Aalto University
School of Business

Algorithmic Pairs Trading: Empirical Investigation of Exchange Traded Funds

Finance

Master's thesis

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Department of Finance
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Master's Thesis
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Abstract
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PURPOSE OF THE STUDY

The objective of this thesis is to study whether the algorithmic pairs trading with Exchange Traded Funds (ETFs) generates abnormal return. Particularly, I firstly study whether the trading strategy used in this thesis generates higher return than the benchmark index MSCI World and secondly even higher return than stocks.

DATA AND METHODOLOGY

The dataset includes over 66,000 possible pairs of ETFs worldwide from 2004 to 2012. In addition, I use the empirical results from the relevant papers in comparison. To test the hypothesis, I first apply cointegration tests to identify ETFs to be used in pairs trading strategies. Subsequently, I select ETF pairs to compose a pairs trading portfolio based on profitability and finally compare the results to the benchmark index and the empirical results of the relevant papers.

RESULTS

The empirical results of this thesis show that pairs trading with ETFs generate significant abnormal return with low volatility from the eight year trading period compared to the benchmark index as well as stocks traded with pairs trading strategy. The cumulate net profit is 105.43% and an annual abnormal return of 27.29% and with volatility of 10.57%. Furthermore, the results confirmed market neutrality with no significant correlation with MSCI World index.

KEYWORDS

Algorithmic trading, cointegration, Exchange Traded Funds, market neutral strategy, pairs trading, statistical arbitrage.

Aalto-yliopiston kauppakorkeakoulu **Tiivistelmä**
Pro gradu -tutkielma **3. kesäkuuta 2013**
Miika Sipilä

ALGORITMINEN PARIKAUPANKÄYNTI: EMPIIRINEN TUTKIMUS PÖRSSINOTEERATUISTA RAHASTOISTA

TUTKIELMAN TAVOITTEET

Tutkielman tavoitteena on tutkia, tuottaako algoritminen parikaupankäynti pörssinoteeratuilla rahastoilla (ETF:llä) epänormaaleja tuottoja. Erityisenä tavoitteenani on ensisijaisesti tutkia, tuottaako käyttämäni kaupankäyntistrategia suurempia tuottoja kuin vertailuindeksi MSCI World ja toiseksi tuottaako se enemmän kuin osakkeet parikaupankäyntimenetelmää käyttämällä.

LÄHDEAINEISTO JA MENETELMÄT

Empiirinen aineisto käsittää yli 66 000 mahdollista paria ETF:stä maailmanlaajuisesti vuosina 2004-2012. Lisäksi käytän merkityksellisten empiiristen tutkimusten tuloksia vertailuissani. Hypoteeseja tutkiessani käytän ensin yhteisintegroitavuustestejä tunnistaakseni ne ETF:t, joita käyttäisin parikaupankäyntistrategiassani. Sen jälkeen valitsen salkkuun parhaiten tuottavat ETF:ien parit ja lopuksi vertailen tuloksia vertailuindeksiin sekä merkityksellisten empiiristen tutkimusten tuloksiin.

TULOKSET

Empiirinen osioni osoittaa, että parikaupankäynti ETF:llä luo merkittävää epänormaalia tuottoa matalalla volatiliteetilla kahdeksan vuoden kaupankäyntijakson aikana verrattuna sekä vertailuindeksiin että osakkeisiin parikaupankäyntistategiaa käytettynä. Kumulatiivinen nettotuotto on 105,43% ja keskimääräinen vuosituotto 27,29% 10,57% volatiliteetilla. Lisäksi tulokset vahvistavat markkinaneutraalisuuden ilman merkittävää korrelaatiota MSCI World indeksiin.

AVAINSANAT

Algoritminen kaupankäynti, yhteisintegroituvuus, pörssinoteeratut rahastot, markkinaneutraali strategia, parikaupankäynti, tilastollinen arbitraasi.

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I would like to thank Mika Huhtamäki, the vice president of Suomen Tilaajavastuu Oy, Norvestia.fi blog writer, and active individual investor, whose generated pairs trading system gave me an inspiration to investigate the algorithmic pairs trading in my Master's Thesis. I would also like to thank him for the help he gave me in generating tools to analyze pairs trading strategies by MATLAB software.

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1. Introduction

1.1. Background and motivation

Algorithmic trading, the trading of securities, based on the buy or sell decisions of computer algorithms, has become more and more widely used in the markets. Tight competition between the traders and downward trend in profitability of pairs trading (Do and Faff, 2010) has created a need to find more efficient trading models. In 2012 12 percent of all the trades in Nordic [1] and 51 percent in the U.S. [2] equity markets has been completed by algorithmic trading.

High-frequency traders such as investment banks, hedge funds and some other institutional traders are using algorithmic trading due to its multiple benefits. These benefit include for example, automatic trading, which decreases the amount of mistakes made by humans and hence, cuts off execution costs. However, individual traders are not using algorithmic trading extensively yet but the interest in it is increasing. This can be seen in the numerous practical literature of algorithmic trading for non-professional traders.

I got my inspiration from Mika Huhtamäki, the vice president of Suomen Tilaajavastuu Oy and active individual investor, who created his own algorithmic pairs trading system. Thus, the potentials of using algorithmic trading and creating an algorithmic trading system itself, gave me inspiration to study this, what is traditionally called, institutional investors' area.

I also combined algorithmic trading with pairs trading, in order to gain significant results with Exchange Traded Funds (ETFs). It is defined by Alexander and Barbosa (2007) as an instrument for investment in a basket of securities and can be transacted at market price any time during the trading day, and throughout the clear picture of algorithmic trading opportunities. Academically, both topics are widely studied separately but combining them

[1] See "Financial News: The Rise And Rise Of The High-Frequency Trader" in *the Wall Street Journal*, January 5, 2012.
[2] See "SEC Leads From Behind as High-Frequency Trading Shows Data Gap" in *Bloomberg Businessweek*, October 1, 2012.

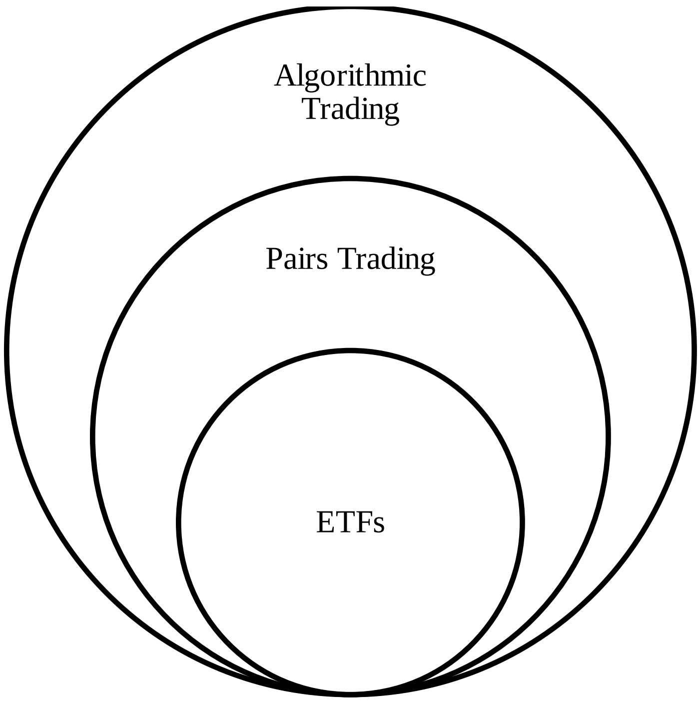
may give clearer picture of the high-frequency traders' ability to generate profit. Especially, how hedge funds can generate profits using professional tools.

Pairs trading is a trading or investment strategy used to exploit financial markets that are out of equilibrium. It is a trading strategy consisting of a long position in one security and a short position in another security in a predetermined ratio. (Elliott et al. 2005) This ratio may be selected in a way that the resulting portfolio is market neutral or dollar neutral. I mainly use the market neutral ratios which replicate highly the first idea of the term "hedge fund" -whose aim is to generate profit despite of the market conditions (Patton, 2009).

Pairs trading strategies have had significant abnormal returns in recent investigations but recently alphas are seem to have fallen or even disappeared (Do and Faff, 2010). Thus, the investors have created new and more efficient methods to find positive alphas and by using algorithm trading for trading pairs, they may have found the most profitable pairs. Therefore, in this study, I aim to investigate whether the "professional" trading methods create significant abnormal return with ETFs. The following figure illustrates the link between algorithmic trading, pairs trading and ETFs in my thesis.

Figure 1 The link between algorithmic trading, pairs trading and ETFs

Figure 1 describes the link between algorithmic trading, pairs trading and ETFs in my thesis. Pairs trading is under the algorithmic trading and ETFs are under the pairs trading.



1.2. Research question

Exchange Traded Funds provide an ideal platform to test whether there would be some statistical arbitrage pairs i.e. a strategy designed to exploit short-term deviations from a long-run equilibrium between two stocks (Caldeira and Moura, 2013). Even if ETFs tend to be liquid, previous literature suggests that the liquidity must also to be taken into account due to, for instance, ability to short selling as well as avoidance of high transaction costs.

My aim is to use some specific algorithm trading methods to prove that abnormal returns in pairs trading have not disappeared, but the methods have transformed to serve as more specific and complicated. The methods may also need more settings and the pairs need to be more specific from a variety of securities being profitable. Specifically, I investigate if the evidences with ETFs support the previous findings in algorithmic pairs trading and if the algorithm trading methods generate even higher returns. I use data on international ETFs from 2004 to 2012. Taking also transaction costs into account I aim to explore whether the algorithm trading is still profitable.

My research question is thus two-fold:

(1) Are there statistical arbitrage pairs that generate significant abnormal return?
(2) Does the usage of ETFs as statistical arbitrage pairs generate even higher abnormal return than stocks?

1.3. Research objectives

Following Caldeira and Moura (2013) I study how algorithmic trading affects the results of the return of pairs trading using Schizas et al. (2011) study as benchmark for the results. Particularly, I study what is the scale of abnormal returns, what is the maximum drawdown on average, what are the volatilities for the abnormal returns and how often pairs with significant abnormal return will be found.

Comparing the results to the previous studies provides a picture of the potential returns generated by hedge fund. As a whole, I aim to determine if the specific methods used in my thesis can generate abnormal return in pairs trading, as in the past, the methods have mainly been used by large institutional investors due to their access to high-tech trading tools.

1.4. Structure of the study

After introducing the study in Chapter 1, Chapter 2 provides the theoretical framework for the study, and outlines the main hypothesis. Chapter 3 discusses the data and methodology used in the paper. Chapter 4 presents the empirical findings and Chapter 5 discusses them in relation to other research projects and concludes the thesis.

2. Literature review

This chapter reviews the previous literature related to algorithmic pairs trading with Exchange Traded Funds (ETFs). First, I explain the terms algorithmic trading, pairs trading and ETFs. After the definitions, I discuss the major literature and the previous studies, as well as the connections between the explained terms. Thereafter, the hypotheses of the thesis are formulated for the empirical part of the study in subchapter 2.4.

2.1. Algorithmic trading

Technology revolution has highly affected the way of financial markets function and multiple financial assets are traded. Algorithmic trading (AT) is a dramatic example of this far-reaching technological change (Hendershott et al. 2011). As mentioned in the Introduction, algorithmic trading is dominating financial markets and it accounts for more than half (51 percent) of U.S. equity volume, up from 35 percent in 2007[3]. Therefore, it now needs more attention and investigation.

The word 'Algorithm' has many definitions. Leshik and Cralle (2011) provide some examples:

- A plan consisting of a number of steps precisely setting out a sequence of actions to achieve a defined task. The basic algo is deterministic, giving the same results from the same inputs every time.
- A precise step-by-step plan for a computational procedure that begins with an input value.
- A computational procedure that takes values as input and procedures values as output.

Trading, generated by algorithmic, needs parameters, being values usually set by the trader, which the algo uses in its calculations. Leshik and Cralle (2011) presented the right parameter

[3] See more from a research of Tabb Group LLC "Written Testimony to the United States Senate Committee on Banking, Housing, and Urban Affairs Washington, DC" by Larry Tabb, September 20, 2012.

setting to be a key concept in algorithmic trading which makes all the difference between winning or losing trades.

After the definition of ‘Algorithm’, the word ‘Algorithmic Trading’ is commonly defined as the use of computer algorithms to automatically make trading decision, submit orders, and manage those orders after submission (Hendershott and Riodan, 2011). AT technique has become a standard in most investment firms (e.g. in hedge funds), but although the usage of AT with individual investors is not seemingly high, the increasingly selection of AT books proves the rising interest and usage of AT with individual investors, too.

2.1.1. History of algorithmic trading

The word ‘Algorithm’ can be traced to circa 820 AD, when Al Kwharizmi, a Persian mathematician living in what is now Uzbekistan, wrote a ‘Treatise on the Calculations with Arabic Numerals.’ After a number of translations in the 12th century, the word ‘algorism’ morphed into our now so familiar ‘algorithm.’ The origin of what was to become the very first algorithmic trade can be roughly traced back to the world’s first hedge fund, set by Alfred Winslow Jones in 1949, who used a strategy of balancing long and short positions simultaneously with probably a 30:70 ratio of short to long. In equities trading there were enthusiasts from the advent of computer availability in the early 1960s who used their computers to analyze price movement of stocks on a long-term basis, from weeks to months. (Leshik and Cralle, 2011)

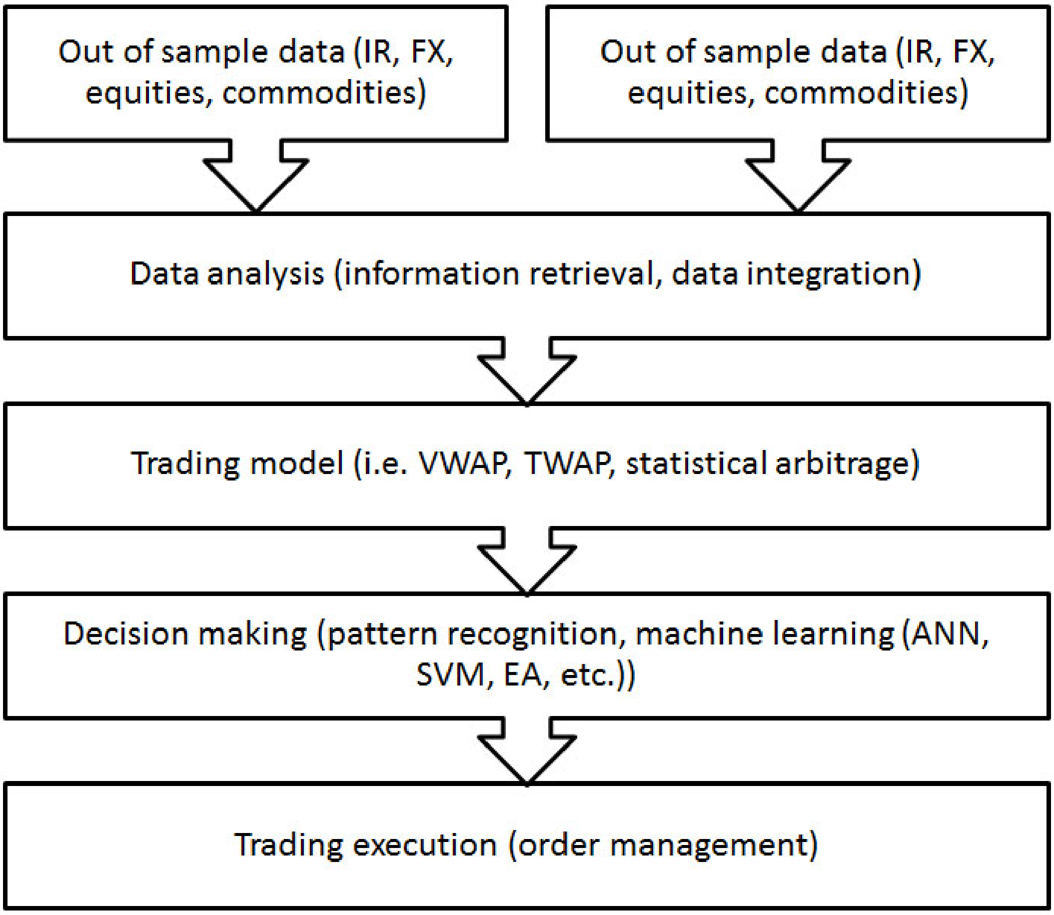
One of the first to use a computer to analyze stock data is said to be Peter N. Haurlan in the 1960s (Kirkpatrick and Dahlquist, pp. 140) and according to Leshik and Cralle (2011) computers came into mainstream use for block trading in the 1970s with the definition of a block trade being $1 million in value or more than 10,000 shares in the trade.

The real start of true algorithmic trading as it now perceived can be attributed to the invention of ‘pair trading’ later also to be known as statistical arbitrage by Nunzio Tartaglia who brought together at Morgan Stanley circa 1980 a multidisciplinary team of scientists headed by Gerald Bamberger. ‘Pair trading’ soon became hugely profitable and almost a Wall Street cult. (Leshik and Cralle, 2011) Thus, my interest become to study algorithmic trading with only pairs in my thesis.

2.1.2. Algorithmic trading strategies

Wang et al. (2009) present a four step trading strategy generation process as shown in Figure 2. The first step includes analysis of market data as well as relevant external news. Computer tools such as spreadsheets or charts often support the analysis, which is very important in order to generate a trading signal and make a trading strategy. The trading model and decision making are the kernel of AT. The last step of the process is the execution of the trading strategy, which can be done automatically by computer.

Figure 2 Algorithmic trading process (Wang et al., 2009)



AT provides traders with the tools to achieve, e.g. a reduction in transaction costs, increase in efficiency, enhancement of risk control, and utilization of information and technology, to make decisions one-step ahead of competitors and markets. Wang et al. (2009) present the most popular algorithmic strategies in their study for the choice of the kernel, i.e. the decision on which trading algorithm to use depending on user's specific investment objectives as well as their styles of market operations.

(1) VWAP – Volume Weighted Average Price

According to Leshik and Cralle (2011), Volume Weighted Average Price algorithmic strategy is probably the oldest and most used. Wang et al. (2009) define VWAP as the ratio of the dollar transaction volume to the share volume over the trading horizon. It is common to evaluate the performance of the traders by their ability to execute orders at prices better than the VWAP over the trading horizon. Berkowitz et al. (2012) have regarded the VWAP benchmark as a good approximation of the price for a passive trader and Leshik and Cralle (2011) as a benchmark for block trades between the Buy side and the Sell side. In addition, Leshik and Cralle (2011) argue the VWAP strategy to be most often used on longer duration orders.

(2) TWAP – Time Weighted Average Price

Wang et al. (2009) define TWAP as the average price of contracts of shares over a specific time, which attempts to execute an order and achieve the time-weighted average price or better. Usually the order is divided equally into a specified number of discrete time intervals, or waves (Leshik and Cralle, 2011). According to Wang et al. (2009), high volume traders use TWAP to execute their orders over a specific time, so they trade to keep the price close to that, which reflects the true market price. They also argue TWAP to be different from VWAP in that orders are a strategy of executing trades evenly over a specified time period.

(3) Stock Index Future Arbitrage

According to Wang et al. (2009) and MacKinlay and Ramaswamy (1988), one of the most important actions in AT is arbitrage. It employs the mispricing between the future market and the spot market and makes strategies in stock index future market, such as short sells, to make risk-free profits.

(4) Statistical Arbitrage

Wang et al. (2009) define statistical arbitrage to be based on the mispricing of one or more assets in their expected values. I.e. arbitrage can be viewed as a special type of statistical arbitrage as well as pairs trading (Caldeira and Moura, 2013), which I have chosen as my strategy in the thesis due to its high historical abnormal returns as well as its potential to perform well in the future.

Wang et al. (2009) also mention a few other widely used trading strategies such as guerilla, benchmarking, sniper, and sniffer. As well as Wang et al. (2009), Leshik and Cralle (2011) refer to iceberg, i.e. a large order hiding, as a common trading strategy. Leshik and Cralle (2011) also present currently popular algos of POV (Percentage of Volume) where the main target is to ‘stay under the radar’ while participating in the volume at a low enough percentage of the current volume not to be ‘seen’ by the rest of the market, ‘Black Lance’ – Search for liquidity, and The Peg – Stay parallel with the market. In the subchapter 2.2. I will provide a more detailed study of the special type of statistical arbitrage, pairs trading, which is my niched interest in the thesis.

2.1.3. Transaction costs

Transaction costs are strongly linked to algorithmic trading because AT is said to decrease the costs of trading in New York Stock Exchange (NYSE) (Hendershott et al. 2011). Kissell (2006) determines transaction costs in economic terms as costs paid by buyers and not received by sellers, and/or costs paid by sellers and not received by buyers. In equity markets, financial transaction costs represent costs incremental to decision prices without regards to who received this amount. Kissell (2006) has unbundled financial transaction costs into nine components: commissions, fees, taxes, spreads, delay costs, price appreciation, market impact, timing risk, and opportunity cost. Chan (2009) has a narrower list but he argues, furthermore, slippage (market impact certainty not constitute the entire position) as one component of transaction costs.

According to Kissell (2006), financial transaction costs are comprised of fixed and variable components and consist of visible and hidden (non-transparent) fees. The fixed-variable categorization follows the more traditional economics breakdown of costs and the visible-hidden categorization follows the more traditional financial breakdown of costs discussed.

Fixed cost components are those costs that are not dependent upon any implementation strategy. They cannot be managed or reduced during implementation. Variable cost components do vary during implementation of investment decision based on the underlying implementation strategy. Variable cost components make up the majority of total transaction costs. Visible or transparent costs are those costs whose cost or fee structure is known in advance (e.g. a percentage of traded value) and hidden or non-transparent costs are those costs whose fee structure is not known in advance with any degree of exactness (e.g. it is not precisely known what the market charges for execution of large block orders until after the transaction has been reguested). (Kissell, 2006) Algorithmic traders need to address these components carefully due to the sensitivity of transaction costs in high frequency trading. Table 1 summarizes the unbundled transaction costs.

Table 1 Unbundled Transaction Costs (Kissell, 2006)

	Fixed	**Variable**
Visible	Commission Fees	Spreads Taxes
Non-Transparent	N/A	Delay Cost Price Appreciation Market Impact Timing Risk Opportunity

My thesis addresses transaction costs in the model presented in the next chapter. Thus, it is extremely important to understand possible components of transaction costs. Kissell (2006) defines each of these:

(1) Commissions

Commissions are payments made to broker-dealers for executing trades. They are generally expressed on a per share basis (e.g. cents per share) or based on the total transaction value (e.g. some basis point of transaction value). Commissions vary from broker to broker and the average commissions have decreased over during time. When the average one-way commission in NYSE was 70 basis points in 1963, the commissions have decreased to 9 basis points in 2009 (Do and Faff, 2012).

(2) Fees

Fees charged during execution include ticket charges assessed by floor brokers on exchange, clearing and settlement costs, SEC transaction fees, and any other type of exchange charge for usage or access to its service. Often, brokers bundle these fees into the total commissions charge.

(3) Taxes

Taxes are a levy assessed to funds based on realized earnings. Tax rates vary by investment and type of return. For example, capital gains, long-term earnings, dividends, and short-term profits can all be taxed at different rates. Sometimes taxes are measured as fixed costs (e.g. Wang, 2003) and in order to simplify the calculations; the fixed nature is widely applied to taxes.

(4) Spreads

Spread cost is the difference between the best offer (ask) and the best bid price. It is intended to compensate broker-dealers for matching buyers with sellers, for risks associated with acquiring and holding an inventory of stocks (long or short) while waiting to unwind the position, and for the potential of adverse selection (transacting with informed investors).

(5) Delay Cost

Delay cost represents the loss in investment value between the time the managers makes the investment decision t_d and the time the order is released to the market t_0. Managers who buy rising stocks and sell falling stocks will incur a delay cost. Any delay in order submission in these situations will result in less favorable execution prices and higher costs.

(6) Price Appreciation

Price appreciation represents natural price movement of stock. For example, how the stock price would evolve in a market without any uncertainty. Price appreciation is also referred to as price trend, drift, momentum, or alpha. It represents the cost (savings) associated with buying stock in a rising (falling) market or selling (buying) stock in a falling (rising) market.

(7) Market Impact

Market impact represents the movement in the price of the stock caused by a particular trade or order. Market impact is one of more costly transaction cost components and always causes adverse price movement. This relates directly to a drag on portfolio performance. Market impact cost depends on order size, stock volatility, side of transaction, and prevailing market conditions over trading horizon such as liquidity and intraday trading patterns, and specified implementation strategy. Do and Faff (2012) studied market impact and found 26 bps market impact for the full sample 1963-2009, 30 bps for the 1963-1988 subperiod, 20 bps for the 1989-2009 subperiods, and 20 bps for the most recent three years. In pairs trading, involving two roundtrips, this magnitude of costs will substantially reduce pairs trading profit.

(8) Timing Risk

Timing risk refers to the uncertainty surrounding the order's exact transaction cost. It is due to uncertainty associated with stock price movement and prevailing market conditions and liquidity. Timing risk is commonly referred to as price volatility or execution risk, but this definition is incomplete. Execution cost uncertainty is also dependent upon actual volumes, intraday trading patterns, cumulative market impact cost caused by other participants, and underlying trading strategy.

(9) Opportunity Cost

Opportunity cost represents the forgone profit of not being able to completely execute the investment decision. The reason is usually due to insufficient liquidity or prices moving away too quickly.

When trading pairs, it is necessary to also have some specific transaction cost component not mentioned before. Do and Faff (2012) use ‘Short selling constraints’ where relative value arbitrageurs in the equity market face short-sale constraints in three forms: the inability to short securities at the time desired (shortability); the cost of shorting in the form of a loan fee, which can be relatively low for the so-called general collaterals or very high for the so-called specials; and the possibility of the borrowed stock being recalled prematurely. D’Avolio (2002) examines the borrowing market using a proprietary sample covering 2000-2001 and discovered that 16% of the stocks in CRSP (Center for Research in Security Prices) that are potentially impossible to borrow are mostly tiny, illiquid stocks priced below $5 and account for less than 0.6% of total market value. The value-weighted cost to borrow the used sample loan portfolio is 25 basis points per annum and only 7% of loan supply (by value) is borrowed, and only 2% (61) of the stocks in an average sample month are recalled. D’Avolio (2002) also found that 91 percent of the stocks lent out cost less than 1% to borrow and the rest accounting a mean fee of 4.3% per annum.

Transaction costs related to pairs trading are to be used in the model described in the next chapters. Pairs trading subchapter will continue the thesis into lower level of algorithmic trading all the way to Exchange Traded Funds which is to be presented in the subchapter 2.3.

2.2. Pairs Trading

Pairs trading is a statistical arbitrage strategy, basically going long on one asset while shorting another asset. Pairs trading is also a special form of short-term contrarian strategy that seeks to exploit violations of the law of one price (Do and Faff, 2012). Thus, the success of contrarian trading violates the weak form, i.e. all past prices of a share are reflected in today's stock price and technical analysis cannot be used to predict and beat a market, in the efficient market hypothesis (Eom et al. 2008). Caldeira and Moura (2013) define pairs trading designed to exploit short-term deviations from a long-run equilibrium between two stocks. Even if this brand new investigation is a working paper, a comparable paper in Portuguese from Caldeira and Portugal (2010) has been published in Revista Brasileira de Finanças (Brazilian Review of Finance). Broussard and Vaihekoski (2012) simply define the profit generation process as a way when an arbitrageur finds stocks whose prices move together over an indicated historical time period. If the pair prices deviate wide enough, the strategy calls for shorting the increasing-price security, while simultaneously buying the declining-price security. Even if their pairs trading methodology follows Gatev et al. (2006) and I am using cointegration method, which follows Caldeira and Moura (2013) and the approach described in Vidyamurthy (2004), the basic profit generation process still holds in both method.

Pairs trading is said to be market neutral strategy in its most primitive form which eliminates the effect of market movements when using just two securities, consisting of a long position in one security and a short position in the other, in a predetermined ratio (Vidyamurthy, 2004). Market neutral portfolio can be generated as Vidyamurthy (2004):

Returns r_A and r_B of shares A and B, with positive betas[4] β_A and β_B, market return r_M and risk-free return[5] r_f can be determined as

$r_A = r_f + \beta_A r_M + \theta_A$

---

[4] Beta of a share is usually positive.
[5] Let here add risk-free return to formula even if Vidyamurthy (2004) did not use.

$r_A = r_f + \beta_A r_M + \theta_A$

Constructing then a portfolio AB which includes a long position on one unit of share A and a short position on r units of share B. The return of the portfolio AB can then be determined as

$r_{AB} = r_A - r r_B$

$r_{AB} = (1\text{-}r)r_f + (\beta_A - r\beta_B)r_M + (\theta_A - r\theta_B)$

Beta of the portfolio AB is then

$\beta_{AB} = \beta_A - r\beta_B$

Beta of market neutral portfolio is zero

$\beta_A - r\beta_B = 0$

Thus, long and short positions are formed by

$r = \frac{\beta A}{\beta B}$ or practically short selling at least m units of share B and long buying at least n units of share A as $\frac{m\ X\ SB}{n\ X\ SA} = r$, when SA and SB are the market prices of shares A and B.

Pairs trading can also be dollar neutral, i.e. self-financing, when theoretically there is no need for capital. However, practically brokers require collateral but the need is still less than 100 percent. These points are one of the reasons why this strategy is a common among many hedge funds. Dollar neutral portfolio has a ratio of r = 1, thus portfolio can be generated as

$1 = \frac{\beta A}{\beta B}$

$n\ X\ SA = m\ X\ SB$

2.2.1. History of pairs trading

According to Vidyamurthy (2004) and Caldeira and Moura (2013), the first practice of statistical pairs trading is attributed to Wall Street by Nunzio Tartaglias quant group at Morgan Stanley on the mid 1980s. Their mission was to develop quantitative arbitrage strategies using state-of-the-art statistical techniques. The strategies developed by the group were automated to the point where they could generate trades in a mechanical fashion and, if needed, execute them seamlessly through automated trading systems. At that time, trading systems of this kind were considered the cutting edge of technology.

They used many techniques and one was trading securities in pairs. They identified pairs of securities whose prices tended to move together. The key idea was to find an anomaly in the relationship, i.e. identify a pair of stocks with similar historical price movements, and then the pair would be traded with the idea that the anomaly would correct itself. Tartaglia and his group used successfully the pairs trading strategy throughout 1987 but after two years of bad results, the group was disbanded in 1989. Nevertheless, the pairs trading has increased in popularity and has become a common trading strategy used by hedge funds and institutional investors. In addition, the tools have become available also for the individual investors with practical literatures, e.g. Quantitative Trading: How to Build Your Own Algorithmic Trading Business by Ernest P. Chan.

2.2.2. Relative-value and statistical arbitrage

According to Ehrman (2006), pairs trading has elements of both relative-value and statistical arbitrage. Nowadays, the majority of arbitrage activity is based on perceived or implied pricing flaws, rather than on fixed price differences with incomplete information between or among certain individuals. I.e. these pricing flaws rather represent statistically significant anomalies of divergences from historically established average price relationships than are not the result of incomplete or untimely information. In other terms, relative-value arbitrage is taking offsetting positions in securities that are historically or mathematically related, but taking those positions at times when a relationship is temporarily distorted. Thus, the most important feature of arbitrage, particularly in terms of how it relates to pairs trading, is the convergence of these flaws back to their expected values.

The common element in relative-value arbitrage or mean reversion strategy is that the manager is making a spread trade, rather than seeking exposure to the general market. Generally speaking, returns are derived from the behavior of relationship between two related securities rather than stemming from market direction. Generally, the manager takes offsetting long and short positions in these securities when their relationship, which historically has been statistically related, is experiencing a short-term distortion. As this distortion is eliminated, the manager profits. (Ehrman, 2006)

Statistical arbitrage is the relative-value arbitrage strategy that is most similar to pairs trading (Ehrman, 2006). Caldeira and Moura (2013) defined statistical arbitrage as a trading or investment strategy used to exploit financial markets that are out of equilibrium. In the investment world, generally, investors are assuming that while markets may not be in equilibrium, over time they move to equilibrium, and the trader has an interest to take maximum advantage from deviations from equilibrium.

Caldeira and Moura (2013) continue the definition by arguing that statistical arbitrage is based on the assumption that the patterns observed in the past are going to be repeated in the future. This is in opposition to the fundamental investment strategy that explores and tries to predict the behavior of economic forces that influence the share prices. Therefore, statistical arbitrage is a purely statistical approach designed to exploit equity market inefficiencies defined as the deviation from the long-term equilibrium across the stock prices observed in the past.

According to Ehrman (2006), statistical arbitrage is based purely on historical, statistical data that is utilized in very short term for numerous small positions and it is almost purely model and computer driven, when any single trade has very little human analysis. I.e. when a statistical model has been created, a computer makes all trading decisions based on the prescreened criteria. It eliminates human emotion from trading equation and enables hundreds of trades a day, and thus very small price movements can generate huge profits. Contrary, it can generate huge losses.

2.2.3. Past investigations and the performance of pairs trading

Bolgün et al. (2010) present that due to the academic research pairs trading is elusive. They argue contrarian trading to have more attention and they claim to know only two recent finance articles on pairs trading. But more closely studied, there are a few other investigations of pairs trading published before 2010. However, higher interest has still appeared only after year 2010, mainly due to gathered high returns; even if the recent studies have shown that the abnormal returns of pairs trading have continuously become lower. For example, Gatev et al. (2006) present, using the data on listed U.S. companies, a drop of the excess return of the top 20 pair’s strategy from 1.18 percent per month to about 0.38 percent per month when the subperiods were 1962-1988 and 1989-2002.

Increased interest in pairs trading has also released literatures onto the market. Earlier mentioned books of “Pairs Trading: Quantitative Methods and Analysis” by Vidyamurthy (2004) and “The Handbook of Pairs Trading: Strategies Using Equities, Options, and Futures” by Ehrman (2006) open the world of pairs trading widely. In addition, one cited book “Quantitative trading: how to build your own algorithmic trading business” by Chan (2009) opens also the structure of pairs trading.

Most of the previous studies concerning the stocks traded in stock exchanges. Hong et al. (2003) studied pairs trading in the Asian ADR market using 64 Asian shares listed in their local markets and listed in the U.S. as ADRs[6]. They found positive annualized profits of over 33% from the Asian markets. Andrade et al. (2005) wrote unpublished working paper using 647 different listed companies on the observation period from 1994 to 2002 and also they found excess returns (10.18% per annum).

Bolgün et al. (2010) present two recent finance articles on pairs trading; Elliot et al. (2005) and Gatev et al. (2006). The paper of Elliot et al. (2005) provides an analytical framework for pairs trading strategy but it intrinsically did not afford empirical research. Instead, as mentioned before, the paper of Gatev et al. (2006) contributes a wide investigation of pairs trading using the U.S. stocks. Thus, Bolgün et al. (2010) used the same methods analyzing dynamic pairs trading strategy for the companies listed in the Istanbul stock exchange. After processing daily data from the different stocks selected from ISE-30 index over the period 2002 through 2008 they found positive average daily returns of 3.36% when ISE30 daily average return performance 0.038% between 2002-2008. However, they argued their trading constraints and trading commissions took away the excess return on pairs mostly but stull yielding excess returns with less volatility than the market portfolio.

Investigations of pairs trading on stocks have been completed also by Papadakis et al. (2007) on Boston University and MIT. They worked on paper following Gatev et al. (2006) and using a portfolio of U.S. stock pairs between 1981 and 2006. They documented annualized excess stock returns of almost 7.7%. In addition, they studied profitability of pairs trading

[6] The stocks of most foreign companies that trade in the U.S. markets are traded as American Depositary Receipts (ADRs). See more http://www.sec.gov/answers/adrs.htm

around accounting information events and found that pairs trades are frequently triggered around accounting information events. Engelberg et al. (2009) examine also pairs trading in the U.S. markets. Their sample was between 1993 and 2006 including common shares traded on NYSE, AMEX and NASDAQ. They found adjusted return of 0.70% per month.

The study from the Brazilian markets has been done by Perlin (2007 and 2009). In the first investigation, he uses the 57 most liquids stocks from the Brazilian financial market between the periods of 2000 and 2006. The profits depends on d, the distance when selling or buying, and the annualized raw returns varied from -33% to +11% but when the negative percentages were with low d and positive percentages with high d. His another study, published in 2009 and based on wider (the 100 most liquids stocks from the Brazilian financial market) data between the same periods, got the annualized raw returns varied from -24% to +38%. However, when the negative percentages were with low d or high d, and positive percentages were between the d values of 1.6 and 2.0.

After the study of Bolgün et al. (2010), empirical investigations in pairs have become more frequent. Binh and Faff (2010) published a paper to study whether simple pairs trading is still working. They follow Gatev et al. (2006) and use similar but wider data containing totally 18,014 pairs from the U.S. stocks from 1962 to 2009. They present excess returns for the subperiods of 1962-1988 (monthly excess return 1.24%), 1989-2002 (0.56%), and 2003-2009 (0.33%) for top 20 pairs.

In the other markets, Broussard and Vaihekoski (2012) present an empirical study of profitability of pairs trading strategy in an illiquid market with multiple share classes using Finnish stock market as an example. They used data over the period of 1987-2008 containing the stocks listed on the OMXH and the number varied between 100 and 150 during the sample period. They found, on average, the annualized return as high as 12.5%. Lastly, a brand new empirical investigation by Caldeira and Guilherme (2013) study the profitability of the statistical arbitrage strategy which is assessed with data from the São Paulo stock exchange ranging from January 2005 to October 2012. This Brazilian empirical analysis containing 50 stocks with largest weights in the Ibovespa index and the strategy exhibited excess return of 16.38% per year.

As noticed, the studies of pairs trading in stocks are the most popular asset class in academic studies of pairs trading. However, there are a few found papers of pairs trading in ETFs produced, but however, with small sample size. Jin et al. (2008) use two ETF securities and

Schizas et al.'s (2011) empirical analysis focusing on 22 international, passive ETFs. I introduce these studies more in in the following subchapter when I present previous investigations and performance of Exchange Traded Funds. Thus, in my thesis, and in the following subchapter, I specifically focus on ETFs.

2.3. Exchange Traded Funds

An exchange traded fund (ETF) is an instrument for investment in a basket of securities that is traded, like an individual stock, through a brokerage firm on a stock exchange. It is similar to an open-ended fund, but makes it more flexible because it can be transacted at market price any time during the trading day, where open-ended fund investors must wait until the end of the day to buy or sell shares directly with a mutual fund company. An ETF can be traded any way as a stock, e.g. short selling is possible[7]. However, some specific ETFs can be quite complicated to short sell, but usually the largest seller, e.g. Standard & Poor's, iShares and MSCI whose ETFs present major part of my sample, are easily short sold.

Besides the ones mentioned, ETFs offer many other benefits, too. In exchange trading, with availability to short selling, limited orders and exemption from the up-tick rule that prevents short selling except after a price increase are also possible. In addition, relatively low trading costs and management fees, diversification, tax efficiency and liquidity are the admitted benefits. ETF market makers publicly quote and transact firm bid and offer prices, making money on the spread, and buy or sell on their own account to counteract temporary imbalances in supply and demand and hence stabilize prices. A basic regulatory requirement for ETFs is that shares can only be created and redeemed at the fund's net asset value (NAV) at the end of the trading day. (Alexander, 2008; Ferri, 2008)

Alexander and Barbosa (2007) present an ETF having low cost structure, the in-kind creation and redemption of shares, arbitrage pricing mechanisms, tax advantages and secondary trading of shares as its main characteristics. They also argue that two main features allow index ETFs to present a low cost structure when the passive management role of the trustee

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[7] See more e.g. from https://www.spdrs.com and http://www.lightbulbpress.com/00clients/S&P_ETF_MICRO/learn_about_etfs_92.html.

and the absence of shareholder accounting at the fund level. Since brokerage firms and banks manage shareholder accounting the ETF trust does not need to keep records of the beneficial owner of its shares and this represents an important cut in the fund's cost structure. However, they address that ETF trading may have brokerage and commission fees that an investor does not face when acquiring or redeeming mutual fund shares.

2.3.1. History of Exchange Traded Funds

ETFs are quite new securities. At the end of 1993 there was only one ETF on the market (Ferri, 2008). This first successful ETF, the Standard and Poor's Depositary Receipt (SPDR – pronounced 'Spider') was released by the American Stock Exchange (AMEX) in 1993. It was designed to correspond to the price and yield performance of the S&P 500 Index. (Alexander, 2007) Since then, the ETF market started to grow slowly but since the beginning of 21st century the market has grown rapidly and the growth is still continuing. Ferri (2008) recorded the rise of ETFs available for investment more than tenfold between December 2003 and December 2008 from 71 to 747 in the U.S. ETF marketplace. Globally and in the U.S. the asset value and the number of ETFs growth are presented in Figure 3 and Figure 4.

Figure 3 Global ETF multi-year growth

Figure 3 describes the growth of the asset value and the number of ETFs at a global level from 2000 to the end of Q1 2012[8].

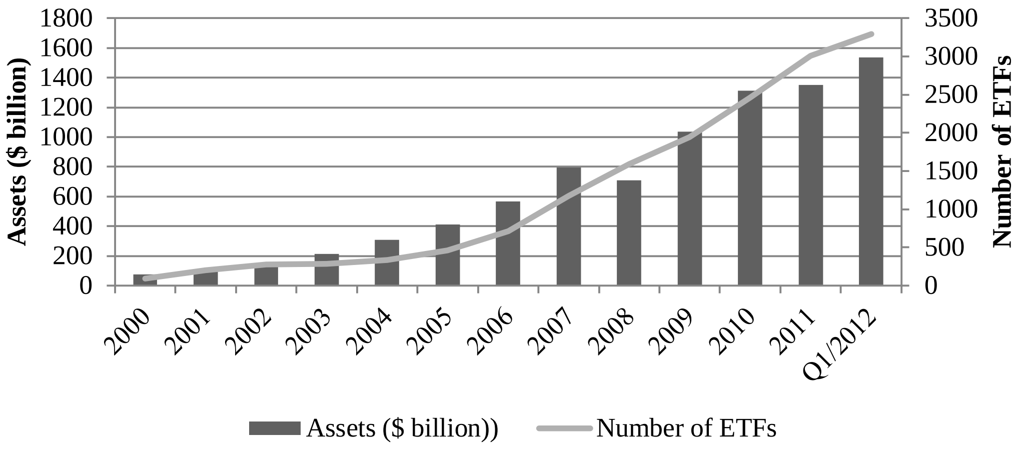
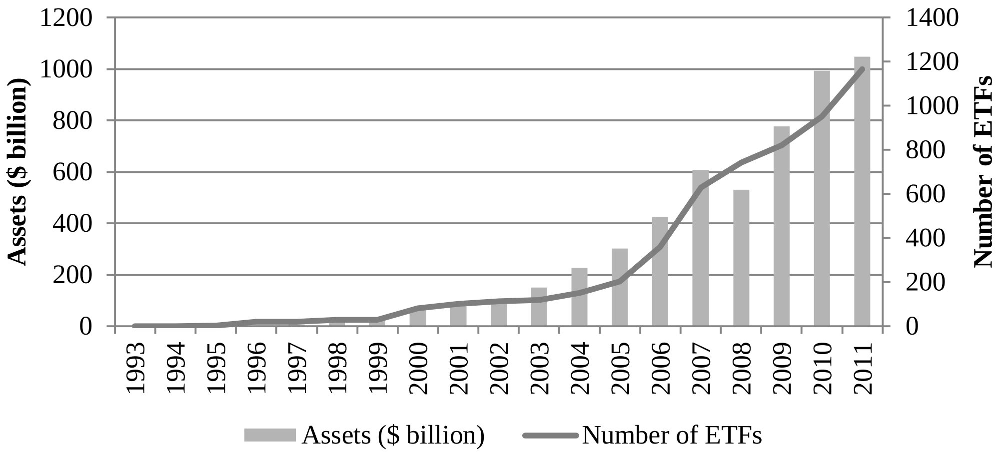


Figure 4 The U.S. ETF multi-year growth

Figure 4 describes the growth of the asset value and the number of ETFs at the U.S. level from 1993 to the end of 2011[9].



[8]See more details from http://www2.blackrock.com/content/groups/internationalsite/documents/literature/etfl_industryhilight_q112_ca.pdf

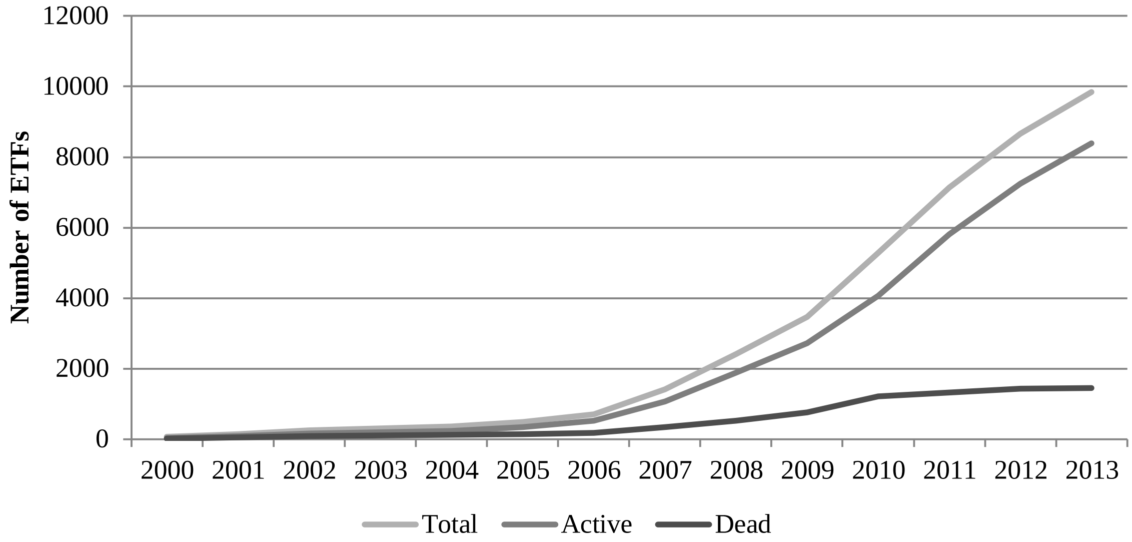
[9] See more details from http://www.ici.org/pdf/2012_factbook.pdf; http://www.investopedia.com/articles/exchangetradedfunds/08/etf-origins.asp

The data in Figure 3 is different to the data downloaded from Datastream due to the lack of global data source which would include all the traded ETFs. However, it does not bias the fact that the ETF market has grown in the recent years exponentially as shown in the following figure.

Figure 5 Datastream ETF multi-year growth

Figure 5 describes the growth of the number of ETFs at the Datastream database from 2000 to the beginning of 2013.

Note: Total is the total number of ETFs since the each year, Active is the number of active ETFs on January 2013 since the each year, Dead is the number of dead ETFs on January since each year. E.g. total of 62 ETFs' data is available in Datastream from 2000 whose 41 are still active and 21 have died before January 2013.



A good example is the first ETF, 'Spider', which accounted its asset value of USD 464 million at the end of 1993 (Ferri, 2008) when the value of total net assets at April 5, 2013 is exceeding USD 129,762 million[10]. In a nutshell, the ETF market and trading has experienced a remarkable growth during the last decade and it is expected to continue its growth.

[10]See State Street Global Advisors https://www.spdrs.com/product/fund.seam?ticker=spy

2.3.2. Past investigations and the performance of Exchange Traded Funds in pairs trading

Academic papers of ETFs in pairs trading are few and far between. As mentioned in the pairs trading subchapter before, when there are a few studies of pairs trading, the studies are mainly focusing on stocks. Studies on pairs trading with some other securities are rare. However, as mentioned before, there are a few studies of pairs trading with ETFs.

Founded investigations have been carried out with small sample size. Jin et al. (2008) use two ETFs and Schizas et al. (2011) have 22 international ETFs. Even if ETFs have the same trading opportunities, e.g. short selling is available, studies with large sample sizes are still missing. I try to fill the gap by studying with over 66,000 pairs.

The study of Jin et al. (2008) uses two ETF securities (SPDR Gold Shares (GLD) and Market Vectors Gold Miners (GDX)) having the sample period from Oct 20, 2006 to July 31, 2008. They showed Sharpe Ratio of 2.87. The more important of the results, is the showing that trading the similar ETFs as pairs can generate high abnormal returns. This pair is perhaps the most famous ETF pair used in pairs trading. Chan (2009) is another who uses this pair in his example.

Another study by Schizas et al. (2011) is an empirical analysis focusing on 22 international, passive ETFs. The investigation period starts on April 1, 1996 with the majority of the ETF records and all ETF data end on March 11, 2009. They presented daily excess returns for top 2 (0.097%), top 5 (0.098%), top 10 (0.085%), and top 20 (0.071%). In the next subchapter, following the relevant previously presented studies, I form hypothesis to my thesis.

2.4. Hypotheses

This subchapter outlines the key hypotheses used in the thesis and links them to the previously presented theory and research questions.

Following my first research question “Are there statistical arbitrage pairs that generate significant abnormal return?” I address first hypothesis to test whether statistical pairs trading strategy generates positive abnormal return. Schizas et at. (2011) have chosen S&P500 index as their benchmark index even if they study ETFs globally. However, I will use MSCI World index[11] as a benchmark index because S&P500 index contains only the U.S. stocks but MSCI World index contains 24 developed markets countries and I study ETFs globally. Thus, my first hypothesis to be tested is

H1: *Statistical pairs trading with ETFs generates positive abnormal return.*

After testing the first hypothesis I will compare the results to more studied stocks. When the first hypothesis tests whether statistical pairs trading with ETFs generates higher returns than the benchmark index, my second hypothesis tests whether ETFs generate higher returns than stocks using the same strategy. Here I use comparable results from the previous studies. Thus, my second hypothesis is to be tested is

H2: *Statistical pairs trading with ETFs generates higher positive abnormal returns compared to the pairs trading with stocks.*

These hypotheses serve as implication to explain firstly whether pairs trading with ETFs is profitable and secondly whether pairs trading, specifically with ETFs, is profitable. Due to the lack of previous studies this study should wider the knowledge of the profit generation models of hedge funds. In addition, this study should give clearer picture of Exchange Traded Funds and these opportunities in the usage of trading. In the next chapter I present data and methodology used in this thesis.

[11] See more from MSCI World Index on MSCI webpage
http://www.msci.com/resources/factsheets/index_fact_sheet/msci-world-index.pdf

3. Data and methodology

This chapter introduces the main data and methodology used in this thesis. The first subchapter describes the sample selection procedure and presents the data sources. The second subchapter presents methodology used and also compared to the other relative methodologies and strategies presented in the earlier studies.

3.1. Sample selection and data sources

The aim of this thesis is to contain as wide sample of ETFs as possible. One challenge in the sample selection is related to scattered data. There is no single marketplace or source where all the data of ETFs or even all the ETFs can be found. Therefore, the useful option was to find a data library which would contain the largest available database. Sources differ whether want to find data from ETFs globally or from a single stock exchange. ETFs are traded in the major stock exchanges, e.g. in New York Stock Exchange, Nasdaq OMX, Tokyo Stock Exchange, London Stock Exchange, and Shanghai Stock Exchange. Those all have their own variable ETF lists but complete list containing all the stock exchanges and those ETFs is not available.

Finally, I settled on Datastream database which serves great amount of international ETFs which allows investigation in the global level. The sample is not inclusive but it allows enough different ETFs to complete the analysis of more pairs than the previous studies. Datastream also includes survivorship bias-free or "point-in-time" data[12]. Thus, I include also dead ETFs data in the investigation, i.e. the data from these ETFs which were alive at the beginning but not at the end of the study.

After choosing the database source, the time period to be analyzed needed to be chosen. Because recently there are no wide scale studies from pairs trading with ETFs, it is appropriate to use relatively long time data. However, I must keep in mind how short time

[12] A historical database of stock prices that does not include stocks that have disappeared due to bankruptcies, delistings, mergers, or acquisitions or suffer from so-called survivorship bias, because only "survivors" of those often unpleasant events remain in the database (Chan, 2009).

ETFs have been traded, i.e. how many ETFs are available in each year. In addition, I must figure out whether the subperiod analysis is possible because of corresponding studies with stocks as well as with ETFs (Schizas et al. 2011) have usually had subperiod analysis (e.g. Gatev et al., 2006; Do and Faff, 2011; Broussard and Vaihekoski, 2012). Datastream provides the following number of ETFs in these years

Table 2 The number of ETFs in Datastream

Table 2 describes the number of ETFs at the Datastream database from 2000 to the beginning of 2013[13].

Note: Total is the total number of ETFs since the each year, Active is the number of active ETFs on January 2013 since the each year, Dead is the number of dead ETFs on January since each year. E.g. total of 62 ETFs' data is available in Datastream from 2000 whose 41 are still active and 21 have died before January 2013.

Year	Total	Active	Dead
2000	62	41	21
2001	142	95	47
2002	243	155	88
2003	307	197	110
2004	366	242	124
2005	495	345	150
2006	705	521	184
2007	1417	1070	347
2008	2414	1882	532
2009	3472	2718	754
2010	5275	4061	1214
2011	7140	5817	1323
2012	8668	7241	1427
2013	9843	8398	1445

I chose years from the beginning of 2004 to the end of 2012 for the analyzing period, summing up to 2,250 observations. These nine years enable sufficiency of different pairs and subperiods to be analyzed. Thus, my unprocessed sample contains 242 active and 124 dead, totaling 366 ETFs from 2004 to 2012. This enables $\binom{366}{2} = 66{,}795$ possible pairs.

[13] The same numbers are also presented in the Figure 4.

After downloading all the data from Datastream, the data should be processed and useless data should be eliminated. Following Caldeira and Moura (2013) and other relevant studies, I use only liquid assets, i.e. I eliminate less liquid assets are not traded on every trading days. Caldeira and Moura (2013) put store by this characteristic for pairs trading, since it often diminishes the slippage effect[14]. They also add that using less liquid stocks may involve greater operational costs (bid and ask spread) and difficulty in renting a stock. After the procession, I got 208 ETFs which enables $\binom{208}{2} = 21{,}528$ possible pairs. The complete list of ETFs is presented in Appendixes. The following table describes the number of the data of the ETFs from the different stock exchanges, markets and currencies.

[14] The disparity between the forecasted transaction price, and its actual price (Borowski, 2006).

Table 3 Details about the ETFs used in the analysis

Table 3 below describes the number of ETFs used in the analysis from different stock exchanges, different markets and different currencies.

Exchange		**Market**		**Currency**	
Australian	4	Australia	4	Australian Dollar	4
Berlin	1	Canada	12	Canadian Dollar	12
Euronext Amsterdam	3	Finland	1	Euro	33
Euronext Brussels	1	France	9	Hong Kong Dollar	3
Euronext Paris	3	Germany	7	Japanese Yen	9
Frankfurt	8	Hong Kong	3	Mexican Peso	1
Helsinki	1	Ireland	20	New Zealand Dollar	1
Hong Kong	3	Japan	9	Singaporean Dollar	1
Johannesburg	4	Luxembourg	2	South African Rand	4
London	6	Mexico	1	Swedish Krona	1
Mexico	1	New Zealand	1	Swiss Franc	2
Milan	13	Singapore	1	Taiwanese Dollar	1
NASDAQ	4	South Africa	4	United Kingdom Pound	5
New York	119	Sweden	1	United States Dollar	131
New Zealand	1	Switzerland	2		
Non NASDAQ OTC	8	Taiwan	1		
Osaka	2	United Kingdom	1		
Singapore	1	United States	129		
SIX Swiss	2				
Stockholm	1				
Taiwan	1				
Tokyo	7				
Toronto	12				
XETRA	2				

To test the hypotheses, an additional data is also necessary. Testing Hypothesis 1 I use MSCI World index data. To test Hypothesis 2, I compare this thesis results to the results of relevant studies. Specifically, Schizas et al. (2011) to the comparison of ETFs, Binh and Faff (2010) to the comparison of U.S. stocks, and Caldeira and Moura (2013) to compare this thesis results to Brazilian market.

3.2. Methodology

I follow the methodology employed in Caldeira and Moura (2013) in pairs' formation and trading. They also follow the approaches or methods described by Politis and Romano (1994), White (2000), Alexander and Dimitriu (2002), Vidyamurthy (2004), Andrade et al. (2005), Dunis and Ho (2005), Hansen (2005), Gatev et al. (2006), DeMiguel et al. (2009), Avellaneda and Lee (2010), and Dunis et al. (2010) in some specific parts in their used methods. Partly, where necessary, I use parts from the methodologies used specifically in pairs trading with ETFs. I.e. the methodology used by Jin et al. (2008) and Schizas et al. (2011). Firstly, I present different methods could be used in the investigation of pairs trading, then I present the strategy and method used in this thesis and finally, I describes the trading strategy.

3.2.1. The main pairs trading methods

Pairs trading methods are usually divided into three main categories according to the methodology discussed in the literature to select and trade pairs. E.g. Do et al. (2006), Bolgün et al. (2010), and Huck (2010) categorize the main methods as

- The distance method
- The cointegration method
- The stochastic spread method

(1) The distance method

Do et al. (2006) describe the distance method where the co-movement in a pair is measured by what is known as the distance, or the sum of squared differences between the two normalized price series. Trading is triggered when the distance reaches a certain threshold, as determined during a formation period. They also present an example from Gatev et al. (1999) where the pairs are selected by choosing, for each stock, a matching partner that minimizes the distance. Huck (2010) densifies the general outline of the distance method to first ‘‘find stocks that move together” then ‘‘take a long short position when they diverge”. Do et al. (2006) and Huck (2010) also define the distance method to be normative and economic free and therefore having the advantage of not being exposed to model mis-specification and mis-estimation but on the other hand, this strategy lacks forecasting ability: if a ‘‘divergence” is observed, the assumption is that prices should converge in the future because of the law of the one price. Huck (2010) present the Gatev et al. (1999, 2006) papers to be most cited papers on the distance pairs trading method but also on pairs trading.

(2) The cointegration method

Do et al. (2006) present the cointegration approach to be outlined in Vidyamurthy (2004) and it is an attempt to parameterize pairs trading, by exploring the possibility of cointegration (Engle and Granger, 1987). Cointegration is the phenomenon that two time series that are both integrated of order d, can be linearly combined to produce a single time series that is integrated of order $d - b$, $b > 0$, the most simple case of which is when $d = b = 1$. As the combined time series is stationary, this is desirable from the forecasting perspective. Huck (2010) densifies the general outline of the cointegration method to first to choose two co-integrated stock price series and then open a long/short position when stocks deviate from their long term equilibrium and finally, close the position after convergence or at the end of the trading period. The most cited paper on the cointegration pairs trading method is the already presented Vidyamurthy (2004). More of the cointegration method will be discussed in the next subchapter.

(3) The stochastic spread method

The stochastic spread method is explicitly modeled by Elliot et al. (2005) as the mean reversion behavior of the spread between the paired stocks in a continuous time setting, where the spread is defined as the difference between the two prices. The spread is driven by a latent state variable, assumed to follow a Vasicek process[15]. By making the spread equal to the state variable plus a Gaussian noise[16] the trader asserts that the observed spread is driven mainly by a mean reverting process, plus some measurement error. (Do et al., 2006)

Do et al. (2006) also describe three major advantages of the above model from the empirical perspective. First, it captures mean reversion which underlies pairs trading. Secondly, being a continuous time model, it is convenient for forecasting purposes. And thirdly, the model is completely tractable, with its parameters easily estimated by the Kalman filter[17] in a state space setting. However, despite the several advantages, De et al. (2006) present this approach

[15] $dx_t = \kappa(\theta - x_t)dt + \sigma dB_t$ where dB_t is a standard Brownian motion in some defined probability space. The state variable is known to revert to its mean θ at the speed κ (Do et al., 2006).
[16] $y_t = x_t + H\omega_t, where\ \omega_t$~N(0,1) (Do et al., 2006).
[17] For introduction to the Kalman filter, see Durbin and Koopman (2001).

to have a fundamental issue is that the model restricts the long run relationship between the two stocks to one of return parity, i.e. in the long run, the two stocks chosen must provide the same return such that any departure from it will be expected to be corrected in the future. According to Huck (2010), a stochastic approach is used by e.g. Elliott et al. (2005) and Do et al. (2006).

The following table 4 summarizes the methods and the relevant studies

Table 4 Comparison of the different methods and relevant studies

Table 4 describes the different methods used in pairs trading in different studies. E.g. Gatev et al. (1999; 2006) use the distance method as their pairs trading method.

Method	Studies
The distance method	Gatev et al. (1999; 2006) Hong and Susmel (2003) Papadakis and Wysocki (2007) Perlin (2007; 2009) Engelberg et al. (2008) Bolgün et al. (2009) Huck (2010) Do and Faff (2010; 2012) Schizas et al. (2011) Broussard and Vaihekoski (2012)
The cointegration method	Herlemont (2003) Vidyamurthy (2004) Lin et al. (2006) Jin et al. (2008) Chan (2009) Caldeira and Moura (2012; 2013) Chiu and Wong (2012) Hanson and Hall (2012)
The stochastic spread method	Elliot et al. (2005) Do et al. (2006) Mudchanatongsuk et al. (2008)

3.2.2. The model

As mentioned before, I follow the model employed in Caldeira and Moura (2013) to the extent that characteristics of pairs trading with stocks are similar to ETFs. In some parts I have also used some other references.

According to Caldeira and Moura (2013), I firstly divide the sample into trading and testing periods. The training period is a preselected period where the parameters of the experiment are computed. The testing period (four months) follows immediately after the training period (one year), where I run the experiments using the parameters computed in the first period. Caldeira and Moura (2013) note that pairs are also treated as parameters in their trading system.

As discussed, I have a choice of three different methods: the distance method, the cointegration method, and the stochastic spread method. Following Caldeira and Moura (2013), I use cointegration method in this thesis. The choice is firstly based on its key characteristics presented by Caldeira and Moura (2010), i.e. mean reverting tracking error, enhanced weight stability and better use of the information comprised in the stock prices. Those attributes allow a flexible design of various funded and self-financing trading strategies, from index and enhanced index tracking, to long-short market neutral and alpha transfer techniques. Secondly, its main advantage is that it enables the use of the information contained in the levels of financial variables. In addition to Caldeira and Moura (2013), Alexander and Dimitriu (2005a, b), Gatev et al. (2006), and Caldeira and Portugal (2010) suggest that cointegration methodology offers a more adequate structure for financial arbitrage strategies. Cointegration method also has potential problems and Broussard and Vaihekoski (2012) argue that one potential problem with using cointegration to select pairs can be found in Hakkio and Rush (1991), who indicate cointegration is a long-run phenomenon that requires long spans of data to make proper common factor inferences. Since they and I use daily data, and only over a year span of time to form potential trading pairs. As a result, I use cointegration approach as a method.

Caldeira and Moura (2013) present cointegration as a statistical feature, where two time series that are integrated of order 1, I(1), can be linearly combined to produce one time series which is stationary, or I(0). They and I use here the pairs trading technique which is based on the assumption that a linear combination of prices reverts to a long-run equilibrium and a trading rule can be constructed to exploit the expected temporary deviations. In general, linear combination of non-stationary time series are also non-stationary, thus not all possible pairs of stocks cointegrate. Caldeira and Moura (2013) continue by arguing the definition

A $n\ x$ 1 time series vector y_t is cointegrated[18] if

- each of its elements individually are non-stationary and
- there exists a non-zero vector γ such that γy_t is stationary.

I use the model which makes the investment strategy to be market neutral, i.e. I will hold a long l and a short s position both having the same value in local currency, so $\propto P_t^l = P_t^s$. Thus, the returns provided should not be affected by the market's direction because this approach eliminates net equity market exposure.

The model used by Caldeira and Moura (2013) has two parts of the pairs trading algorithm

1. Pairs selection algorithm
2. Trading signals algorithm

The first algorithm is essentially based on cointegration testing and the second creates trading signals based on predefined investment decision rules.

(1) Pairs selection algorithm

Caldeira and Moura (2013) present the objective of the pairs selection algorithm to identifying pairs whose linear combination exhibits a significant predictable component that is uncorrelated with underlying movements in the market as a whole. This can be done first by checking if all the series are integrated of the same order, I(1). I will do this by the way of Augmented Dickey Fuller Test (ADF) which is the extended version of Dickey Fuller test[19] by including extra lagged in terms of the dependent variables in order to eliminate the problem of autocorrelation, i.e. $\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{i=1}^{p} \beta_1 \Delta Y_{t-1} + \varepsilon_t$ (Mushtaq, 2011).

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[18] For more details about cointegration analysis, see Johansen (1995); Hamilton (1994).

[19] Dickey Fuller test is a formal test of stationarity which examine the null hypothesis of an autoregressive integrated moving average (ARIMA) against stationary and alternatively. E.g. equation with constant and time trend $\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \varepsilon$ and testing the hypothesis $H_0: \gamma = 0$, and $H_1: \gamma < 0$. The null hypothesis is tested via t-statistics by formula $t = \frac{\gamma^\wedge - \gamma H_0}{SE(\gamma^\wedge)}$. For more details about Dickey Fuller test, see (Mushtaq, 2011).

Having passed the ADF test, cointegration tests are performed on all possible combination of pairs. To test for cointegration I adopt Engle and Grangers 2-step approach and Johansen test, following Caldeira and Moura (2013). Both the ADF test and the tests for cointegration have been processed on MATLAB software[20].

Engle and Granger (1987) provide a Representation Theorem stating that if two or more series in y_t are co-integrated, there exists an error correction representation taking the following form:

$$\Delta y_t = A(l)\Delta y_t + \gamma z_{t-1} + \varepsilon_t$$

where γ is a matrix of coefficient of dimension $n\ x\ r$ of rank r, z_{t-1} is of dimension $r\ x\ 1$ based on $r \leq n-1$ equilibrium error relationships, $z_t = \propto' y_t$[21], and ε_t is a stationary multivariate disturbance. (LeSage, 1999)

LeSage (1999) also presents the Engle and Grangers 2-step approach which is used in the case of only two series y_t and x_t in the mode, when it can be used to determine the co-integrating variable that will be added to VAR model in first differences to make it an error correction (EC) model. The first step involves a regression: $y_t = \theta + \alpha x_t + z_t$ to determine estimates of $\propto$ and z_t. The second step carries out tests on z_t to determine if it is stationary, I(0). If I find this to be the case, the condition $y_t = \theta + \alpha x_t$ is interpreted as the equilibrium relationship between the two series and the error correction model is estimated as:

$$\Delta y_t = -\gamma_1 z_{t-1} + lagged(\Delta x_t, \Delta y_t) + c_1 + \varepsilon_{1t}$$

$$\Delta x_t = -\gamma_2 z_{t-1} + lagged(\Delta x_t, \Delta y_t) + c_2 + \varepsilon_{2t}$$

where $z_{t-1} = y_{t-1} - \theta - \alpha x_{t-1}, c_i$ are constant terms and ε_{it} denote disturbances in the model.

Johansen's test determines the number of cointegrating relations and also implements a multivariate extension of the 2-step Engle and Granger procedure. I.e. the Johansen procedure

[20] The functions used in the tests are available at www.spatial-econometrics.com and at the book of Chan (2009).

[21] The vector y_t is said to be co-integrated if there exists an $n\ x\ r$ matrix $\propto$ such that $z_t = \propto' y_t$ (LeSage, 1999).

provides a test statistic for determining$r$, the number of co-integrating relationships between the n variables in y_t as well as a set of r co-integrating vectors that can be used to construct error correction variables for the EC model[22].

(2) Trading signals algorithm

After detecting cointegrating relations, I need to follow a couple of trading rules to determine when to open and when to close a position. Following Caldeira and Moura (2013), I calculate first the spread between the shares as $\varepsilon_t = P_t^l - \gamma P_t^s$, where ε_t is the value of the spread at time t. Accordingly, I compute the dimensionless z-score to measure the distance to the long-term mean in units of long-term standard deviation as $z_t = \frac{\varepsilon_t - \mu_\varepsilon}{\sigma_\varepsilon}$.

I use the same basic rules as Caldeira and Moura (2013) in some parts because the similar rules have been used in the other academic studies, too. Firstly, I open a position when the z-score hits the 1.5 standard deviation thresholds from above or from bellow which indicates a signal of the mispricing ETFs in terms of their relative value to each other. In the case of z-score hits the -1.5 standard deviation threshold, the portfolio of pairs is below its long-run equilibrium value. Thus, one should buy the portfolio, i.e. buying stock l and selling stock s. Contrary, if z-score hits the 1.5 standard deviation threshold from above, the portfolio of pairs is above its long-run equilibrium value or overvalued. Thus, one should sell the portfolio short, i.e. selling stock l and buying stock s. Then the position is closed and z-score zero again. Caldeira and Moura (2013) underline that in all cases opening or closing a position means buying and selling the stocks simultaneously. These values are especially significant when transaction costs change. For instance, at the case of rising transaction costs, it could be useful to widen the thresholds when the number of transaction decreases.

Added to these basic rules, Caldeira and Moura (2013) use some other rules to prevent from losing too much money in unfavorable trades. They use a stop-loss to close the position if the ratio develops in an unfavorable way. They choose the maximum loss of 7% after having considered the stop loss constraints of 3%, 5% and 7%, and even if giving the similar results,

[22] For more details about Johansen's test, see Johansen (1995) ; (LeSage, 1999).

the case of a position loses of 7% rarely come back to a positive performance. However, stop loss constraints are not always considered in academic research. Caldeira and Moura (2013) show examples of Elliot et al., 2005; Gatev et al., 2006; Perlin, 2009; Gatarek et al , 2011 and Nath (2006) as an exeption that adopts a stop-loss trigger to close the position whenever the distance widens further to hit the 5^{th} or the 95^{th} percentile. However, Caldeira and Moura (2013) validate their choice of using stop loss in their study by it being fundamental in practice to avoid large losses. Finally, they never keep a position for more than 50 days, justifying in-sample profitability of the strategy decreasing with time and basing their in-sample result, they present 50 days to should be enough time for the pairs to revert to equilibrium, but also a short enough time not to lose time value. They also validate their arguments for the rules basing totally on statistics and predetermined numbers. Schizas et al. (2011) do not use stop-loss but they use the 20-day trading horizon and also 60-day horizon in some parts in their study of pairs trading on international ETFs. As a result, I use the rules of Caldeira and Moura (2013) to avoid huge losses instead of not using stop-loss as well as 50-day trading horizon based on the past empirical results. The trading signals and rules can be summarized as

Buy to open if	$z_t < -1.50$
Sell to open if	$z_t > 1.50$
Close short position if	$z_t < 0.50$
Close long position if	$z_t > -0.50$
Use a stop loss and close position if	$r_{it}^{raw} < -2.00$
Close position if	$t_i > 50$

where z_t is the dimensionless z-score, r_{it}^{raw} is the net return for pair i on day t, and t_i is the number of the trading days for pair i.

In the pairs selection process, I apply an approach used in the study of Caldeira and Moura (2013) and introduced by Dunis et al. (2010). According to the approach by Dunis et al.

(2010), I select the pairs for trading based on the best in-sample Sharpe ratios[23]. Thus, I follow Caldeira and Moura (2013) by forming the portfolio of 20 best trading pairs, i.e. the pairs with the greatest Sharpe ratios in the in-sample simulations and use them to compose a pairs trading portfolio to be employed out-of-sample. However, as Caldeira and Moura (2013) note, Goetzmann et al. (2002) and Gatev et al. (2006) have shown in their studies that Sharpe Ratios can be misleading when return distributions have negative skewness, but as in their study this would not be a concern in my study, too, because the returns to pairs portfolios seem to be positively skewed which, instead, would bias my Sharpe ratios downward.

After selecting 20 highest Sharpe ratio pairs, four months of pairs trading are carried out. At the end of each trading period the position that was opened and closed, and a new trading period ending on the last observation of the previous trading period is initiated. Now stocks and pairs can be substituted and all parameters are re-estimated. This procedure used in the paper of Caldeira and Moura (2013) continues in a rolling window fashion until the end of the sample.

Calculating the returns I follow, again, Caldeira and Moura (2013). Firstly, the net return for pair I on day t can be defined as,

$$r_{it}^{raw} = \ln\left[\frac{P_t^l}{P_{t-1}^l}\right] - \gamma \ln\left[\frac{P_t^s}{P_{t-1}^s}\right] + 2\ln(\frac{1-C}{1+C})$$

where P_t^l is the price of the ETF in which I have a long position on day t, P_t^s is the price of the ETF I am shorting on day t, and C refers to transaction costs.

Secondly, Caldeira and Moura (2013) define the daily net return to a portfolio of N pairs on day t as,

$$R_t^{net} = \sum_{i=1}^{N} w_{it} R_{it}$$

[23] Sharpe ratio is calculated using the formula $\frac{r_{it}-r_f}{\sigma_{it}}$, where r_{it} is the annualized return for pair i on day t, r_f is the annualized risk-free return, and σ_{it} is the annualized standard deviation for pair i on day t.

where w_{it} is the weight of each pair in the portfolio (in my application is 1/N), and the corresponding simple net return R_{it} can be derived as,

$$R_{it} = e^{r_{it}} - 1$$

where r_{it} is the continuously compounded monthly return $((\ln(\frac{P_t}{P_{t-1}}))$[24].

Finally, I should also add the transaction costs into my thesis. As presented in the subchapter 2.1.3., there are many different components to be included into the transaction costs. The usage of the transaction costs varies a lot in the different academic papers. Some (e.g.Engelberg et al., 2008; Do and Faff, 2010; Schizas et al., 2011; Hanson and Hall, 2012) ignore the transaction costs totally, usually to simplify their analysis, and others (e.g. Gatev et al., 2006; Caldeira and Moura, 2013) pay high attention to the costs gathered from the transactions. Because the trading costs significantly affect the performance of algorithmic trading and pairs trading, especially due to multiple or high frequency trading, I include them into my thesis. I compared the transaction costs used in the relevant studies and as a result, I use 0.25% per trade as my transaction cost because it is used in a paper investigating in the international market and thus not over optimize the low transaction costs (e.g. the transaction costs in the U.S. market which seems to have the lowest rates). It also addresses the changes in the nine year investigation period. And because ETFs are usually priced equally with stocks the comparison with different transaction costs between relevant studies is worthwhile. Caldeira and Moura (2013) define the ratio consisting 0.1% of brokerage fee for each share, plus slippage for each share (long and short) of 0.05%, and 0.2% of rental cost for short positions (average rental cost is 2% per year per share) accounting an average 0.1% for each share when every other trade is short selling. The following table 5 summarizes the transaction costs used in the relevant studies

[24] See more details about the derivation process from Caldeira and Moura (2013).

Table 5 Comparison of the transaction costs between relevant studies

Table 5 describes the transaction costs used in different studies. E.g. Caldeira and Moura (2012; 2013) use the transaction cost of 0.25% per trade in their studies (2012) and (2013).

Note: N/A indicates that the transaction costs are not used in the study.

*An average transaction cost between 1963 and 2002

**The study does not contain empirical investigation

***The transaction costs have been used but not presented in the study

****An average transaction cost between 1963 and 2009. They apply a discount of 20% annually to the transaction costs. E.g. Transaction costs in 1974 0.90% and in recent years less than 0.10%.

Studies	Transaction cost (per trade)
Gatev et al. (2006)	0.405%*
Herlemont (2003)	N/A**
Hong and Susmel (2003)	N/A
Vidyamurthy (2004)	N/A**
Elliot et al. (2005)	N/A**
Do et al. (2006)	N/A
Lin et al. (2006)	N/A
Papadakis and Wysocki (2007)	N/A
Perlin (2007; 2009)	0.1%; 0.1%
Engelberg et al. (2008)	N/A
Jin et al. (2008)	N/A
Mudchanatongsuk et al. (2008)	N/A**
Bolgün et al. (2009)	0.21 %
Chan (2009)	0.05 %
Huck (2010)	N/A***
Do and Faff (2010; 2012)	N/A; 0.34%****
Schizas et al. (2011)	N/A
Broussard and Vaihekoski (2012)	0.20 %
Caldeira and Moura (2012; 2013)	0.25%; 0.25%
Chiu and Wong (2012)	N/A**
Hanson and Hall (2012)	N/A

Additionally, Caldeira and Moura (2013) use a fully invested weighting scheme, which I also follow. They cite Broussard and Vaihekoski (2012) where argued the fully invested scheme to be less conservative as it assumes capital is always divided between the pairs that are open. Thus, I assume in practice each pair is given the same weight at the beginning of the trading period. I.e. for the fully invested weighting scheme, the money from a closed pair is invested in the other pairs that are open and if a pair is reopened, the money is invested back by redistributing the investment between the pairs according to their relative weights.

Calculating the statistics, I follow the interesting statistics and these formulas by Caldeira and Moura (2013) where the pairs trading portfolios performance are examined in the terms of the cumulative return (R^A), variance of returns ($\hat{\sigma}^2$), Sharpe ratio (SR) and Maximum Drawdown (MDD)[25] which are computed as,

$$R^A = 252 * \frac{1}{T}\sum_{t=1}^{T} R_t$$

$$\hat{\sigma}^A = \sqrt{252} * \frac{1}{T}\sum_{t=1}^{T}(R_t - \hat{\mu})^2$$

$$SR = \frac{\hat{\mu}}{\hat{\sigma}}, \text{ where } \hat{\mu} = \frac{1}{T}\sum_{t=1}^{T} w_{it} R_{it}$$

$$MDD = \sup_{t \in [0,T]} \left[\sup_{s \in [0,t]} R_s - R_t \right]$$

3.2.3. The trading strategy

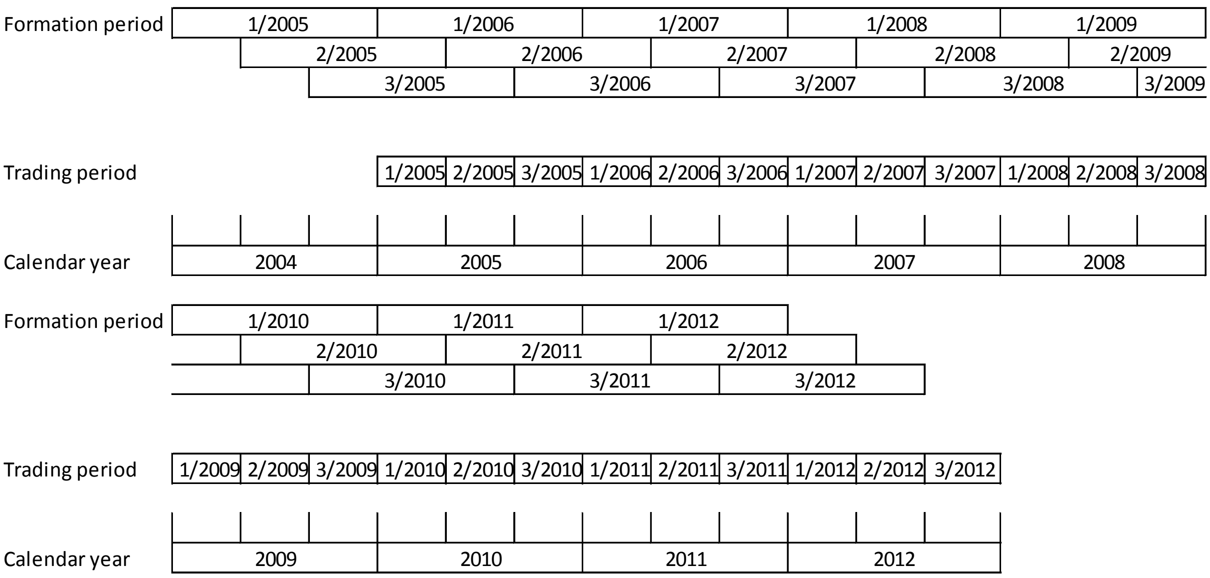
My trading strategy consists of two periods: training period and trading period. Training period, which duration is 12 months, is a formation period from which the top 20 pairs portfolios will be formed. Firstly, I eliminate the pairs which will not meet the cointegration requirements at the 10% significance level and then I choose top 20 pairs portfolio based on 20 pairs with highest Sharpe ratios and after that I move to trading period, which duration is four months and which results are the returns generated with the used strategy. I.e. I first choose the best pairs to be traded based on their performance during last year, before I start trading these for the next four months.

[25] MDD is defined as the maximum percentage drop incurred from a peak to a bottom in a certain time period (Caldeira and Moura, 2013).

My data consists of the time series data of 208 ETFs after the first procession from January 2004 to the end of December 2012. The first training period starts from the beginning of January 2004 and the last from the beginning of September 2011. The first trading period starts after the first training or formation period ends, from the beginning of January 2005 and the last after the last training period ends, from the beginning of September 2012. The following figure 6 shows all the formation and trading periods.

Figure 6 Formation and trading periods' alternation

Figure 6 presents the alternation of the 12-month formation and 4-month trading periods. First, formation period 1/2005 for the first 12 months starts at the beginning of the calendar year 2004 and ends at the end of the calendar year 2004 followed by the first trading period 1/2005 for the first 4 months starts at the beginning of the calendar year 2005 and ends at the end of April of the calendar year 2005. The second formation period 2/2005 lasts for the end of April of the calendar year 2005, partly overlapping the first (1/2005), the third (3/2005), and the forth (1/2006) formation periods. Second trading period 2/2005 is followed by the latest trading period of calendar year 2005 and the trading periods never overlap. The upper figure contains the entire formation periods from 1/2005 to 1/2009 and the partly formation periods of 2/2009 and 3/2009. The trading periods from 1/2005 to 3/2008 are presented in the upper figure. Formation periods are continuing in the lower figure from 2/2009 to 3/2012 and trading periods from 1/2009 to 3/2012. The last formation period in the sample is from September of the calendar year 2011 to end of August of the calendar year 2012 and the last trading period for the September of the calendar year 2012 to the end of the sample.



With the presented references, and using the discussed data and methods I present my empirical results in the next chapter.

4. Empirical results

In this chapter, the empirical results of this study are presented. First, in subchapter 4.1 I present my main results related to the results of top 20 portfolios, including the output from the cointegration tests. Subchapter 4.2 shows the empirical results by presenting the results of the subperiod analysis. Last, in subchapter 4.3 I describe the results of the comparison to past studies.

4.1. Main results

My main results contain both examples and summaries of whole investigation. Table 6 shows the descriptive statistics for the top 20 pairs in the sample period from September 2005 until the end of August 2006. Of the 21,528 possible pairs, maximum of 2,278 passed the cointegration tests of Johansen and Engle-Granger. Of those cointegration passed pairs, 20 pairs of the greatest in-sample Sharpe ratio were selected to be used out-of-sample.

The top 20 ETF pairs were selected from the whole sample size and thus any categorization has not been done, e.g. selecting pairs from the same sector or using any other relation in pairs formation but cross-checking all the different combinations. However, some common characteristics are noticeable. High returns are often generated from similar ETFs, e.g. the similar ETF traded in two separate marketplaces. In addition, quite small amount of ETFs present the most of the top 20 pairs.

In-sample simulations generate very high Sharpe ratios when transaction costs are not taken into account. But it is also notable, that even if all top 20 pairs present positive Sharpe ratio in-sample simulations, not all obtained positive return in the out-of sample trading period. For instance, all the 20 ETFs have positive Sharpe ratio in in-sample simulations of the period from September 2005 to the end of August 2006 but 4 of the 20 pairs showed negative result as from -15.28% to -1.00% in the portfolio during the out-of-sample period from September 2006 to the end of December 2006. I also calculated the maximum drawdown duration, which describes the time of the fall in days in respect to the peak of the cumulative return. According to the almost same statistical results form as Caldeira and Moura (2013), the results for the top 20 pairs from an example period are presented in the following table, which is an example result table of top 20 pairs collected from one formation period (from the beginning of September 2005 to the end of August 2006), ranking based on the best in-sample

Sharpe ratios, to the trading period (from the beginning of September 2006 to the end of December 2006) out-of-sample results.

Table 6 Descriptive statistics of the pairs. Sample period 2006:09 to 2006:12.

Table 6 describes the following statistics for the top 20 pairs organized with the greatest descending Sharpe ratios. The first two columns, “ETF 1” and “ETF 2”, describe the selected pairs; “EG (ADF)” refers to Engle-Granger Augmented Dickey Fuller (ADF) cointegration test and “JH” refers to Johansen cointegration test for out-of-sample period; “SR” refers to Sharpe Ratio for in-sample period; “MDD Duration(days) refers to maximum drawdown duration in days and “Net Ret.(%)” refers to the net return for out-of-sample period.

Note: The 90% critical value for ADF is -3.08 and for Johansen test it is 10.47. Pairs have been selected using top 20 in-sample Sharpe ratios after passing the cointegration tests. However, in out-of-sample period the pairs not necessary pass the cointegration tests. Sharpe ratios have been calculated with 4% risk-free rate and without transaction costs. MDD Duration(days) have been calculated related to informative statistics even if the stop loss algorithm holds.

	ETF 1	ETF 2	EG (ADF)	JH (λ_{tr})	SR(in-sample)	MDD Duration(days)	Net Ret.(%)
	266864	14915K	-5.94	20.53	5.03	10	-1.77
	266864	266866	-5.99	21.79	4.75	12	1.66
	268291	13264R	-6.03	26.33	4.59	6	12.03
	268291	27126W	-3.83	5.66	4.41	13	6.19
	266868	14327M	-7.06	35.63	4.13	0	-1.44
	268291	13699M	-3.9	5.77	4.13	6	6.76
	268291	41388V	-3.23	9.55	4.08	4	2.81
	13699M	27126W	-7.57	27.72	4.08	16	1.66
	266866	14915K	-6.85	25.72	4.06	16	-5.10
Pairs	268291	873445	-2.16	9.6	3.98	4	8.34
	15110D	27553M	-5.87	24.13	3.96	8	4.02
	268291	291561	-6.75	27.83	3.83	10	12.65
	13264R	27126W	-4.22	5.19	3.77	56	2.19
	13264R	291561	-5.68	25.07	3.63	9	-1.00
	689912	292242	-2.96	5.03	3.56	15	10.15
	13264R	41388V	-3.07	12.69	3.52	5	1.78
	13821V	14558P	-6.77	35.92	3.45	9	0.73
	292589	689912	-4.12	13.39	3.45	39	9.29
	14558P	292927	-2.14	6.97	3.43	4	9.87
	689915	292598	-2.81	11.01	3.32	8	1.90

The codes of ETFs used in the previous table 6 are downloaded from Datastream. Very often the used top 20 pairs are similar ETFs but traded in the different marketplaces. Here, for example, 266864 (Daiwa Exchange Traded Fund-Topix) and 14915K (Nikko Exchange Traded Index Fund Topix) are both representing all stocks in the Tokyo Price Index but these are traded in the different marketplaces which affects to the pricing. Secondly, 13264R (iShares Dow Jones EURO STOXX 50 (de)) and 27126W (Lyxor Dow Jones Eurostoxx (Milan) 50) are very similar in a same way, too. But also, here are some pairs which are more different with their characteristics, e.g. 292589 (iShares Trust Dow Jones United States BAS Materials) and 689912 (Select Sector Standard and Poor's Depositary Receipt Trust SBI Basic Industries) but meet the cointegration requirements in out-of-sample, too. Instead, two other significantly different ETF pairs (268291 (Exchange Traded Fund B1-MSCI Euro) and 873445 (iShares MSCI Canada Index), and 689912 (Select Sector Standard and Poor's Depositary Receipt Trust SBI Basic Industries)) do no longer meet cointegration requirements in out-of-sample.

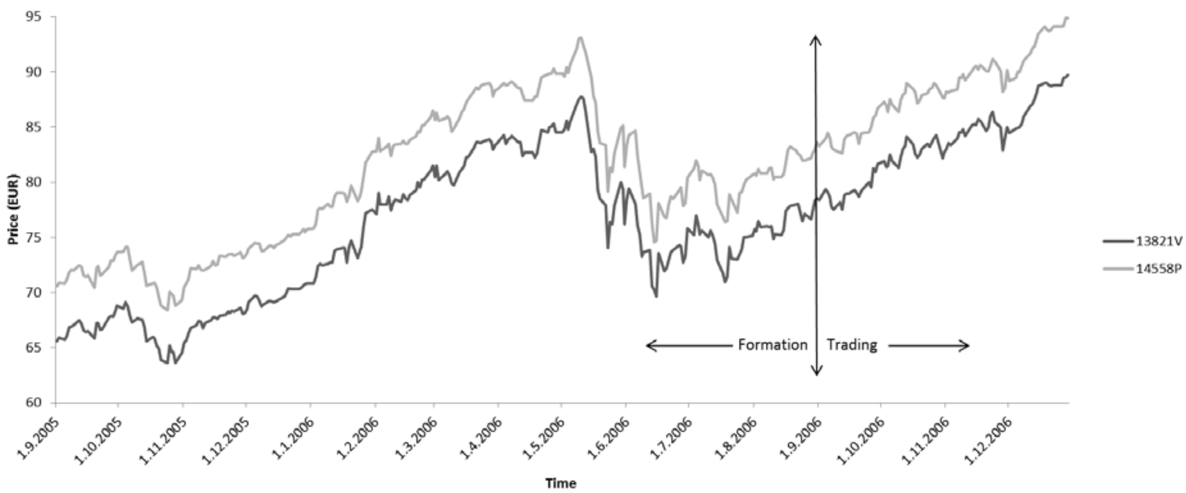
Figure 7 presents the evolution of the z-score of residuals of an example pair iShares MDAX (de) (13821V) against Indexchange Investment (XETRA) (14558P). These ETFs are good examples of cointegrated, well performed, pairs because these are similar ETFs traded in the different marketplaces. Citing Caldeira and Moura (2013), the z-score measures the distance to equilibrium of the cointegrated residual in units of standard deviations, i.e. how far away is a given pair from the theoretical equilibrium value associated with my model. The first graph shows the evolution of the prices for the example ETFs and the formation and the trading periods. The second graph shows the z-score and the thresholds for the pair of these example ETFs.

The second graph of the figure 7 describes well how the trading strategy has been completed. The pair is open every time its spread exceeds the thresholds. For instance in an example graph the spread exceeds the threshold -1.5 standard deviation at point a when I buy to open. Secondly I wait when the pairs’s spread is higher than -0.5 standard deviation, i.e. at point b, and then I close my long position. After these opening and closing positions I have made four transaction: at the opening buy long ETF 14558P and sell short ETF 13821V at point a, and at the closing sell long 14558P and close short 13821V at point b. Here, duration between the opening and closing, i.e. one operation, is one day. Points c and d show the similar operation and points e and f show the inverse transactions, i.e. when the spread exceeds the threshold 1.5 standard deviation I open the position by selling short ETF 14558P and buying long ETF

13821V at point e. Thereafter, I close the position when the spread exceeds the threshold 0.5. standard deviation at point f by closing short ETF 14558P and selling long ETF 13821V. The duration in this operation is also one day.

Figure 7 Evolution of the ETF prices and z-scores of 14558P versus 13821V from 2005:09 to 2006:12.

Note: Normalized spread and the times when the positions are open. The pair is open every time its spread exceeds the thresholds.



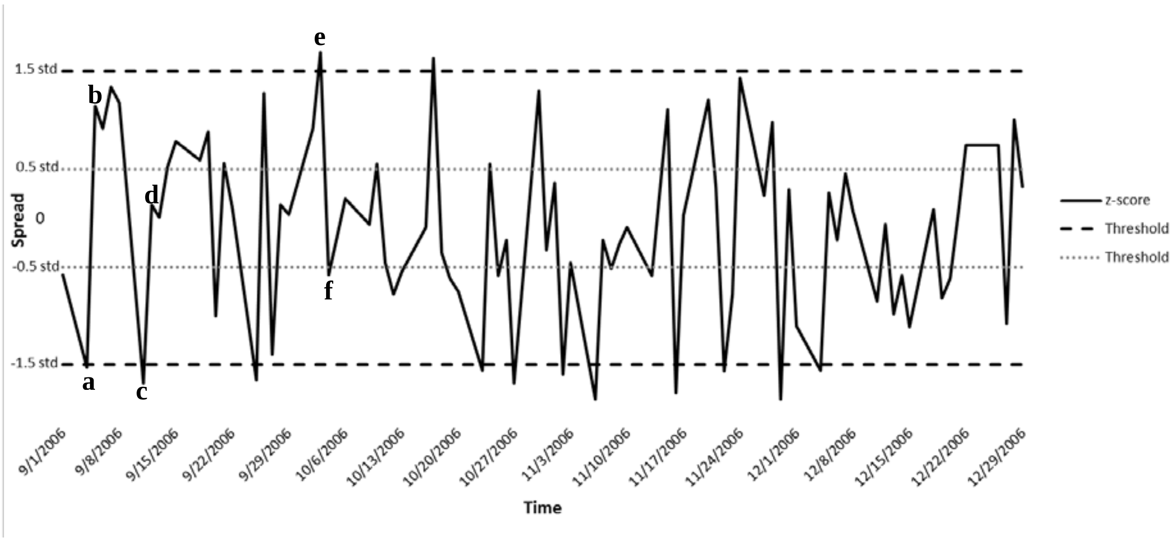


Figure 8 is again a good example of similar ETFs traded in the different marketplaces. ETF 14327M (Daiwa Exchange Traded Fund-Nikkei 225) and ETF 266868 (Nikko Exchange Traded Index Fund 225) are cointegrated and these have another basic characteristic: very high peak. Here, I open the position at point g when the spread is as high as 4.08 and I close the position on next day at point h with the z-value of -0.78.

Figure 8 Evaluation of z-scores of 14327M versus 266868 from 2005:09 to 2006:12.

Note: Normalized spread and the times when the positions are open. The pair is open every time its spread exceeds the thresholds.

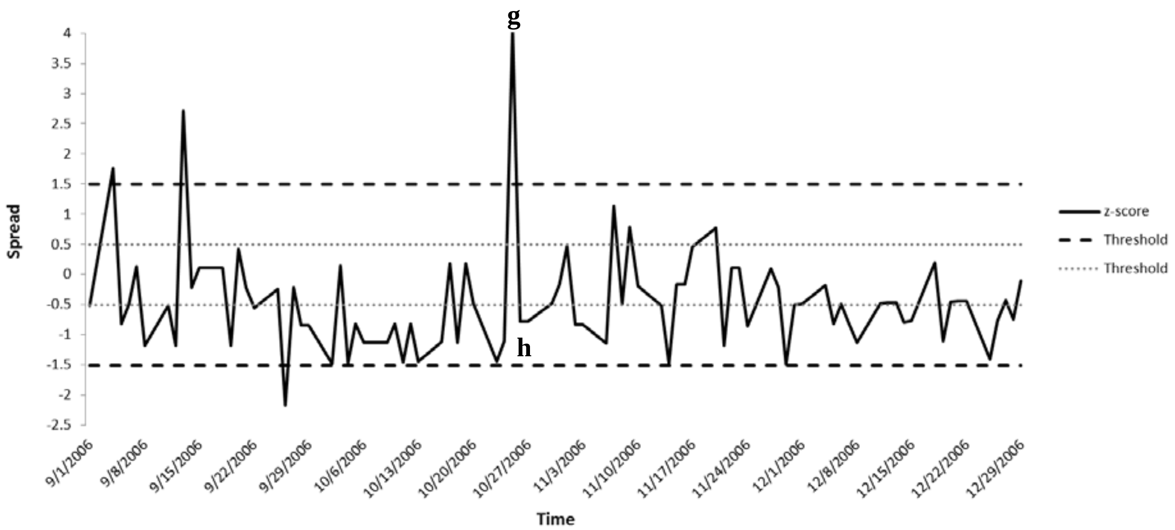


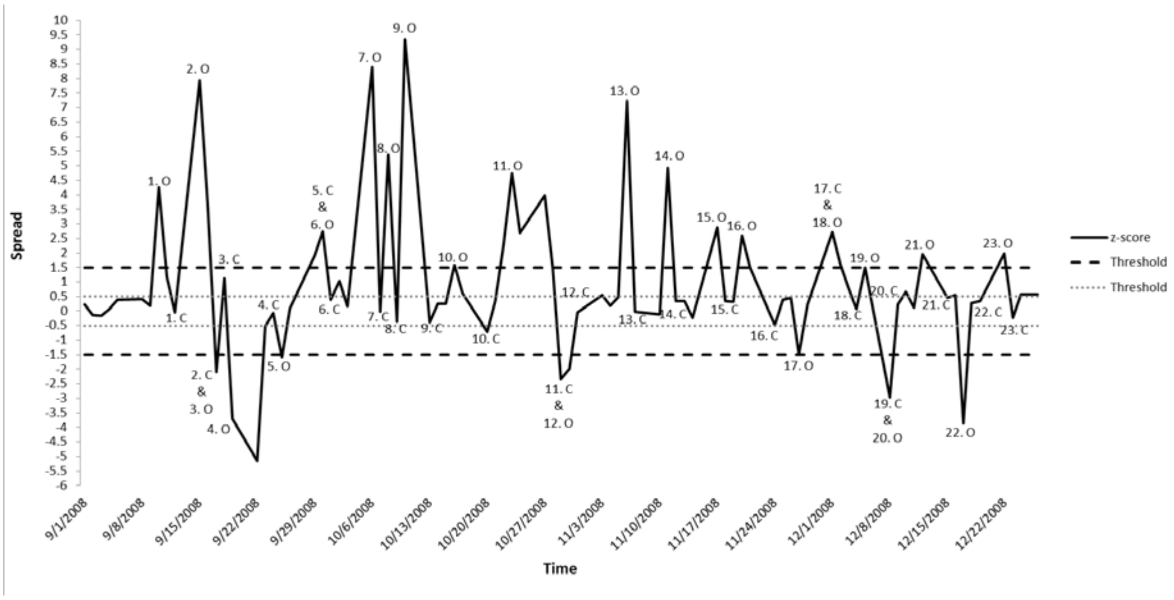
Figure 9 presents two different results. First graph presents a pair which is highly cointegrated and traded frequently during the examination period and second graph presents a pair which is not cointegrated in out-of-sample and thus has no trading activity.

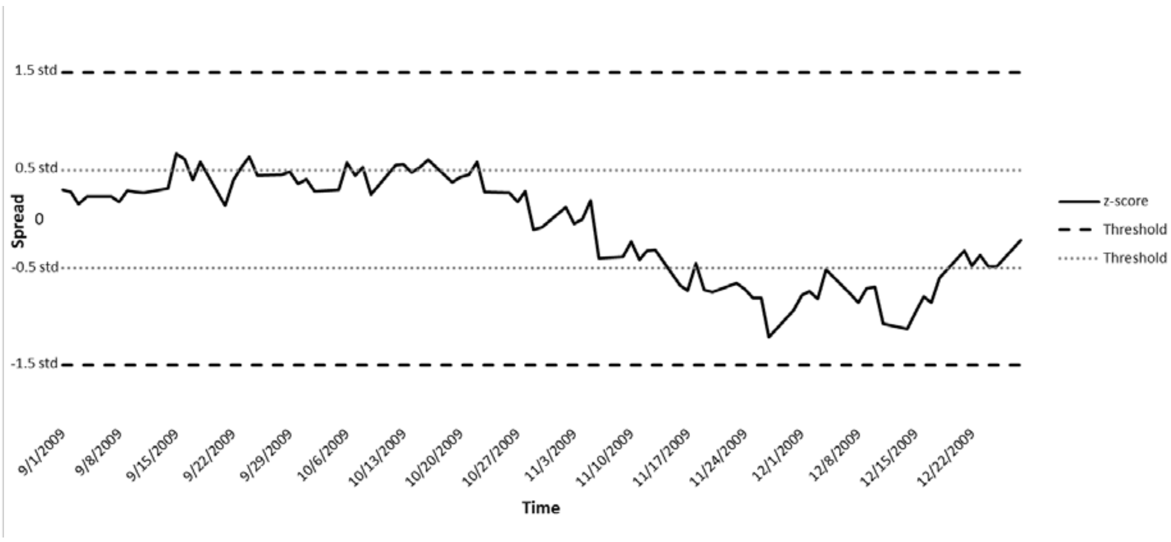
Figure 9 Evaluation of z-scores of 27126W versus 13699M from 2008:09 to 2008:12 and 27127H versus 689915 from 2009:09 to 2009:12

The upper graph presents graphically the shifts in spreads of an example of exceptionally performed pair during its out-of-sample period. Number in labels is an ordinal number of operation and letter whether the operation is opening (O) or closing (C) position. E.g. “10. O” indicates tenth opening position and “10. C” indicates tenth closing position. Two labels combined indicate that there are closing and opening positions at the same point. E.g. “11. C & 12. O” indicates eleventh closing position and twelfth opening position.

The lower graph presents graphically the shifts in spreads of an example of poorly performed pair during its out-of-sample period.

Note: Normalized spread and the times when the positions are open. The pair is open every time its spread exceeds the thresholds.





As seen in the first graph of Figure 9, ETF 27126W (Lyxor Dow Jones Eurostoxx (Milan) 50) and ETF 13699M (Lyxor Exchange Traded Fund Dow Jones ES 50) are highly cointegrated generating value of -5.56 in ADF-test when the critical value at 1% significance level is -4.03. I.e. spread is varying with regularity on the both side of the z-value of zero and, in addition, varying is high and frequent. The graph presents high variation (z-values from -5.15 to 9.33) as well as high frequency (23 operations, i.e. 23 opening and 23 closing positions). This eligible cointegrated pair generated net return of 10.64% in that 4 month trading period.

Second graph of Figure 9, instead, presents an undesirable pair of ETF 27127H (iShares Russell Mid Cap Growth Index Fund) and ETF 689915 (Consumer Discretionary Select Sector Standard and Poor's Depositary Receipt Fund). The pair is not cointegrated in the out-of-sample period with the value of -1.98 when the critical value at 10% significance level is -3.09. The variation in spread is neither enough to open any single position (spread does not exceed threshold values of -1.5 or 1.5) and thus, there is no net return in that 4 month trading period.

Table 7 summarizes the statistics of return for the pairs' portfolios using the full sample period from the beginning of 2004 until the end of 2012. Following Caldeira and Moura (2013), the profitability calculated and shown generated from this out-of-sample analysis has already been discounted for transaction costs[26]. First five results in the table 7 were available after the data mining and the rest after the out-of-sample analysis. Especially notable results are high average annualized returns with relatively low volatility of 10.45% in annualized terms, and a low correlation of -0.51 with the market indicate my strategy to be market neutral as designed.

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[26] The cost considered is 0.25% per trade on average, summing up to 1.0% per operation including two trades in opening and two trades in closing the position. Costs related to renting ETFs sold short were considered to be 2% per year.

Table 7 Statistics of returns of unrestricted pairs trading strategies, from 2005:01 to 2012:12

Table 7 summarizes the statistics of my pairs trading strategy from the whole sample size and from the whole sample period.

Note: The sample period is from January 2004 to December 2012, while the out-of-sample simulations were performed from January 2005 to December 2012. I.e. the first 12 months of the out-of-sample are training period and the rest 8 years are a trading period divided into the subperiods of four months. Average daily net returns are maximum and minimum average daily net returns between single pairs.

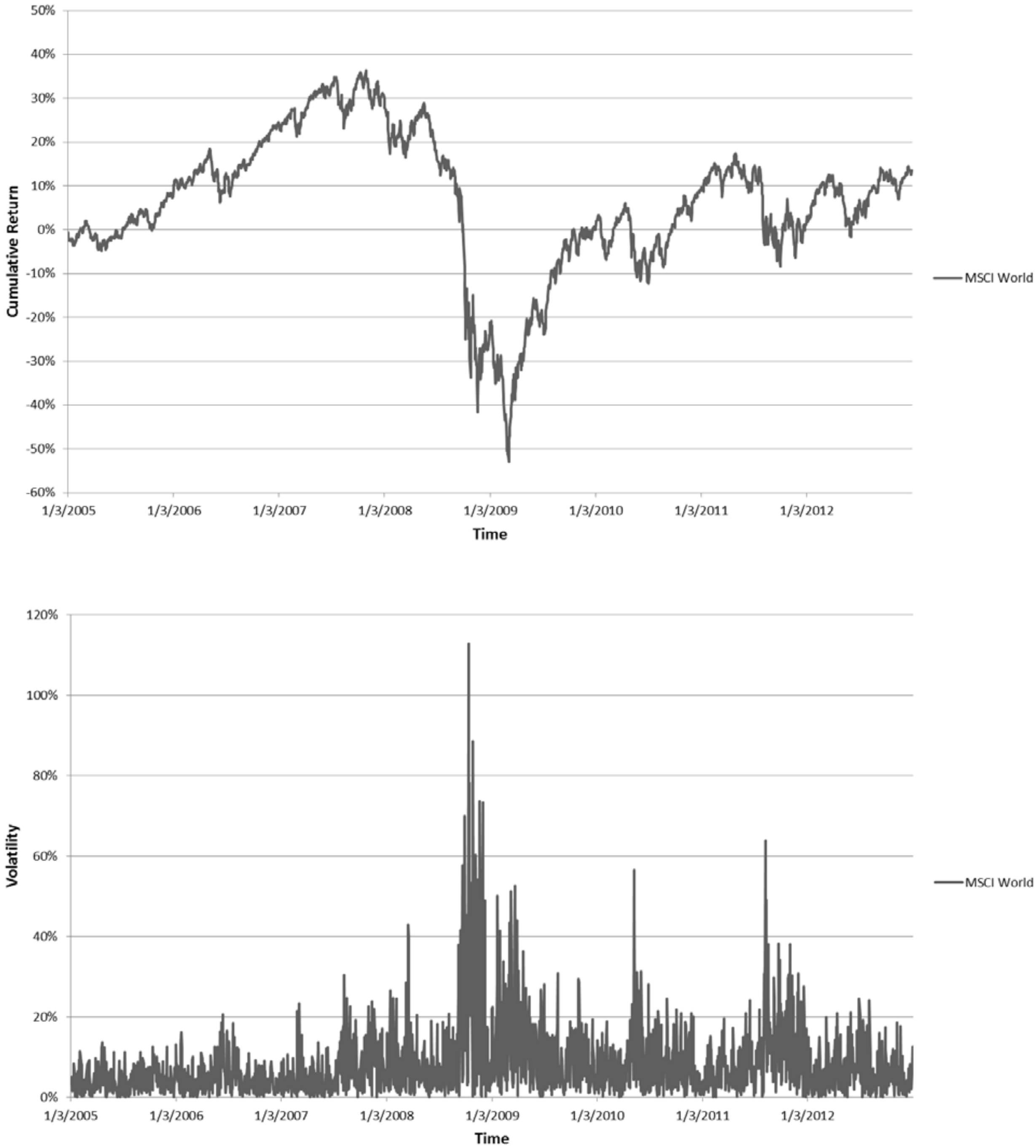
Summary Statistics of the Pairs Trading Strategy	
# of observations in the sample	21528
# of days in the training window	250
# of days in the trading period	84
# of trading periods	24
# of pairs in each trading period	20
# min of cointegrated pairs in a trading period	1413
# max of cointegrated pairs in a trading period	2278
Average annualized return	41.88%
Average annualized net return	27.29%
Annualized volatility	10.45%
Annualized Sharpe Ratio	3.55
Average largest daily net return	0.49%
Average lowest daily net return	-0.26%
Cumulative profit	105.43%
Spearman correlation coefficient	-0.51
Skewness	0.85
Kurtosis	0.32
Maximum Drawdown	10.82%

Caldeira and Moura (2013) emphasize the presented maximum drawdown of the strategy, which is a simple measure of the fall in percentage terms with respect to the peak of the cumulative return, and can be used as a measurement of how aggressively the strategy's leverage can be increased. I also calculated maximum drawdown, even if I used stop-loss algorithm in my strategy, accounting 10.82%. Skewness of 0.85 describes the returns to be positively skewed when the standard deviation overestimates risk. Kurtosis of 0.32, instead, describes fatter tails than would be observed in a normal distribution

I used MSCI world as my benchmark index to investigate my Hypothesis 1. Figure 10 presents the cumulative return and volatility of MSCI World index.

Figure 10 Cumulative return and Volatility of MSCI World Index, from 2005:01 to 2012:12.

Note: The first panel of the figure describes cumulative profit of the MSCI World index and the second panel shows annualized volatilities.



As seen in the first panel of Figure 10 the cumulative log return of 13.51% does not exceed my cumulative log return of 105.43% and the performance of MSCI World index is not as smooth as I have with ETF pairs trading, accounting -54.61% drop in 2008. In addition, the annualized mean return is only 1.69% when the pairs trading strategy generates 27.29%.

Second panel of Figure 10 presents the volatility of MSCI World index accounting the average annual volatility of 8.36% which is a bit lower than in the pairs trading strategy (10.45%). However, Kurtosis, which is sometimes referred as the "volatility of volatility", is a way higher (8.79) than I have with ETFs (0.32). The panel shows a high peak in 2008 volatility (14.01% annualized average) which is referred in earlier studies (e.g. Caldeira and Moura (2013)) and also my pairs trading strategy generates highest subperiodic volatility (17.63%) in 2008. Table 8 in the next subchapter presents the subperiodic statistics of my trading strategy.

Calculating t-statistic[27] for abnormal return of ETF pairs trading strategy generates t-value of 53.06 exceeds the value of 99% confidence interval (2.58). Thus, I can accept my Hypothesis 1, i.e. statistical pairs trading with ETFs generates positive abnormal return, at the 1% significance level.

4.2. Subperiod analysis

According to Caldeira and Moura, I discuss the subperiod analysis in an annual level. I present it in Table 8 which summarizes annual statistics of pairs trading strategies. The table includes the values in the trading period from 2004 to 2012 of maximum, minimum, median and mean returns as well as standard deviation, skewness, kurtosis, accumulating net profit (log-return), Sharpe ratio and Maximum drawdown. I follow DeMiguel et al. (2009) to test the statistical significance of the difference between the variances and Sharpe ratios of the returns for pairs trading and the stationary bootstrap of Politis and Romano (1994) generating 1,000 bootstrap samples with smoothing parameter q = 0.25 as Caldeira and Moura (2013.

[27] T-statistic is calculated using the standard formula of $t = \frac{\hat{\beta}_j - \beta_{j,0}}{SE(\hat{\beta}_j)}$ where $SE(\hat{\beta}_j) = \frac{s}{\sqrt{n}}$

Table 8 The P&L (in %) of the statistical arbitrage strategy for 8 years

Table 8 summarizes the out-of-sample statistics for the annual percentage net returns on portfolio of top 20 pairs between 2005:01 and 2012:12. Max, Min, Median, Mean and Accum are maximum, minimum, median, mean and accumulating returns in the presented years. Std, Skew, Kurt, Sharpe and MDD are standard deviation, skewness, kurtosis, Sharpe ratio and Maximum drawdown in these years. The P-values are computed using the stationary bootstrap of Politis and Romano (1994) generating 1,000 bootstrap samples with smoothing parameter q = 0.25.

Note: Sharpe ratios are calculated avoiding transaction costs. MDDs have been calculated related to informative statistics even if the stop loss algorithm holds.

Year	Max	Min	Median	Mean	Std	Skew	Kurt	Accum	Sharpe	MDD
2005	10.99	6.20	9.95	8.13	5.69	0.23	0.55	7.81	3.76	2.52
					(0.000)			(0.000)	(0.000)	
2006	12.41	7.51	11.45	10.01	7.01	3.18	1.69	9.54	3.80	4.14
					(0.000)			(0.000)	(0.000)	
2007	20.44	8.46	14.04	13.33	8.80	0.67	1.27	12.52	3.04	5.96
					(0.000)			(0.000)	(0.000)	
2008	64.83	39.01	59.55	53.11	17.63	0.24	-0.64	42.60	4.14	10.82
					(0.000)			(0.000)	(0.000)	
2009	67.64	22.81	48.75	46.59	12.32	0.28	-0.97	38.25	3.77	5.69
					(0.000)			(0.000)	(0.000)	
2010	42.15	14.95	18.75	25.34	10.43	1.01	0.44	22.58	3.31	10.29
					(0.000)			(0.000)	(0.000)	
2011	48.89	18.78	30.08	36.11	12.78	0.92	0.56	30.83	3.27	9.89
					(0.000)			(0.000)	(0.000)	
2012	40.79	8.21	29.36	25.70	9.92	0.27	-0.38	22.87	3.33	6.45
					(0.000)			(0.000)	(0.000)	
All Time	67.64	6.20	27.74	27.29	10.57	0.85	0.32	105.43	3.55	10.82

The presented table shows us the profitable strategy in every year, the worst performance in year 2005 with a mean net profit of 8.13% and volatility of 5.69%. Instead, the best performance in year 2008 generates a net mean profit of 53.11% with volatility of 17.63% which shows the strategy to perform especially well in economy downturn (MSCI World Index -54.61%). This is one of the reasons why hedge funds are using pairs trading strategy of one of their main strategies. Thus, the pairs trading strategy with ETFs seems to perform well in every subperiods. Also skewness is positive in every year which means that standard deviation overestimates risk. Instead, kurtosis varies from negative to positive, i.e. thicknesses of tails vary mutually between the thicknesses of normal distribution.

However, the pair trading strategy is very sensitive for transaction costs. Transaction costs vary in different marketplaces and even a small rise affects significantly to profitability due to the characteristic of high frequent trading. Thus, my results can be too high or too low. In addition, even if ETFs can theoretically be available to short sell, practically it is not always easy or possible. Even the marketplaces can forbid short selling for some period as occurred in last financial crisis. These issues should be considered when reviewing the results.

4.3. Comparative analyses

In this subchapter, I compare my results to both randomly selected pairs and the past studies. Comparison to randomly selected pairs is the performance measurement of my trading strategy. To check the profitability of the strategy I follow Caldeira and Moura (2013) and use bootstrap method and the simplest comparison with a naïve trading strategy which can be done by generating randomly trading signals and trade according to them. As Gatev et al. (2006), I conduct a bootstrap where I compare the performance of my pairs to random pairs.

Caldeira and Moura (2013) describe the process by firstly setting the historical dates in which the various pairs are open and in each bootstrap replacing the actual ETFs with two random ETFs with similar prior one-day returns as the ETFs in the actual pair. As they did, I bootstrap the entire set of trading dates 2516 times. They obtain it using the same percentage transaction costs for both the long as the short position the net return of the naïve strategy

$$R_t^{Naive} = \sum_{i=1}^{N} w_{i,t} r_{i,t} + 2N ln\left(\frac{1-C}{1+C}\right)$$

On average I found the mean returns of random pairs to be 1.70% annually with the Sharpe ratio of 0.48. Which are significantly lower than the results I presented in Table 7.

In the Table 9 I compare my results to the past studies. I chose a few relevant studies to give the brief picture of the differences of the performance between the different securities as well as figure out whether to accept Hypothesis 2 or not. However, due to the different given periods, the results are not fully comparable especially in an annual level but briefly show the results of these studies.

Table 9 Comparison of the performances of past studies

Table 9 compares a few relevant studies by these annual percentage excess mean returns and Sharpe ratios to the values of my study. Excess returns are calculated by using MSCI World index as benchmark index. Due to the manners of representation the values are not fully comparable but give a brief picture of the results of the past studies.

	Sipilä (2013)		Caldeira and Moura (2013)		Do and Faff (2010)		Schizas et al. (2011)	
Year	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe
2003								
2004								
2005	0.008	3.76						
2003-2005							0.023	0.089
2006	-0.065	3.80	0.127	1.72				
2007	0.065	3.04	0.186	2.69				
2008	1.077	4.14	-0.151	0.12				
2009	0.227	3.77	0.239	1.8				
2006-2009:03							0.022	0.065
2003-2009					0.0288	0.831		
2010	0.162	3.31	0.003	1.49				
2011	0.440	3.27	-0.065	1.35				
2012	0.133	3.33	0.017	1.38				
All Time	0.256	3.55	0.050	1.241				

As seen the excess mean returns on average are higher in my investigation. Even if the relevant studies present higher returns in some subperiods the returns are only slightly higher and, in addition, my returns are significantly smoother and positive. Especially years in economic downturn seem to generate higher excess returns. Thus, I accept Hypothesis 2 at the 1% significance level (t-value of 42.70).

5. Discussion and conclusions

The purpose of this thesis was to investigate algorithmic pairs trading with Exchange Traded Funds. The study was motivated by recent findings in the performance of pairs trading. In addition, the lack of empirical investigation of pairs trading, especially with other securities than stocks, gave me interest to investigate pairs trading with ETFs. Opportunity to use the trading methods in a real life trading makes the results of this thesis more useful and applicable.

The analysis was performed by following mainly the model discussed in Caldeira and Moura (2013) but also comparing with the other studies in order to verify the relevance of the study. Brand new and relevant study allows me to use the latest academic knowledge and this verifies that the model is up to date. The used strategy is based on cointegration, examining the mean-reversion of pairs. I used totally 21,528 possible pair combinations in cointegration tests in order to identify stock pairs that share a long term equilibrium relationship. Performed Engle and Grangers and Johansen's tests shrunk the possible pairs into maximum of 2,278 cointegrated pairs, from each formation period were obtained. After the cointegration tests, I calculated the standardized spread between the ETFs and I simulated trades in-sample. Subsequently, I selected 20 pairs with highest Sharpe ratios in-sample to the top 20 portfolio to be traded out-of-sample.

The research questions that the current study set out to answer were:

(1) Are there statistical arbitrage pairs that generate significant abnormal return?
(2) Does the usage of ETFs as statistical arbitrage pairs generate even higher abnormal return than stocks?

And related to the research questions I generated two hypotheses

H1: *Statistical pairs trading with ETFs generates positive abnormal return.*

H2: *Statistical pairs trading with ETFs generates higher positive abnormal returns compared to the pairs trading with stocks.*

The main findings of the study show that pairs trading with ETFs generate significant abnormal return with low volatility from the eight year trading period. The cumulate net profit is 105.43% and an annual mean of 27.29% and with volatility of 10.57%. Furthermore, the results confirmed market neutrality with no significant correlation with MSCI World index.

The present findings are in contrast with those of Caldeira and Moura (2013) since the both investigations generate positive abnormal return with low volatility and low correlation with the benchmark index. Comparison to the benchmark index of MSCI World and the other studies also validate my results since the results of comparison studies (e.g. Do and Faff (2010); Schizas et al. (2011)) are parallels. However, comparing with Schizas et al. (2011) the abnormal return is significantly higher due to wider repertoire of ETF pairs to the portfolio. Thus, the findings suggest that I accept both of my hypotheses as summarizes in the following Table 10.

Table 10 Summary of the results

The table summarizes the hypotheses and main findings related to them.

	Hypotheses	Empirical evidence
H1	*Statistical pairs trading with ETFs generates positive abnormal return.*	Strong support at the 1% significance level.
H2	*Statistical pairs trading with ETFs generates higher positive abnormal returns compared to the pairs trading with stocks.*	Strong support at the 1% significance level.

5.1. Suggestions for further research

This thesis fills the gap in the pairs trading investigations by introducing the algorithmic pairs trading with ETFs first time with large sample size. However, since the data for the study was daily data, the implications made should be considered as suggestive only between the days. Thus, possible further studies could concentrate on pairs trading investigation with intraday data. This could still widen the picture of hedge funds’ profitability as they are high frequency trading. It could also be possible that profitability would be significantly higher in intraday trading than trading only daily. Furthermore, the trading horizon could fall.

I started the discussion on pairs trading with different securities comparing stocks with ETFs, but there is also a need for the investigations of pairs trading with different securities (e.g. commodities) to a warrant more research. Due to the lack of these kinds of studies, wider comparisons could generate huge potential for using pairs trading also out of the hedge fund world and thus increasing the market efficiency. Finally, transaction costs play a major role in pairs trading, therefore in-depth, up-to-date, investigation of transaction costs related to pairs trading is needed.

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Appendix: List of Exchange Traded Funds

Note: Appendix contains 202 ETFs with information of names, Datastream codes and exchange places used in the investigation. 6 collinear ETFs have been deleted.

Expanded Name	DS Code	Exchange
Allmerica Securities Trust SHBI	680435	New York
Amundi Exchange Traded Fund Standard and Poor's Euro (Paris-SBF)	41388V	Euronext Paris
Amundi Exchange Traded Fund Standard and Poor's Europe (Milan) 350 Fund	27552R	Milan
Biotechnology Holders Trust	277719	Non NASDAQ OTC
Broadband Holdrs Trust Depositary Receipt	286770	New York Stock Exchange (NYSE) Arca
Consumer Discretionary Select Sector Standard and Poor's Depositary Receipt Fund	689915	New York Stock Exchange (NYSE) Arca
Credit Suisse ETF (CH) ON SMI	290302	SIX Swiss
Daiwa AM Exchange Traded Fund-Banks	15363H	Tokyo Stock Exchange
Daiwa Exchange Traded Fund-Nikkei 225	14327M	Osaka Securities Exchange
Daiwa Exchange Traded Fund-Topix	266864	Tokyo Stock Exchange
ETFS Metal Securities Australia Physical Gold	26995N	Australian
Exchange Traded Fund B1 Ethical Euro	26829X	Milan
Exchange Traded Fund B1-MSCI Euro	268291	Milan
Fidelity Commonwealth Trust NASDAQ Composite Index Tracking Stock	27706U	NASDAQ
First Trust Value Line 100 Exchange Traded Fund	27119K	New York Stock Exchange (NYSE) Arca
First Trust Value Line Dividend Fund	27397J	New York Stock Exchange (NYSE) Arca
Guggenheim Standard and Poor's 500 Equal Weight Exchange Traded Fund	26997V	New York Stock Exchange (NYSE) Arca
Hang Seng H-Share Index Exchange Traded Fund	28198F	Hong Kong
Health Care Select Sector Standard and Poor's Depositary Receipt	689913	New York Stock Exchange (NYSE) Arca
Hyperion 2005 Investment Grade Opportunity Term Trust	327965	New York
Indexchange Investment (XETRA)	14558P	XETRA
Indexchange Investment (XETRA) Tecdax ex	14558N	XETRA

Internet Architecture Holdings Deposit Recovery	286142	New York Stock Exchange (NYSE) Arca
Internet Holders Trust Depositary Receipt	274609	Non NASDAQ OTC
Internet Infrastructure Holdings Deposit Recovery	286141	New York Stock Exchange (NYSE) Arca
iShares Barclays 1-3 Year Treasury Bond Fund	26102F	New York Stock Exchange (NYSE) Arca
iShares Barclays 20 Year Treasury Bond Fund	26102J	New York Stock Exchange (NYSE) Arca
iShares Barclays 7-10 Year Treasury Bond Fund	26119D	New York Stock Exchange (NYSE) Arca
iShares Barclays Tips Bond Fund	28201L	New York Stock Exchange (NYSE) Arca
iShares Core Standard and Poor's 500 Exchange Traded Fund	292325	New York Stock Exchange (NYSE) Arca
iShares Core Standard and Poor's Mid-Cap Exchange Traded Fund	292395	New York Stock Exchange (NYSE) Arca
iShares Core Standard and Poor's Small Cap Exchange Traded Fund	292402	New York Stock Exchange (NYSE) Arca
iShares Core Total United States Bond Market Exchange Traded Fund	27692V	New York Stock Exchange (NYSE) Arca
iShares DAX (de)	13264P	Frankfurt
iShares Dex Universe Bond Index Fund	289780	Toronto
iShares Dow Jones (AMS) Eurostoxx 50	15110D	Euronext Amsterdam
iShares Dow Jones (Frankfurt) Eurostoxx 50	291561	Frankfurt
iShares Dow Jones (Milan) Eurostoxx 50	27553M	Milan
iShares Dow Jones EURO STOXX 50 (de)	13264R	Frankfurt
iShares Dow Jones Eurostoxx 50	14677Q	London
iShares Dow Jones STOXX 50	14677R	London
iShares Dow Jones STOXX 50 (Milan)	27126X	Milan
iShares Dow Jones United States Consumer Goods Sector Services Index Fund	292605	New York Stock Exchange (NYSE) Arca
iShares Dow Jones United States Consumer Services Sector Index Fund	292598	New York Stock Exchange (NYSE) Arca
iShares Dow Jones United States Total Market Index Fund	292590	New York Stock Exchange (NYSE) Arca
iShares Euro Corporate Bond	26885L	London
iShares Financial Times Stock Exchange 100	291580	London
iShares MDAX (de)	13821V	Frankfurt
iShares MSCI Australia	873442	New York Stock Exchange (NYSE) Arca
iShares MSCI Austria	873443	New York Stock Exchange (NYSE) Arca
iShares MSCI Belgium Capped Investable Market Index Fund	873444	New York Stock Exchange (NYSE) Arca

iShares MSCI Brazil Index Fund	292927	New York Stock Exchange (NYSE) Arca
iShares MSCI Canada Index	873445	New York Stock Exchange (NYSE) Arca
iShares MSCI China Index Exchange Traded Fund	14828X	Hong Kong
iShares MSCI Eafe Index Fund CAD-Hedged	28217Q	Toronto
iShares MSCI Emerging Markets Index Fund	26960H	New York Stock Exchange (NYSE) Arca
iShares MSCI EMU Index	298993	New York Stock Exchange (NYSE) Arca
iShares MSCI France	873446	New York Stock Exchange (NYSE) Arca
iShares MSCI Germany	873447	New York Stock Exchange (NYSE) Arca
iShares MSCI Hong Kong	873448	New York Stock Exchange (NYSE) Arca
iShares MSCI Italy	873450	New York Stock Exchange (NYSE) Arca
iShares MSCI Japan Index Fund	873419	New York Stock Exchange (NYSE) Arca
iShares MSCI Malaysia	873418	New York Stock Exchange (NYSE) Arca
iShares MSCI Mexico	873417	New York Stock Exchange (NYSE) Arca
iShares MSCI Netherlands Investable Market Index Fund	873416	New York Stock Exchange (NYSE) Arca
iShares MSCI Pacific ex Japan Index Fund	14729T	New York Stock Exchange (NYSE) Arca
iShares MSCI Singapore EWS 100	873415	New York Stock Exchange (NYSE) Arca
iShares MSCI South Africa Index Fund	26775V	New York Stock Exchange (NYSE) Arca
iShares MSCI South Korea	292242	New York Stock Exchange (NYSE) Arca
iShares MSCI Spain	873453	New York Stock Exchange (NYSE) Arca
iShares MSCI Sweden	873452	New York Stock Exchange (NYSE) Arca
iShares MSCI Switzerland	873451	New York Stock Exchange (NYSE) Arca
iShares MSCI United Kingdom	873449	New York Stock Exchange (NYSE) Arca
iShares NASDAQ Biotechnology Index Fund	13527V	NASDAQ
iShares Russell Mid Cap Growth Index Fund	27127H	New York Stock Exchange (NYSE) Arca
iShares Russell Mid Cap Index Fund	27127M	New York Stock Exchange (NYSE) Arca
iShares Russell Midcap Value Index Fund	15294K	New York Stock Exchange (NYSE) Arca
iShares Standard and Poor's 500 (Milan)	26830V	Milan
iShares Standard and Poor's 500 Index Fund CAD-Hedged	13912Q	Toronto
iShares Standard and Poor's Gssi National Resources Index Fund	14729U	New York Stock Exchange (NYSE) Arca

iShares Standard and Poor's Gsti Semiconductor Index	14331U	NASDAQ
iShares Standard and Poor's Gsti Software Index Fund	14331T	New York Stock Exchange (NYSE) Arca
iShares Standard and Poor's Gsti Technology Index Fund	13689W	New York Stock Exchange (NYSE) Arca
iShares Standard and Poor's Latin America 40 Index Fund	14729V	New York Stock Exchange (NYSE) Arca
iShares Standard and Poor's Topix 150 Index Fund	14729W	New York Stock Exchange (NYSE) Arca
iShares Standard and Poor's/TSX 60 Index Fund	274910	Toronto
iShares Standard and Poor's/TSX Capped Composite Index Fund	13591L	Toronto
iShares Standard and Poor's/TSX Capped Energy Index Fund	13708U	Toronto
iShares Standard and Poor's/TSX Capped Financials Index Fund	13733J	Toronto
iShares Standard and Poor's/TSX Capped Information Technology Index Fund	13708W	Toronto
iShares Standard and Poor's/TSX Capped Reit Index Fund	26392N	Toronto
iShares Standard and Poor's/TSX Completion Index Fund	13641X	Toronto
iShares Tecdax (de)	13788P	Frankfurt
iShares Trust Cohen and Saint RLT	13484V	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones Select Dividend Index Fund	27984D	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States BAS Materials	292589	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Energy	292604	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Financial Security	292401	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Financial Services Composite	292603	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Healthcare	292602	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Industrial	292601	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Real Estate Index Fund	292600	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Technology Sector	292327	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Telecom	292400	New York Stock Exchange (NYSE) Arca
iShares Trust Dow Jones United States Utilities	292599	New York Stock Exchange (NYSE) Arca
iShares Trust iBoxx Invest Top Investment Grade Corporate Bond Fund	26102C	New York Stock Exchange (NYSE) Arca
iShares Trust MSCI Eafe Index Fund	14442F	New York Stock Exchange (NYSE) Arca
iShares Trust Russel 2000 Growth Index Fund	298997	New York Stock Exchange (NYSE) Arca
iShares Trust Russel 2000 Value Fund	298996	New York Stock Exchange (NYSE) Arca

iShares Trust Russel 3000 Growth Fund	299000	New York Stock Exchange (NYSE) Arca
iShares Trust Russel 3000 Value Fund	298999	New York Stock Exchange (NYSE) Arca
iShares Trust Russell 1000 Growth	292397	New York Stock Exchange (NYSE) Arca
iShares Trust Russell 1000 Index	292326	New York Stock Exchange (NYSE) Arca
iShares Trust Russell 1000 Value	292396	New York Stock Exchange (NYSE) Arca
iShares Trust Russell 2000 Index Fund	292398	New York Stock Exchange (NYSE) Arca
iShares Trust Russell 3000	292399	New York Stock Exchange (NYSE) Arca
iShares Trust S&P500 / Bar Value	292394	New York Stock Exchange (NYSE) Arca
iShares Trust S&P500 Growth Index Fund	292393	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's 100 Index	26828Q	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Euro Plus	299010	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Global	274773	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Global 100 Index	255785	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Global Energy Sector Index Fund	14784J	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Global Financials Sector Index Fund	14784K	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Global Healthcare Sector Index Fund	14784L	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Global Information Technology Sector Index Fund	14784M	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Mid Capital Growth	298995	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Mid Capital Value	299004	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Small Capital Growth	299012	New York Stock Exchange (NYSE) Arca
iShares Trust Standard and Poor's Small Capital Value	299011	New York Stock Exchange (NYSE) Arca
Julius Baer MCO Global Value Merged See 36092V	698562	Frankfurt
Lyxor Dow Jones (Milan) Industrial Average	27552N	Milan
Lyxor Dow Jones Eurostoxx (Milan) 50	27126W	Milan
Lyxor Dow Jones Global (Milan) Titans 50	28247H	Milan
Lyxor Exchange Traded Fund Bel 20 Lyxor International Asset Management	26338D	Euronext Brussels
Lyxor Exchange Traded Fund CAC 40	13658T	Euronext Paris
Lyxor Exchange Traded Fund Dow Jones ES 50	13699M	Euronext Paris
Lyxor Exchange Traded Fund Financial Times Stock Exchange MIB	28013P	Milan

Lyxor NASDAQ-100 (Milan)	27552U	Milan
Market 2000 Holdrs Touche Remnant Depositary RCT	263796	New York Stock Exchange (NYSE) Arca
Merrill Lynch and Company Retail Holders Trust	13854J	Non NASDAQ OTC
Naftrac 02	15421T	Mexico
NASDAQ 100 European (Milan) Tracker	27552P	Milan
Nikkei 300 Stock Index Listed Fund	141401	Tokyo Stock Exchange
Nikko Exchange Traded Index Fund 225	266868	Tokyo Stock Exchange
Nikko Exchange Traded Index Fund Topix	14915K	Tokyo Stock Exchange
Nomura AM Banks	15379P	Tokyo Stock Exchange
Nomura AM Exchange Traded Fund-NK225	14327N	Osaka Securities Exchange
Oil Service Holders Trust	13505H	Non NASDAQ OTC
OMXH25 Index Share Exchange Traded Fund	27462D	Helsinki
Pharmaceutical Holders Trust	281715	Non NASDAQ OTC
Polaris Taiwan Top 50 Tracker Fund	27223X	Taiwan
Powershares Exchange Trust Fund Dynamic Over the Counter Portfolio	26997X	New York Stock Exchange (NYSE) Arca
Powershares Exchange Trust Fund Trust Dynamic Market Portfolio	26997W	New York Stock Exchange (NYSE) Arca
Powershares QQQ Trust Series 1	696044	NASDAQ
Regional Bank Holders Trust	292699	Non NASDAQ OTC
Satrix 40 Trust	280237	Johannesburg
Satrix Fini	26689J	Johannesburg
Satrix Indi	26689N	Johannesburg
Sector Standard and Poor's Deposit Receipt Trust Inter Financial	689917	New York Stock Exchange (NYSE) Arca
Sector Standard and Poor's Depositary Receipt Trust SBI Consumer Staples	689914	New York Stock Exchange (NYSE) Arca
Sector Standard and Poor's Depositary Receipt Trust SBI Inter Industries	689918	New York Stock Exchange (NYSE) Arca
Sector Standard and Poor's Depositary Receipt Trust SBI Interest Technology	699936	New York Stock Exchange (NYSE) Arca
Sector Standard and Poor's Depositary Receipt Trust SBI INT-Utilities	694406	New York Stock Exchange (NYSE) Arca
Select Sector Standard and Poor's Depositary Receipt Fund SHBI Energy	689916	New York Stock Exchange (NYSE) Arca
Select Sector Standard and Poor's Depositary Receipt Trust SBI Basic Industries	689912	New York Stock Exchange (NYSE) Arca
Semiconductor Holdrs Trust (Berlin) Depositary Receipt	296242	Berlin

Smarttenz	865647	New Zealand
Software Holders Deposit Receipt Software 12/40	265533	Non NASDAQ OTC
Standard and Poor's Depositary Receipt AEX Exchange Traded Fund	13886H	Euronext Amsterdam
Standard and Poor's Depositary Receipt Dow Jones Global Titans Exchange Traded Fund	265649	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Dow Jones Industrial Avenue Exchange Traded Fund	674511	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Dow Jones Wilshire Real Estate Investment Exchange Traded Fund	13845Q	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Dow Jones Wilshire Total Market Exchange Traded Fund	266349	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Index Shares Funds 50 Dow Jones Eurostoxx Fund	26393C	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Index Shares Funds Dow Jones STOXX 50 Fund	26393D	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Morgan Stanley Technology Exchange Traded Fund	265650	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Standard and Poor's 500 Exchange Traded Fund Trust	327719	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Standard and Poor's 500 Growth Exchange Traded Fund	265639	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Standard and Poor's 500 Value Exchange Traded Fund	265642	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Standard and Poor's 600 Small Cap Growth Exchange Traded Fund	265648	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Standard and Poor's 600 Small Cap Value Exchange Traded Fund	265644	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Standard and Poor's Midcap 400 Exchange Traded Fund Trust	152675	New York Stock Exchange (NYSE) Arca
Standard and Poor's Depositary Receipt Standard and Poor's/ASX 200 Fund	15154P	Australian
Standard and Poor's Depositary Receipt Standard and Poor's/ASX 200 Listed Property Fund	15206K	Australian
Standard and Poor's Depositary Receipt Standard and Poor's/ASX 50 Fund	15155C	Australian
Standard and Poor's Depositary Receipt Straits Times Index Exchange Traded Fund	26377N	Singapore
TD Standard and Poor's TSX Composite Index Fund	13601P	Toronto
Telecommunications Holdrs Depositary Receipt	281716	Non NASDAQ OTC
Topix Exchange Traded Fund	266866	Tokyo Stock Exchange
Tracker Fund of Hongkong	691916	Hong Kong
Trackhedge Property	27212E	Johannesburg
United Bank of Switzerland Fund Management Switzerland Exchange Traded Fund SMI	28195C	SIX Swiss
United Bank of Switzerland-Exchange Traded Fund MSCI Japan	25500R	Frankfurt
Van Kampen Advantage Pennsylvania Municipal Income Trust	326879	New York
Van Kampen Merritt Municipal Income Trust	519756	New York

Van Kampen Pennsylvania Quality Municipal Trust	546175	New York
Van Kampen Strategic Sector Municipal Trust	327662	New York
Vanguard Extended Market Exchange Traded Fund	28025R	New York Stock Exchange (NYSE) Arca
Vanguard Total Stock Market Index Fund	13917E	New York Stock Exchange (NYSE) Arca
Wireless Holders Trust	269931	New York Stock Exchange (NYSE) Arca
Xact OMX	29281P	Stockholm