existing academic literature on the copula-based pairs trading. For example, Liew and Wu (2013), Xie et al. (2014) and Augustine (2014) show that copula-based method is able to generate better performance in pairs trading. However, the empirical evidence is scarce and concerns only small amount of pairs per study. Although, one must consider that the average profits with copula method in this study are actually in the similar range as with Augustine's study (2014).

Stander et al. (2012) state that the main drawback of using copula-based pairs trading strategy is that the strategy is profitable if trading costs are not taken into account. If the trading costs are included, the profits disappear and turn often to losses. Stander et al. (2012) show disappointing results with copula-based pairs trading strategy similarly to this study.

Ferreira (2008) states that the heart of copula theory is the hypothesis that the copula captures the co-movement of the pair accurately enough to identify trading opportunities that the standard linear correlation analysis is not robust enough to accomplish. Four out of five selected pairs in this study were best fitted to Student-t copula. This copula dependency structure is linear and reminiscent to the normal distribution. Therefore, it might not be surprising that the traditional methods are faring well in comparison to the copula method as they are robust enough to handle the linear dependency structures. This might especially be true when considering the multiple share classes of the same company.

Previous empirical evidence of pairs trading in Finnish stock market has proven it to be profitable in several cases with the traditional distance method. (Kupiainen 2008, Rinne & Suominen 2011, Broussard & Vaihekoski 2012) The excess returns in Broussard & Vaihekoski's (2012) research are similar to the excess returns presented in this study.

4.6 Limitations of the research

This study is calculation-heavy and actual pairs trading contains several different aspects that the pairs trader has to consider. In order to make this study extensive but compact enough, there are some limitations that are applied in conducting this study.

First of all, the main aim of this study is to compare different methods and the results that these methods produce. Therefore it is not crucial to optimize or compare different parameters with the execution of pair formation or pairs trading.

This study disregards the transactions costs that heavily impact the profitability of pairs trading. Transactions costs include costs of buying and shorting stocks. Some studies have evidence that pairs trading can be profitable even with involving transactions costs (Gatev et al. 2006).

This study is conducted on the basis of daily closing prices. When using the closing prices, the bid-ask spread is not taken into account. With closing prices the returns are based on prices that are no longer available unless the trades are executed at the start of the following day before any price adjustments.

The rebalancing of the pairs trading portfolio is also neglected and the trades are executed with equal weights with no rebalancing frequency. Rebalancing is done to ensure the market neutrality of the pairs trading portfolio. However, too frequent rebalancing results in high transactions costs.

According to Stander et al. (2012), pairs trading strategy relies heavily on the liquidity of the stocks. Liquidity ensures that the trades would be easy to enter and exit. The liquidity seems to increase the available amount of trading opportunities. Also volatility of the stocks produces more trading opportunities. (Stander et al. 2012) The Finnish stock market has a low level of liquidity and the selected pairs are neither the most traded nor the most liquid ones. Therefore, the selected pairs and Finnish stock market might not be that desirable for pairs trading. However, Broussard and Vaihekoski (2012) and Kupiainen (2008) end up to contradictory conclusions.

This study implements the trades with no risk management methods. Usually some stop-loss and stop-profit limits are used. These mean that the positions are closed if the returns are over or under certain threshold. These limits are used to preserve profits and prevent losses if the stocks start to diverge too much. There are also limits for the time span for which the positions are allowed to be open. Trades are then closed automatically if this threshold is crossed.

In real-life pairs trading applications the parameters for methods are constantly updated so that they are reliable and not out of date. This study uses simplified static formation and trading periods. The parameters like

spread, copula parameters, cumulative distribution functions or confidence levels are neither updated. In real-life they should be updated quarterly or even monthly. The different ways to standardize the stock prices could also create different results. Comparative pairs trading studies are troublesome as the different parameters could lead to different results and therefore, different conclusions.

5 CONCLUSIONS AND SUMMARY

This study was conducted to test a new and alternative copula-based method to the execution of pairs trading with stocks. Pairs trading was implemented and tested with three separate methods: copula, cointegration and distance. Based on the previous literature, distance and cointegration methods were shown to be the most popular and traditional methods used in the pairs trading. The comparable pairs trading strategies were executed in the Finnish stock market for five best stock pairs. Stock pairs were formed and selected based on the cointegration-based pair formation method.

Based on the selected stock pairs and limitations of this study, the copula method did not generate more trading opportunities or higher profits than the more traditional methods. However, the copula method generated the most stable returns. The standard linear correlation analysis seems to capture the co-movement of the selected pairs well enough and this might be due to the multiple share classes of the same companies. Hence, the copulas do not add value to the identification of trading opportunities. Copulas can generally capture the dependency structure better than the more traditional methods relying on several assumptions but this is not always the case.

This study contributes to the scarce empirical evidence on the pairs trading profitability with copula-based methods. Currently, contradictory results of their profitability exists and it is not well known what are the fundamentals and optimal execution parameters for the copula-based pairs trading applications.

All the methods were still proven to be profitable even with the one-day waiting rule. Therefore, this study gives further support to the previous empirical literature on the profitability of pairs trading both globally and especially in the Finnish stock market. Anyhow, the limitations of this study are quite restrictive and that is why it is highly likely that the actual pairs

trading would generate lower or even negative returns due to costs and other factors.

Copula-based pairs trading generally lacks empirical research evidence. The recommendations for future research include using copulas in pair formation, optimizing the parameters of copula-based pairs trading applications and long-term intraday trading applications.

REFERENCES

Akaike, H. (1969). Fitting autoregressive models for prediction. *Annals of the Institute of Statistical Mathematics*, 21, 243-247.

Akaike, H. (1979). A bayesian extension of the minimum aic procedure of autoregressive model fitting. *Biometrika*, 66, 237-242.

Akaike, H. (1992). Information theory and an extension of the maximum likelihood principle. *Breakthroughs in Statistics*, 1, 610-624.

Alexander, C., Dimitriu, A. (2005). Indexing and Statistical Arbitrage: Tracking error or cointegration? *The Journal of Portfolio Management*, Winter 2005. 15 p.

Anderson, T.G., Dais, R.A., Kreiss, J-P., Mikosch, Th.V. (2009). *Handbook of Financial Time Series*. Springer-Verlag, Berlin, Germany. 952 p. ISBN 978-3-540-71296-1.

Andrade, S.C., di Pietro, V., Seasholes, M. S. (2005). *Understanding the Profitability of Pairs Trading*. Working Paper. University of California, Berkeley and Northwestern University. 25 p.

Ang, A., Chen, J. (2002). Asymmetric correlations of equity portfolios. *Review of Financial Studies*, 63, 443-494.

Augustine, C. (2014). *Pairs Trading: A Copula Approach*. Master's Thesis. University of Cape Town. 58 p.

Berger, T., Missong, M. (2014). Copulas and portfolio strategies: an applied risk management perspective. *Journal of Risk*, 17, 2, 51-91.

Bowen, D., Hutchinson, M., O'Sullivan, N. (2010). High frequency equity pairs trading: transaction costs, speed of execution and patterns in returns. *Journal of Trading*, 2010, 5, 31-38.

Brechmann, E.C. (2013). Statistical inference of vine copulas using the R-package VineCopula. Working paper. 66 p.

Broussard, J.P., & Vaihekoski, M. (2012). Profitability of Pairs Trading Strategy in an Illiquid Market with Multiple Share Classes. *Journal of International Financial Markets, Institutions and Money*, 22, 5, 1188-1201.

Caldas, B., Caldeira, J., Moura, G. (2014). Is Pairs Trading Performance Sensitive to the Methodologies?: A Comparison. Working paper. *Quantitative Finance*, ANPEC. 18 p.

Clegg, M. (2014). On the Persistence of Cointegration in Pairs Trading. Independent research paper. 25 p.

Do, B., Faff, R., Hamza, K. (2006). A New Approach to Modeling and Estimation for Pairs Trading. Working paper, Monash University. 31 p.

Do, B., & Faff, R. (2010). Does Simple Pairs Trading Still Work? *Financial Analysts Journal*, 4, 66, 83-95.

Ehrman, D. (2006). *The handbook of pairs trading: strategies using equities, options, and futures*. John Wiley & Sons, New Jersey, USA. 258 p. ISBN 0-471-72707-5.

Eichler, A. (2011). Italy, France, Spain, Belgium Ban Short Selling In Order To Protect Markets. *The Huffington Post*, October 2011.

Enders, W. (2010). *Applied Econometric Time series*. 3rd edition. John Wiley & Sons, New Jersey, USA. 500 p. ISBN: 978-0470-50539-7

Engelberg, J., Pengjie, G., Jagannathan, R. (2009). An Anatomy of Pairs Trading: The Role of Idiosyncratic News, Common Information and Liquidity. Working Paper. University of California, San Diego, University of Notre Dame and Northwestern University. 67 p.

Engle, R., Granger, C. (1987). Co-integration and error correction: representation, estimation and testing. *Econometrica*, 55, 2, 251-276.

Ferreira, L. (2008). New tools for spread trading. *Futures: News, Analysis & Strategies for Futures, Options & Derivatives Traders*, November 2008, 38-41.

Gatev, E., Goetzmann, W.N., Rouwenhorst K.G. (1999). Pairs trading: performance of a relative value arbitrage rule. Yale School of Management, NBER Working Paper, 7032.

Gatev, E., Goetzmann, W.N., Rouwenhorst, K.G. (2006). Pairs Trading: Performance of a Relative-value Arbitrage Rule. *Review of Financial Studies*, 19, 3, 797-827.

Hannan, E.J., Quinn, B.G. (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society, B*, 41, 190-195.

Hendershott, T., Jones, C.M., Menkveld, A.J. (2011). Does Algorithmic Trading Improve Liquidity?. *Journal of Finance*, 66, 1-33.

Hoel, C.H. (2013). Statistical Arbitrage Pairs: Can Cointegration Capture Market Neutral Profits? Master Thesis, Norwegian School of Economics. 53 p.

Hu, L. (2003). Dependence Patterns across Financial Markets: a Mixed Copula Approach. *Applied Financial Economics*, 16, 10, 717-729.

Huck, N. (2013). The high sensitivity of pairs trading returns. *Applied Economics Letters*, 20, 1301-1304.

Huck, N., Afabuwo, K. (2015). Pairs trading and selection methods: is cointegration superior? *Applied Economics*, 47, 6 599-613.

Jacobs, H., Weber, M. (2015). On the determinants of pairs trading profitability. *Journal of Financial Markets*, 23, 75-97.

Jaworski, P., Durante, F., Härdle, W., Rychlik, T. (2010). *Copula Theory and Its Applications*. Springer, Berlin, Germany. 327 p. ISBN 978-3-642-12464-8.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and and Control*, 12, 231-254.

Kauppalehti. (2016a). Stora Enso Oyj (STE). [online document]. [Accessed 17 April 2016]. Available at
<http://www.kauppalehti.fi/5/i/porssi/porssikurssit/osake/?klid=1052>

Kauppalehti. (2016b). Raisio Oyj (RAI). [online document]. [Accessed 17 April 2016]. Available at
<http://www.kauppalehti.fi/5/i/porssi/porssikurssit/osake/?klid=1000>

Kauppalehti. (2016c). Stockmann Oyj Abp (STC). [online document]. [Accessed 17 April 2016]. Available at
<http://www.kauppalehti.fi/5/i/porssi/porssikurssit/osake/?klid=1058>

Kauppalehti. (2016d). Metsä Board Oyj (METS). [online document]. [Accessed 17 April 2016]. Available at
<http://www.kauppalehti.fi/5/i/porssi/porssikurssit/osake/?klid=1074>

Kauppalehti. (2016e). Citycon oyj (CTY). [online document]. [Accessed 17 April 2016]. Available at

<http://www.kauppalehti.fi/5/i/porssi/porssikurssit/osake/?klid=1111>

Kauppalehti. (2016f). Sponda Oyj (SDA). [online document]. [Accessed 17 April 2016]. Available at

<http://www.kauppalehti.fi/5/i/porssi/porssikurssit/osake/?klid=1006>

Kat, H.M. (2003). The dangers of using correlation to measure dependence. *The Journal of Alternative Investments*, 6, 2, 54-58.

Kim, K. (2011). Performance Analysis of Pairs Trading Strategy Utilizing High Frequency Data with and Application to KOSPI 100 Equities. Working Paper. Cambridge, School of Engineering and Applied Science, Harvard University. 23 p.

Kupiainen, J. (2008). Pairs Trading -strategy in Finnish Stock Market: Stock Analysis from 2004 to 2007. Master's Thesis. Lappeenranta School of Business. 81 p.

Liew, R., Wu, Y. (2013). Pairs trading: A copula approach. *Journal of Derivatives & Hedge Funds*, 19, 1, 12-30.

Ling, H. (2006). Dependence Patterns across Financial Markets: a Mixed Copula Approach. *Applied Financial Economics* 16, 10, 717-729.

MacKinnon, J. (1991). Critical Values for Cointegration Tests. *University of California San Diego Discussion Paper*, 90, 4, 267-276.

Mendes, B., Accioly, V. (2013). Robust pair-copula based forecasts of realized volatility. *Applied Stochastic Models in Business and Industry*, 30, 183-199.

Metsä Board. (2016). Usein kysyttyä. [online document]. [Accessed 17 April 2016]. Available at <http://www.metsagroup.com/fi/Taloustietoa/Metsa-Group-sijoituskohteena/Sivut/default.aspx>

Miao, G. (2014). High Frequency and Dynamic Pairs Trading Based on Statistical Arbitrage Using a Two-Stage Correlation and Cointegration Approach. *International Journal of Economics and Finance*, 6, 3, 96-110.

Nayak, A., Ugalmugale, M., Gaikwad, V., Attar, V. (2014). A Study of the Copula Approach to Pair Trading. *International Journal of Knowledge Based Computer System*, 2, 1, 14-21.

Nordby, J.B. (2013). Return and Risk Exposure in Pairs Trading: Evidence from the German Equity Market. Master's Thesis. Copenhagen Business School. 166 p.

Papadakis, G., Wysocki, P. (2007). Pairs Trading and Accounting Information. Working Paper. Boston University and Massachusetts Institute of Technology. 31 p.

Perlin, M. S. (2009). Evaluation of Pairs Trading Strategy in the Brazilian Financial Market. *Journal of Derivatives & Hedge Funds*, 15, 122-136.

Pizzutilo, F. (2013) A Note on the Effectiveness of Pairs Trading For Individual Investors. *International Journal of Economics and Financial Issues*, 3, 3, 763-771.

Raisio. (2016). Osakepääoma ja osakelajit. [online document]. [Accessed 17 April 2016]. Available at <http://www.raisio.com/osakepaaoma-ja-osakelajit>

Rinne, K., Suominen, M. (2011). How Some Bankers Made a Million by Trading Just Two Securities?. Aalto University School of Economics, Working Paper. 25 p.

Schwarz, G. (1978). Estimating the dimension of a Model. *The Annals of Statistics*, 6, 2, 461-464.

Stander, Y., Marais, D., Botha, I. (2012). Trading strategies with copulas. *Journal of Economic and Financial Sciences*, 6, 1, 83-108.

Stockmann. (2016). Usein kysyttyä. [online document]. [Accessed 17 April 2016]. Available at <http://www.stockmanngroup.com/fi/usein-kysyttya>

Stora Enso. (2016). Osakemuunto. [online document]. [Accessed 17 April 2016]. Available at <http://www.storaenso.com/lang/finland/Pages/Share-Conversation.aspx>

Teetor, P. (2011). Better Hedge Ratios for Spread Trading. Working Paper. 11 p.

Vidyamurthy, G. (2004). Pairs trading: quantitative methods and analysis. John Wiley & Sons, New Jersey, USA. 210 p. ISBN 0-471-46067-2.

Xie, W., Liew, R.Q., Wu, Y., Zou, X. (2014). Pair Trading with Copulas. Working Paper. 37 p.

Xie, W., Wu, Y. (2013). Copula-Based Pairs Trading Strategy. Asian Finance Association 2013 Conference. 15 p.

APPENDICES

Appendix 1. Distance-based method, spreads and thresholds

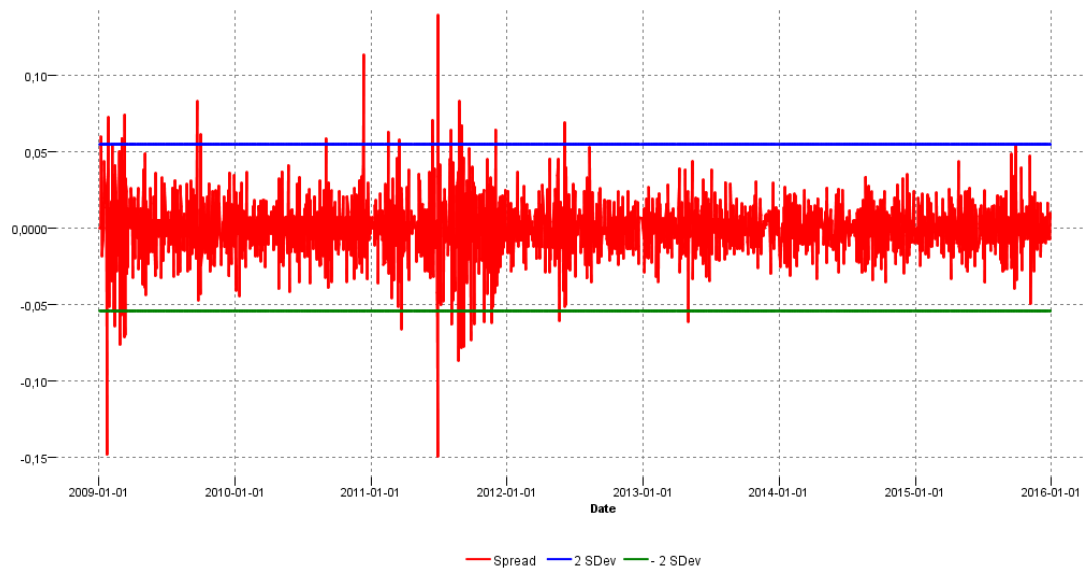


Figure 1. Spread and thresholds for Raisio Oyj Vaihto-osake and Raisio Oyj K during the trading period

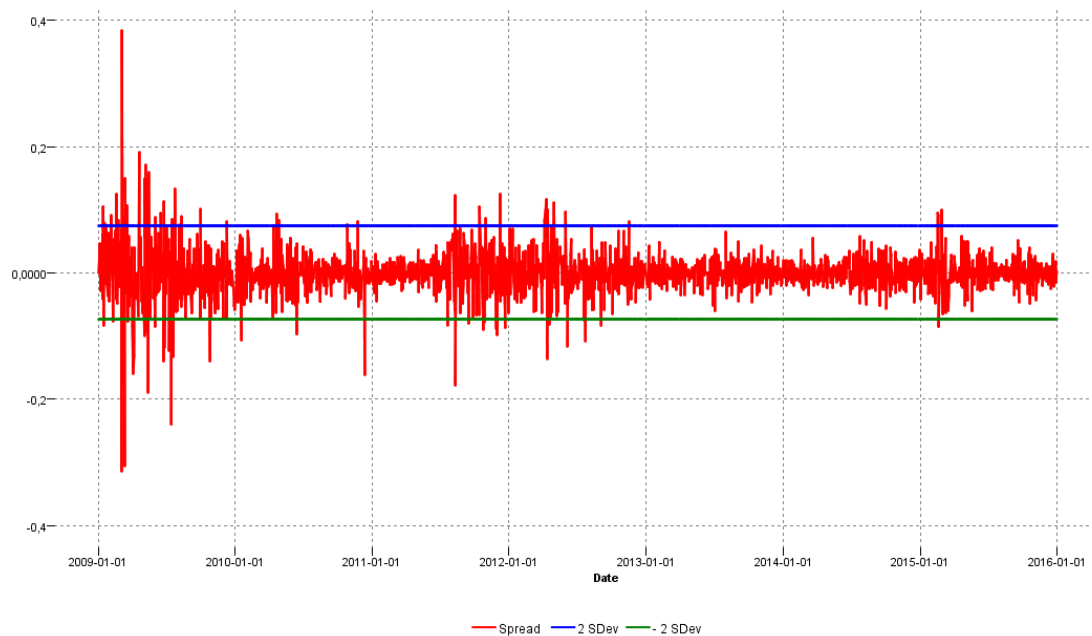


Figure 2. Spread and thresholds for Metsä Board Oyj A and Metsä Board Oyj B during the trading period

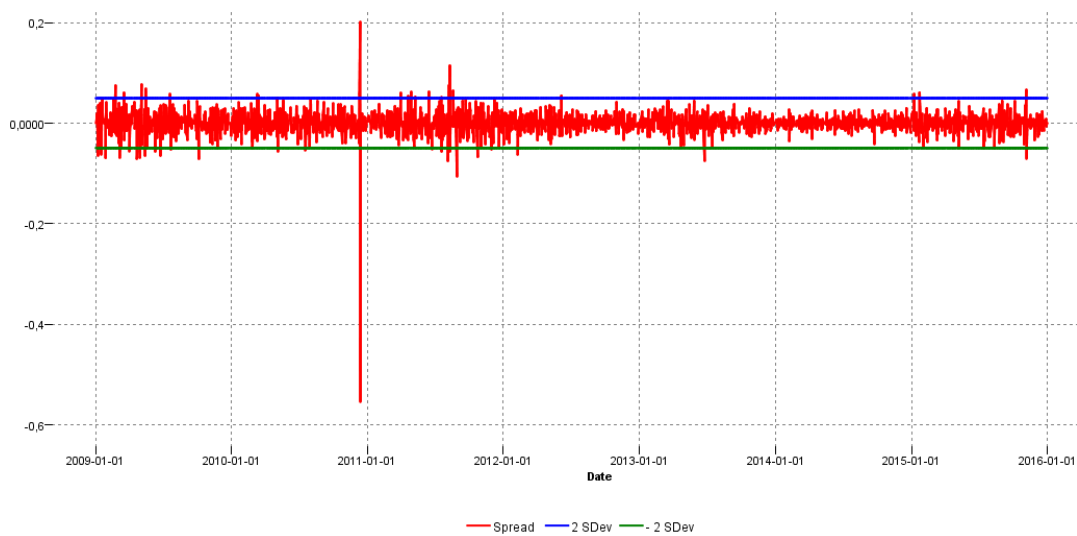


Figure 3. Spread and thresholds for Stockmann Oyj Abp A and Stockmann Oyj Abp B during the trading period

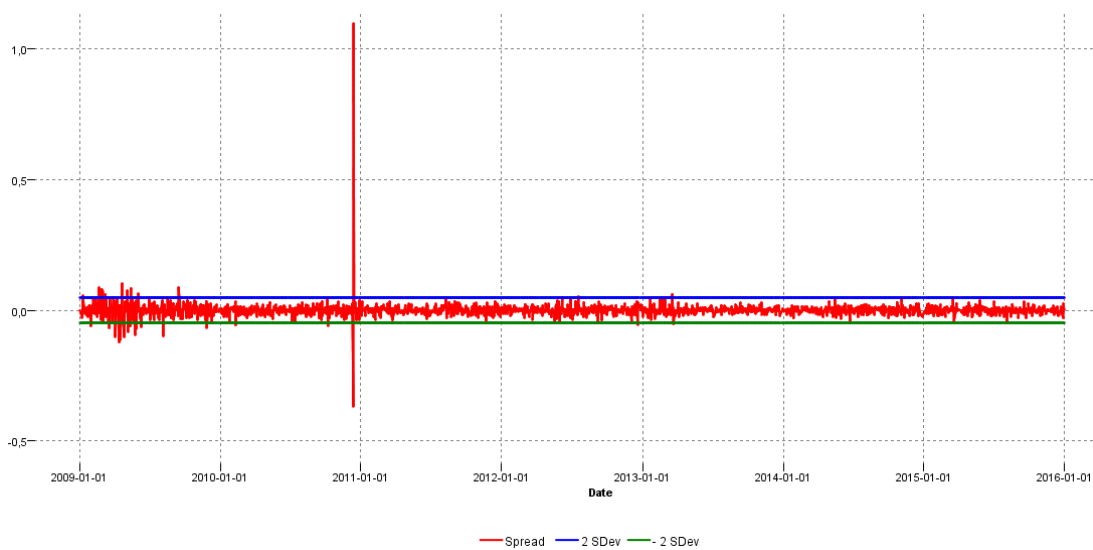


Figure 4. Spread and thresholds for Citycon Oyj and Sponda Oyj during the trading period

Appendix 2. Cointegration-based method, spreads and thresholds

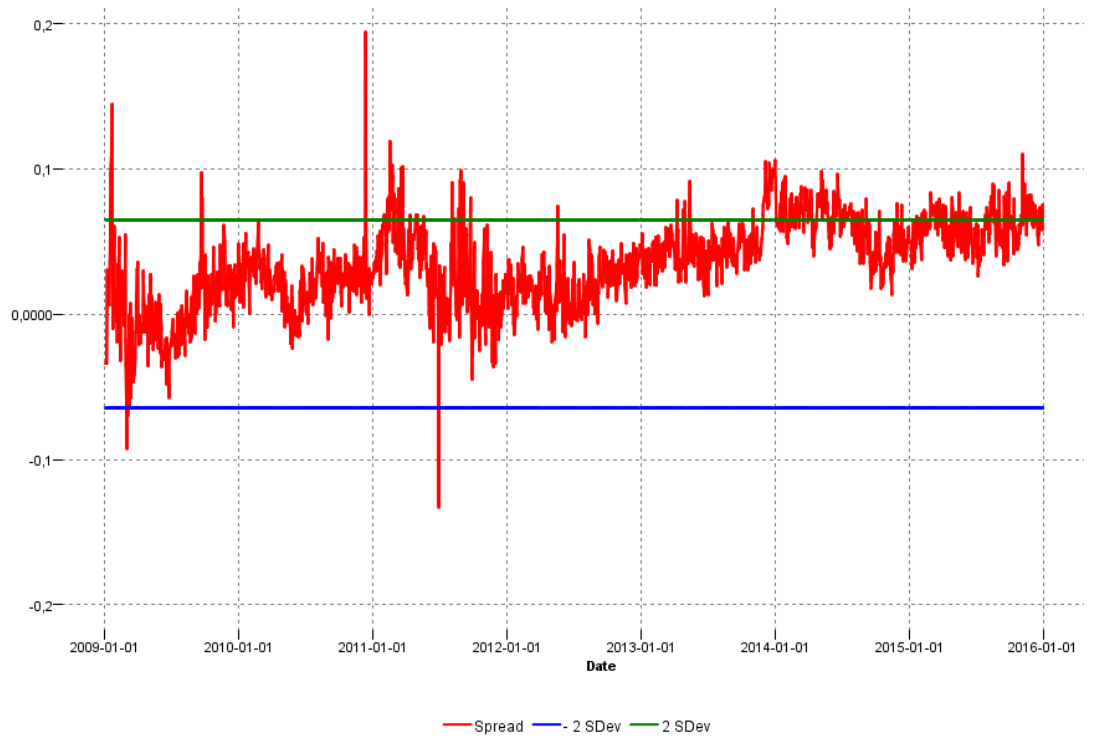


Figure 1. Spread and thresholds for Raisio Oyj Vaihto-osake and Raisio Oyj K during the trading period

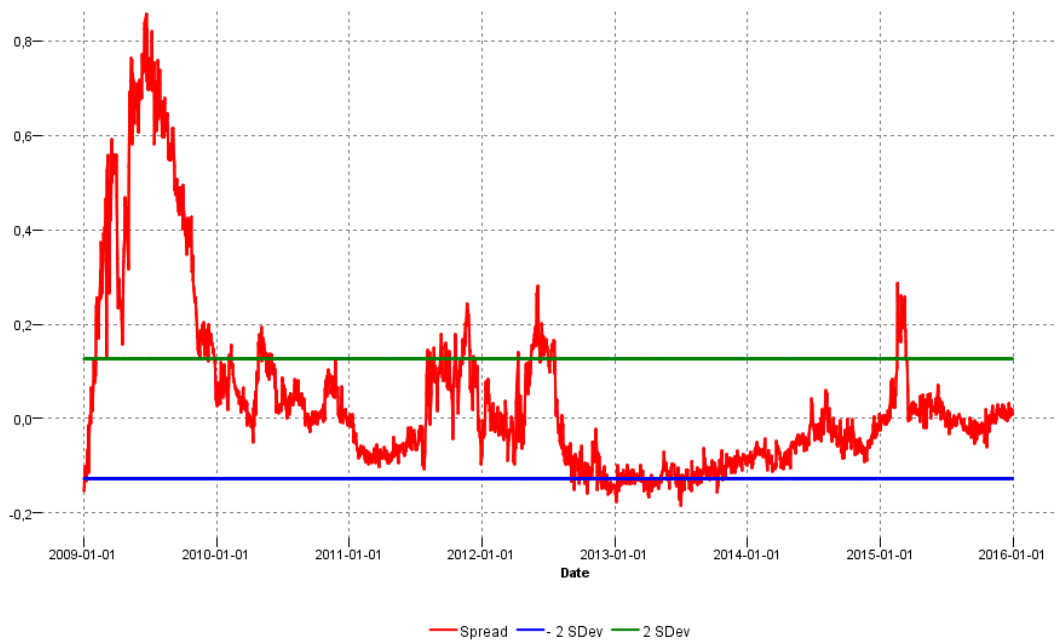


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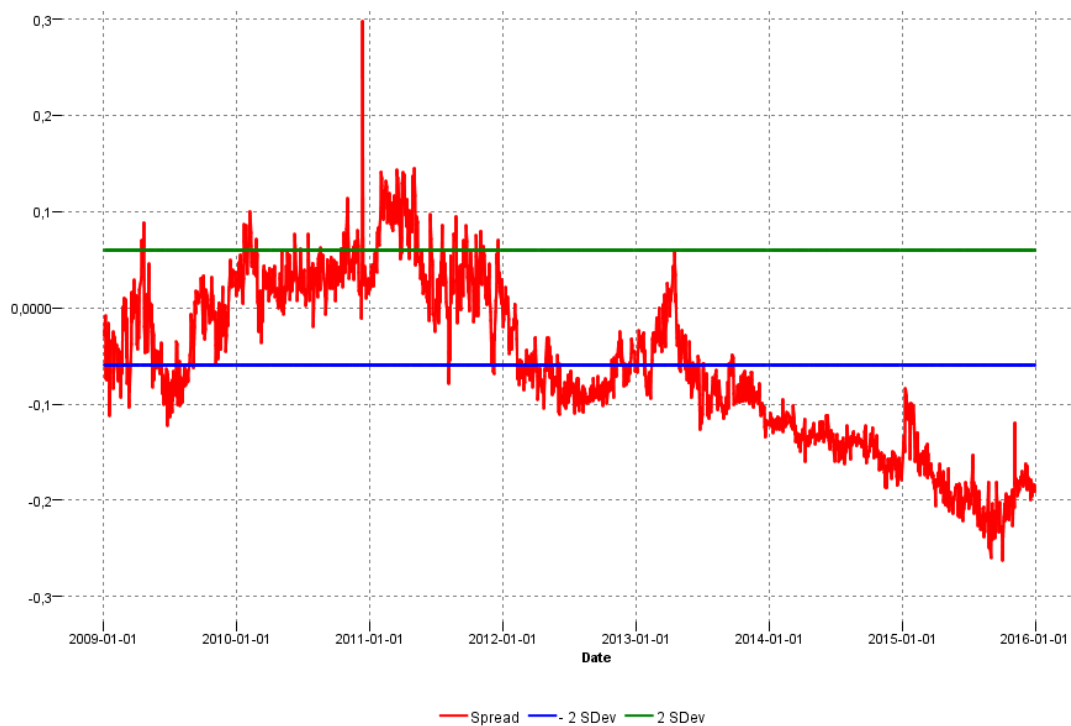


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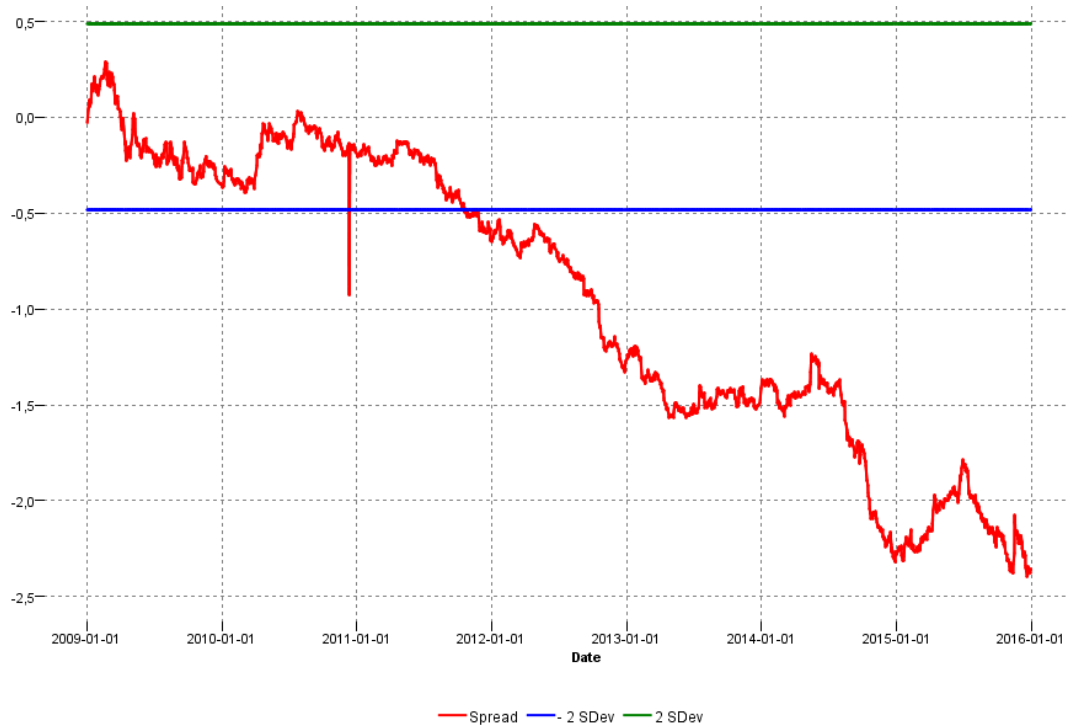


Figure 4. Spread and thresholds for Citycon Oyj and Sponda Oyj during the trading period