Louvain School of Management

Pairs trading using exchange-traded funds: a profitability analysis of the strategy under minimum volatility constraints.

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ABSTRACT

Exchange-traded funds, ETFs, are one of the biggest financial innovation of this last decade and have seen a huge growth these last years. In this thesis, I made empirical analyses about the profitability of the pairs trading strategy, a well-known strategy used by many hedge funds. While they usually apply this strategy with stocks, this thesis focuses on the profitability when using exchange-traded funds. Indeed, these securities seem to have the characteristics that increase the profitability of the strategy, while not having those that decrease it.

Keywords: *Exchange-traded funds, ETFs, Pairs trading, market-neutral strategy, volatility, hedge fund, algorithmic trading.*

My first thoughts are for my parents, who gave me all the support needed to succeed these studies.

Then, I would like to thank Romain Henneton, who helped me to structure my algorithm in MATLAB and gave me support to use this tool I never used before. To continue on the practical aspect, I also would like to thank my supervisor, Luc Henrard.

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INTRODUCTION

2.

Exchange-traded funds have seen a huge growth in their assets under management and in their number in the last decade, and will probably continue to do so for many years. More and more investors choose to put their money in exchange-traded funds instead of investing in mutual funds because of their unique characteristics. By offering the diversification advantage of mutual funds at a lower cost, they continue to attract new investors every day and offer a lot of new investment opportunities. Moreover, exchange-traded funds offer something that mutual funds don't: exchange-listing. They can be bought at any moment at their market price and, like stocks, can be sold short or bought on margin. This unique feature makes ETF a perfect instrument for investors who want to access easily to foreign market or hedge their portfolio.

However, as they trade like a stock, they also have their own supply and demand. The price of the fund can be temporarily different from the price of the underlying assets, resulting in a discount or a premium. Nonetheless, for most ETFs, these price inefficiencies are temporary and quickly corrected by the in-kind creation and redemption process that keeps the price in line with the Net Asset Value of the fund. I discovered that ETFs covering the same index offer the same cumulative return most of the time, but one performs sometimes less than the other before going back to the same level. There was a systemic and recurrent behavior, and I wanted to know how to exploit this…

Originally, pairs trading consist to find two stocks that are correlated and whose prices tend to move together based on their historical value. Once the investor found these stocks, he tracks their prices and start to trade when their normalized price diverges by a certain amount. At this moment, he takes a short position in the stock with the higher price and a long position in the cheaper. By doing so, the positions generate profit when their price converges to their common normalized price. This market-neutral strategy is commonly used by hedge funds, and there is a lot of discussion about it on trading platform. However, there are few academic research about its profitability and even less about its profitability using exchange-traded funds, making it interesting to study…

During my researches, I first tried to understand which factors make the strategy profitable or not and under which circumstance it yields profit. I discovered that the profitability is negatively impacted by the presence of idiosyncratic news and earning announcement for only one of the stocks (Chen, Chen and Li (2012); Engelberg et al. (2009); Papadakis and Wysocki (2007)).

Nonetheless, this factor isn’t a concern when working with ETFs. Moreover, ETFs are not exposed to bankruptcy risks, which increase even more the potential profitability of the strategy. Another benefit of ETFs regarding pairs trading could be the international exposure offered by these products. Indeed, studies of Engelberg et al. (2009) have shown that the international exposure in the selected stocks increases the profitability of the strategy, which has been confirmed by Schizas et al. (2011) two years later.

I wanted to test the profitability of this strategy for two reasons: first, I love programming and finance, especially investment strategies. Thus, when I discovered the existence of pairs trading and its application to algorithmic trading, I quickly wanted to make my thesis about it. Moreover, I saw during my internship that most of my colleagues were using Matlab in their researches, while I had no clue on how it works. I have now a better idea of the possibility offered by this program and I’m really happy with that, given my willingness to work in asset management. On the other side, I saw during my first readings that the results about the profitability nowadays are mitigated. While some students might have been discouraged about this uncertainty, it increased even more my curiosity about it and I wanted to make my own opinion. Given that, the objective of this thesis is to provide an empirical analysis about the profitability of the strategy using ETFs and assess if it is still profitable or not. The second objective is to see if applying this strategy is worth compared to only invest in an ETF covering the S&P500.

My findings revealed that the strategy is indeed not profitable when using the classic parameterization used with stocks pairs trading. Indeed, by using the classic strategy, the algorithm tends to pick the most price-efficient ETFs covering the same index, which have no sense. However, when adding some minimum standard deviation requirement during the formation period, the strategy appears to be really profitable… especially during the crisis. During my researches, I tested seven different constraints regarding this standard deviation requirement. The goal was to find the optimal one on a risk-reward basis, and show if the strategy is profitable or not. Then, I tested if the optimal strategy yields a higher return than an ETF tracking the S&P500. Indeed, famous investors like Warren Buffet says that hedge funds often fail to produce a higher return than their benchmark. They argue that investing in ETF is more profitable and cheaper, so I wanted to make my own opinion about it with this strategy.

4.

Last but not least, I also tested the diversification effect of allocating one part of the portfolio to an ETF covering the S&P500. I tested 9 different allocations, with the objective to find the optimal one and assess if there is a positive effect of the diversification on the risk-adjusted return.

Finally, with the goal to have a wide view on ETFs and pairs trading, this thesis is constructed as follows. Part 1 consist in the theoretical framework of both exchange-traded funds and pairs trading. As exchange-traded funds share the characteristics of multiple fund structure, it starts by describing these structures to have a good understanding of how ETF works. Then comes the analysis of the structure and characteristics of ETF itself. This part ends with the analysis of the different pairs trade methodologies and its previous profitability analysis. Afterwards, the second part describes the methodology I used and the results of the strategy with the different parameterizations, including an in depth analysis of the optimal one. A final section concludes.

PART I

THEORETICAL FRAMEWORK

I. Description of the “classic” investment funds

In order to have a better understanding of the way ETFs are working, a small description of all different categories of investment funds is interesting. Indeed, ETFs are a mix of all these different funds, which makes this investment vehicle really unique and so popular. It takes the exchange-trading advantage of Unit Investment Trust (UIT) and Closed-end funds (CEF) while having the price stability of Open-End Funds (OEF) with the creation and redemption process. Given that, the price of ETFs is always in line with the price of their underlying assets, even if there are peaks in their trading volume. However, some inefficiencies in their pricing exist, making them sold at a discount or a premium for some small period of time. This anomaly will be discussed later in this thesis.

1. Active versus passive investing

In the diversified investment landscape, investors can choose between two main styles of investing: Active portfolio management and passive portfolio management. These two styles, even if they can share the same fund structures, are very different. The active management has the objective to provide the highest level of return for their investors, while keeping the desired level of risk (Abner, 2013). The mission of active management is to maximize their return compared to its benchmark, using their own strategies based on their own feelings. This return can be measured by the Alpha, which can be defined as “*the difference between a portfolio’s risk-adjusted return and the return of an appropriate benchmark portfolio*” (Fuller, 2000, p.4). However, Madhavan (2016) research reported that only 10% of the total active funds have beaten their benchmark in 2014, while the average of the active manager underperformed the passive manager in the period between 2010 and 2014. He also pointed that, following the purity hypothesis (also named Dunn’s Law), active manager tends to outperform their benchmark when it performed poorly and not because they took better investing decisions. This discovery can explain the preference of investors for passive style, and the spectacular growth of this kind of structure over the last decade.

The goal of passive investing is quite different. In this kind of investment vehicle, investors put their money in order to get the same return than a given basket of securities in function of their own strategy, of their own feelings about the market. Given that, passive manager has to be as close as possible to the benchmark they replicate (Madhavan, 2016). This kind of investing has seen a huge growth for the two past decades. According to Allen and Hebner (2017), passive investing represented 85% of the new inflow in the fund Industry and a value of more than $610 billion. Two third of this inflow went to Exchange-Traded Funds. As these funds are passively managed, it implies lower costs for the investors as there is no need to pay a manager for his services and his skills. This partly explains the expansion and growth of the funds based on this strategy in the investment landscape. Investing in these investment vehicles is most of the time part of the investors' own strategy, as they offer exposure to specific region or sectors in one single security. Furthermore, "*the investment style of active-management is zero-sum if one ignores fees: Collectively active bets must sum to zero, so in aggregate, active management cannot outperform an index.*" (Sharpe, 1991, pp. 7). So if we can't beat the market, why don't we just buy it? This simple assumption increased the potential of passive investing.

These two investment style can be applied in four main fund structure, with different characteristics: Open-end funds (OEF) like mutual funds, closed-end funds, Unit Investment Trust (UIT) and Exchange-Traded Funds (ETF). However, Exchange-Traded Funds are mainly passive investing, with the goal to track a basket of securities of a region or sector index. These different types of funds will be analyzed in detail in the four next sections.

2. Open-end fund (Mutual fund)

It is the main structure in the investment landscape. In a mutual fund, investors put their money together to reduce their individual transaction costs and to increase diversification via a bigger pool of money to be invested (Madhavan, 2016). At any time, they can increase or decrease their position in the fund by buying or selling shares at the Net Asset Value (NAV) of the end of the day. According to Abner (2013), the NAV of the fund is calculated at the end of each day, with the new asset value and the new number of shares. In an open-end fund, the fund manager creates new shares when investors want to enter and redeem existing shares when investors want their money back.

This process, described by Abner (2013) and Madhavan (2016) is called in-cash creation and redemption process. When an investor wants to invest in the fund, the fund manager gives him some shares in exchange of cash and reinvested in the portfolio of the fund. When an investor wants to leave the fund, the fund manager sells some positions in the portfolio gives the cash back to the investors in exchange of its fund shares. With this process, the value of the fund can always be assessed at the end of each day, and doesn't move with its own supply and demand.

Furthermore, as mentioned previously, the value of the fund can be assessed by the NAV. It is the value of all the assets owned by the fund at the end of the day, divided by the number of shares outstanding (Madhavan, 2016). Given that, the fluctuation in the value of the NAV follows the fluctuation of the positions in its portfolio and is not impacted by the change in the fund's ownership. This allows investors to assess the performance of the fund, by looking at the move in its price. This creation and redemption process is typical to open-end funds and will be discussed in more details later in the thesis.

3. Closed-end fund (CEF)

As its name suggests, closed-end funds are funds closed for new investors (and so for the creation of new shares) after its Initial Public Offering (IPO). Once the fund is created, the number of shares stays constant and its price move with the supply and demand. The structure of the premium or the discount is different than in an Open-End Fund. While OEFs have a short term premium/discount linked to the lag between the supply and demand of the shares and the creation and redemption process, closed-end funds can keep their premium/discount for a longer term. This depends on the investment structure of the fund and the supply and demand of the underlying assets.

According the US Securities and Exchange commission (2013) report about closed end fund, closed-end funds are not forced to buy back their shares from investors as there is no creation and redemption process. Given that, unlike Open-end funds, CEFs can invest more in illiquid assets and with more freedom as there is no need to cut positions overnight, if an investor wants its money back.

4. Unit Investment Trust

Unit Investment Trust (UITs) is the third type of investment product proposed to investors. According to US Securities and Exchange commission (2013) report about Unit Investment Trusts, UITs are investment companies that are a mix of both Open-End Funds and Closed-End Funds. Like closed-end funds, UITs also issue their share once during a public offering and the number of shares is fixed. These shares are called units and are tradable on exchanges. However, they also offer the possibility to investors to redeem their shares at the NAV of the underlying assets, like

OEF. The difference stands in the fact that UITs usually have a limited lifetime. At the initial public offering, the UIT define a termination date at which the fund will sell all its assets and give the cash back to their investors. According to Madhavan (2016), UIT usually keep their investment fixed and makes few modifications in the positions given this limited lifetime. Investors can then easily assess the duration of their investment. Note that these investment companies are the less popular amongst investors. Furthermore, this popularity is decreasing every year given the other diversified investment opportunities offered to investors, with a higher flexibility.

II. Exchange-Traded fund

Finally, let's describe briefly the hottest investment company of the last decades: Exchange-Traded Funds. As its name suggests, ETFs are funds that are traded on exchanges like a single stock. ETFs are a mix between all the previous fund structure, taking the best of each of them. As they create and redeem shares like an open-end fund, it makes the price of the instrument really close to its NAV, even if the fund has its own supply and demand. However, ETFs are not considered as open-end funds in the United States because of the limited capacity of these funds in redeeming their shares (Ramaswamy, 2011).

By the creation and redemption process, market makers keep the price of the fund close to its NAV by exploiting the arbitrage opportunities between the fund and its underlying assets (Madhavan, 2016). The structure is also inspired of Closed-End Funds and Unit Investment Trust in the sense that they are exchange-traded on regular exchange markets. Then, people can buy or sell the fund throughout the day, without have to wait the end of the day like in open-end funds. It is the combination of these structures that made this investment product so popular, and foster the incredible growth in the last years… Making it interesting to study.

While ETFs usually track an equity index, there is a huge quantity of different ETFs with multiple purpose (Abner, 2013). For instance, investors can buy ETFs replicating a basket of equities from a given sector, a basket of bonds or even ETFs that track the price of a commodity. By doing this, investors have the opportunity to own a diversified product with only one transaction and in a single product.

Furthermore, as they trade like stocks, they can be bought on margin, sold short and investors can also buy derivatives on ETFs (Abner, 2013). This makes ETFs a really useful instrument when an investor wants to hedge his positions, but also for short-term speculations about macro-economic events that can have an impact on the whole market or the whole sector (Madhavan, 2016). Moreover, Alexander and Barbosa (2007) reported that this ability to short-sell and the low transaction costs coming from the high competition makes ETFs very coveted by hedge fund, and interesting to apply in pairs trading.

1. The story of the first ETF

According to Ferri (2006) and Madhavan (2016), the story of Exchange-Traded Funds starts in the mid-1990s' with Nathan Most, the presumed creator of ETFs. When he was 73 years old, he created the first version of an ETF for the American Stock Exchange. This product, designed to track the return of the S&P500, was the starting point of the huge market we can see today. His idea was simple: creating a fund that holds all the companies of an Index, while allowing investors to buy/sell the shares of the fund on stock exchanges at a low cost.

However, buying and selling all the underlying securities of an index would have been really expensive. Given its background in commodities trading, he had a wonderful idea to lower the costs: an in-kind creation and redemption process (Gastineau, 2010). While mutual funds also use the creation and redemption process to match the supply and demand of their shares, ETF would use the in-kind structure and thus avoiding most of the fees and tax on capital gain related to the selling of the securities. According to Gastineau (2010), in-kind creation process is different from the classic one in the way that, instead of buying the securities, the fund interacts directly with the market-maker or big institutional investors as a "storage company". Indeed, the market maker gives the shares to the ETF sponsor, and they receive ETF shares in exchange (Abner, 2013). These shares will then be sold on the market via the market makers like classic stocks. By doing so, exchange-traded funds offer lower expense fees because they don't really buy or sell the securities. By doing so, they avoid the tax on capital gain that would usually be diluted amongst all investors in the fund. They just store them, give a receipt to the market maker who sell these receipts in the market. In-kind creation and redemption process will be discussed later in more details.

2. The in-kind creation and redemption process in physical structure: Keystone of ETFs

The first step in the issuances of ETFs shares stands in the primary markets. In this market, the ETF sponsor and the Authorized participant (AP) meets for the exchange of ETFs shares. Usually, they proceed together the in-kind creation and redemption process of the ETFs shares, to fit the supply and demand of the security and keeping its price as close as possible to the NAV of the fund (Abner, 2013). This process is the keystone of the ETF structure and allow investors to buy and sell as many shares as they want with a small market impact (Gastineau, 2010).

This process, as described by Abner (2013) and Madhavan (2016) among others, consist in the creation of new ETFs shares when there is an excess demand and the repurchase of the shares when there is an excess supply. Indeed, unlike mutual funds, ETFs are traded intraday via several stocks exchanges. This mean that the flow of investors meets first in the secondary market when they want to enter or leave the fund. But if the supply and demand doesn't fit, the Authorized Participant is doing its liquidity provider job and fits the gap between the investors flow. An important concept in this process is the concept of creation unit, defined as "*the set of underlying components of ETF that can be exchanged with the issuer for a certain quantity of ETF shares When shares of the ETF are being redeemed, this basket is also typically used; however, it can be different"* (Abner, 2013, p.32). A creation unit is then the minimum number of shares (usually 50.000) that an Authorized Participant can exchange for the related basket of securities. For each creation unit, a fixed number of shares of shares of each underlying stock (in function of their weight in the index) is exchanged, which is basically the creation process.

For instance, imagine this fictional example of the index XYZ, which is weighted in function of the market capitalization of the underlying companies.

INDEX XYZ

	Stock A	Stock B	Stock C	Stock D
Weight	47%	30%	15%	8%
Stock price	150 €	75 €	82 €	12 €

Table 1:Index XYZ

If the price of the ETF is 100€ and a creation unit is 50 000 shares, each creation unit of the XYZ ETF will be composed of 15 667 shares of A, 20 000 shares of B, 9 146 shares of C and 33 333 shares of D for a value of 5 million €, as we can see in the table below:

XYZ ETF Creation Unit composition

	Stock A	Stock B	Stock C	Stock D
Total value	2 350 000 €	1 500 000 €	750 000 €	400 000 €
# Shares	15666,667	20000	9146,341	33333,33

Table 2: XYZ ETF Creation Unit composition

AP are able to provide that much shares because of their liquidity provider activity. They have a lot of different stocks in their inventory, allowing them to exploit the bid-ask spread by buying at the best bid and selling at the best ask.

So, when there is an excess inflow in the fund, the Authorized Participant exchange a multiple of the basket of securities of the creation unit, and the ETF gives him the corresponding number of newly created ETFs shares (Abner, 2013). By this in-kind structure of the process, Exchange-Traded Funds avoid the tax on capital gains, as they don't literally buy the assets. They just exchange a basket of securities in exchanges on some of their shares. For the redemption, this is the inverse process. AP gives back the excess shares and get the basket of securities in exchange. Again, the ETF is not literally selling the assets. And that's one of the main advantages of ETFs, making them so tax efficient. Indeed, as there is no real capital gain on the assets, ETFs don't have to pay tax on capital gain, and this tax isn't diluted amongst all investors (Abner, 2013; Madhavan, 2016). This is particularly interesting when there is a lot of movement in the fund's shareholders.

By doing so, Authorized Participant exploits the small arbitrage opportunities from the mismatch between the price of the fund and the value of the underlying assets. But exploiting that kind opportunities expose them to two kinds of risks (Petajisto, 2016): First, as they hedge their positions every time they proceed to the creation or redemption of ETF shares, they are exposed to the timing risk. The price of the underlying assets can change between the moment they bought/sold these assets and the moment they hedge their positions. Second, they can face high transaction costs, especially when they are trading some illiquid assets. However, according to Gastineau (2010), exploiting arbitrage opportunities in liquid ETF is not always profitable for Authorized Participant because the market is too efficient. Their main sources of revenue then come from their inventory management activities. This allow them to make money with the bid-ask spread of the securities by selling at the best ask or buying at the best bid (Gastineau, 2010).

This arbitrage between the price of the ETF and the underlying securities is an important feature of the product, because this is what keeps the price of the security close to the NAV of the fund. Arbitrageurs thus play a key role in the efficiency of ETFs pricing. However, studies (Ackaert and Tian (2008); Petajisto (2016)) have shown that ETFs are sometimes sold at a discount or a premium, proving that inefficiencies in the pricing of these securities could exist.

While exploiting arbitrage opportunities between the ETFs and the underlying securities can be really hard and expensive for retail investors, exploiting pricing inefficiencies of ETFs could be cheaper and more realizable at individual investor level. The next session will discuss in details these inefficiencies in order to detect how we can evaluate these premium and if it can be possible to exploit them in a profitable way.

These typical characteristics make the application of the pairs trading strategy on Exchange-Traded Funds interesting for three reasons: First, the creation and redemption mechanisms make the behavior of the price easy to anticipate, as they systematically converge to the NAV with the arbitrage mechanisms. This can be interpreted as a strong mean-reversion process. Second, as the tax efficiency of ETF makes them more profitable than classic mutual funds, it leads to a huge increase in the popularity of the product. This popularity made the sector really competitive and increase the number of available ETFs on the market, increasing the possible pairs applicable on the strategy. Third, as the competition increase in the ETF sector, more and more ETF sponsor offer to trade ETF at low or no commission, which makes the strategy even more interesting given its high sensitivity to trading costs.

3. Inefficiencies in the pricing of ETF

While arbitrage mechanisms in the creation and redemption process makes the prices of the ETF close to the NAV of the fund, it is not always the case. Some inefficiencies in the price of the product exist, resulting in a premium or a discount compared to the fundamental value and NAV of the fund. Studies (Abner, 2013; Ackaert and Tian, 2008; Cheng, Massa and Zhang, 2013; Petajisto, 2016) show that the price of the ETF is affected by the liquidity of the security, but also by the liquidity of the underlying assets, leading then to some temporary mispricing. If an investor wants to assess and anticipate the premiums of an ETF, it is then important to understand the factors that induce this premium. ETFs behave like a stock and have their own liquidity represented by the daily volume of transaction. But investors also have to take the liquidity of the underlying stocks into account. Given that, Abner (2013) shows that we can also assess the liquidity of the ETF with the implied liquidity, which is the liquidity of the less volatile underlying asset of the index.

3.1. Valuation of Exchange-Traded Funds

According to Abner (2013), there are four different methods to calculate the fundamental value of an ETF. The Net Asset Value (NAV), the Indicative Value (IV), the estimated Net Asset Value (eNAV) and the price.

The Net Asset Value of an ETF is the most straightforward way to assess its value, which is simply the assets under management divided by the number of shares outstanding. Like mutual funds, ETFs disclose their NAV once a day at the end of each training session. While it is a great backward-looking measure of the fund value, using NAV for trading strategies can lead to wrong decisions and results. Because it represents the value of the last closing trading session, it is a stale measure of the value of the underlying assets (Abner, 2013).

Because ETFs are traded intraday, an end-of-day value is most of the time a stale measure of the value of the security. Given that, another measure can be used to assess the value of ETF: the Indicative Value (IV) or Intraday Indicative Value (IIV) (Abner, 2013). IV is a better measure of the ETFs value because it takes into account the latest price of all the underlying assets and calculate the value of the fund based on these prices. However, for active intraday trading, it is still not an accurate enough measure because IV is published only once every 15 seconds, while most of the stocks are priced every ticks.

> *"There is no trading desk in the world that would trade a product using a value that is calculated only every 15seconds. Trading currently takes place in microseconds by some of the fastest participants, yet the fastest-growing investment product in history currently publishes portfolio valuations only every 15seconds"* (Abner, 2013).

Moreover, when the ETF and the underlying basket trades in different time zones, IV doesn't give a "real time" value anymore. So, even if this measure is better than the NAV, it is still needed to improve it to have more real time data. The solution stands in the estimated Net Asset Value.

The estimated Net Asset Value (eNAV) is another measure of the value of Exchange-Traded Funds. This is particularly useful when an ETF is trading in another time zone than its underlying basket, making its value difficult to assess with the Indicative Value. According to Abner (2013), the eNAV consist of an adjusted value of the IV with the percentage change in the proxy trading vehicle. This proxy trading vehicle represents the investor's own expectations of what can drive the price of underlying assets up or down when the market is close. It can be the FX rates, the S&P500 or the incorporation of any events that can affect the price of the underlying assets (Abner, 2013). Every investors assess their own eNAV, do determine their own fair value the fund should be traded. Given that, investors should pay attention on this subjective nature of the different valuations, especially when the underlying assets are not traded. Indeed, some securities might be evaluated at a premium or a discount because of the time lag between two time-zone, while they are in fact not correctly evaluated (Abner, 2013).

3.2. *Inefficiencies in the valuation*

Because ETFs have a similar structure to closed-end funds (they can be exchange on market), they can be sold at a discount or a premium. And because they also have the same structure as open-end funds, they can create and redeem shares when there is a mismatch between supply and demand. This structure mix makes the price of the ETF deviate from the NAV, but given the efficiency of the market, this price will then converge to its fundamental value (i.e. the fund NAV). This unique characteristic of ETF makes it a perfect instrument for pairs trading strategy.

Ackaert and Tian (2008) argue that these inefficiencies come from shocks in the liquidity and volume of transaction of the security. Efficiency having a positive relationship with these two factors. Moreover, Engelberg et al. (2009) showed in their analysis that the profitability of the strategy increases in the presence of liquidity shocks, these shocks can have an even bigger impact when applying the strategy on ETFs.

Note that, according Cheng, Massa and Zhang (2013), the flows in ETFs are mainly associated with institutional investors, as creation units represent often several millions of dollars. Given that, the efficiency in the price is strongly related to the number and the size of arbitrageurs on a given ETF. However, according to Petajisto (2016), ETFs that trade on a different time zone are much more difficult hedge, and then exploiting arbitrage opportunities is harder too. This reduces the price efficiency of these ETFs and allow for bigger mispricing. Furthermore, analysis of Ackaert et Tian (2008) showed that country ETFs (i.e. ETFs that tracks the performance of a basket from another country) tends to have a higher level of mispricing, which is consistent with Petajisto (2016) analysis. Moreover, Alexander and Barbosa (2007) research showed the link between price inefficiencies and trading costs. They highlighted that ETF with higher trading costs tend to be sold at a discount, while ETFs with lower trading costs are most of the time sold at a premium.

Petajisto (2016) also argue that larger and highly traded ETFs proceed more often to creation and redemption process, even for small mispricing. Given that, these funds are supposed to offer smaller and ephemeral mispricing. Furthermore, they found that the premiums can positively predict future convergence to the NAV on the next 10 trading days because of the arbitrage mechanisms. We will see later in this thesis that the optimal trading period for a pair is between 10 and 20 trading days, which confirms again that ETFs can be a great instrument for the strategy.

Regarding the factors that foster mispricing, Petajisto (2016) highlighted two main factors: The first one is the trading volume, as it generates price pressure on the ETF. The second one is the amount of arbitrage capital, as it allows for more creation and redemption. The amount of arbitrage capital has then a negative relationship with mispricing, as it drives the price close to NAV.

4. Risks when using exchange-traded funds

Even if exchange-traded funds often offer a high degree of diversification, they are still exposed to risks linked to their unique structure. The specialized website ETF.COM (2017) highlighted the major risks when buying exchange-traded funds. First, ETFs are more exposed to the market risks than individual stocks, as they cover a basket of stocks. Second, more and more ETFs offer exotic exposure, with leverage or not. This complexity and the differential between the liquidity of the fund and its underlying assets can create high price inefficiencies and unexpected negative returns, especially during high withdrawal period. Another kind of risks that investors may face is the shutdown risks. Indeed, as any other funds, the fund might not be as popular as expected and may be closed. In this case, the fund is liquidated and investors get their cash back. While this is the best case scenario, investors may sometimes suffer losses linked to the liquidation costs, and is then source of risks.

From another perspective, exchange-traded funds can also threaten the stability of the financial market. Indeed, according to Ben-David, Franzoni and Moussawi (2016), ETFs can act as transmission conduit for liquidity shocks. During market turmoil, liquidity providers can stop their intermediation activity because they lack of trustable pricing information. This could amplify even more the liquidity shocks and the transmission to other assets. One of the main example of illiquidity dissemination is the flash crash of August 2015, where the intraday low of the S&P500 was -5.3% while the intraday low of the S&P500 ETF was -25.9%.

Based on this small analysis, we can see that exchange-traded funds are not without risks. With its unique structure, ETFs bring some risks that doesn’t concern individual stocks or mutual funds. As with every other security, investors who wants to put their money in exchange-traded funds needs to do it with cautious and document themselves about the risks of the product.

III. Pairs trading strategy

1. What is pairs trading strategy?

According to Gatev, Goetzmann and Rowenhorst (2006), the concept of pairs trading is to find and create pairs of two stocks whose price have moved similarly during a given historical period and making profit when they converge by taking a long-short position. Pairs trading has also been defined as *"taking a bet that the price paths of two stocks that have historically moved together will converge again after any divergence."* (Engelberg et al., 2009, p.1), *"the practice of taking simultaneous short and long positions in two similar securities (pairs) when their price spread exceeds a specified threshold"*. (Smith and Xu, 2017, p.1), *"a contrarian strategy that seeks to exploit violations of the law of one price. […] Pairs trading identifies stocks of close economic substitutes that have historically moved together over a long horizon, and buys the losers and sells the winners in the pairs only when they have significantly moved apart."* (Do and Faff, 2012, p.261)

These pairs are in general close substitute to each other, which can explain why their price move together. The goal is to exploit the spread between these two securities by assuming that their price will converge to a common normalized value, and then making a profit. The profitability of pairs trading comes from the convergence of their normalized price by taking a long position on the cheapest security and a short position on the most expensive. By doing so, as we assume that their price will converge (because they did historically), the long position will generate a profit by going upward and the short position by going downward. Furthermore, the definition of the law of one price says that *"if two assets are equivalent in all economically relevant respects, then they should have the same market price"* (Bodie, Kane and Marcus, 2014, p. 328). Given so, two securities that share the same payoff structure must have the same price. So when we trade two stocks with a similar price behavior, with similar payoff structure, we can assume according to the law of one price that their price will converge over time if their price has diverged previously.

2. Methodologies

As mentioned previously, pairs trading consists in trading two similar securities that share a common price behavior, showing a high correlation in their normalized price. Many studies (Engelberg et al., 2009; Gatev et al., 2006; Schizas et al., 2011; Smith and Xu, 2017 among others) have analyzed how to produce return by using this similarity. This section will then compare these studies in order to find the best methodology to apply on ETFs.

Every author reports two main steps in the strategy: The formation period to identify the pairs of securities that would fit the best for the strategy, and the trading period when these pairs are traded following parameters determined at the beginning of the strategy. The studies (Engelberg et al., 2009; Gatev et al., 2006; Schizas et al., 2011) that analyze the profitability of the strategy also identify one last step consisting of computing the return produced. One of the first academic study about pairs trading have been done by Gatev et al. (2006) and their methodology has been considered as a standard since. However, even if every author uses the same “two-step” methodology, they have different opinions regarding the parameterization of these steps.

As mentioned above, Gatev et al. (2006) methodology is divided into two periods: The formation period to find the best pairs and the trading period for the application of the strategy. They used a 12-months formation period and a 6-months trading period. However, the duration of these period is chosen arbitrarily and has been criticized later by Engelberg et al. (2009), Schizas et al. (2011) and Smith and Xu (2017) and will be analyzed later in this section.

2.1. The choice of the best pairs: The formation period

According to Gatev et al. (2006), Engelberg et al. (2009), Schizas et al. (2011) and Smith and Xu (2017), the formation period consists in the creation of the best pairs based on their historical prices. During this period, the investors will select the pairs that will compose its portfolio based on two different methods: The distance approach and the cointegration approach. Note that there is also a third method called the stochastic approach, but given the lack of academic literature about it, it won’t be covered in this thesis. The formation period is characterized by several parameters: the size of the period, the methodology and the number of pairs selected.

2.1.1. Two mains approach in the selection

- **The distance approach**

The distance method, as described by Smith and Xu (2017), is the selection of two securities based on the closeness of their price in the formation period, on a normalized basis. The best pairs are those with the minimum average squared deviation between their prices. The distance approach follows the three-step process presented below, as described by Gatev et al. (2006):

STEP1: Normalization of the price, which can be interpreted as a one-dollar investment at time 0.

$$p_t^i = \prod_{t=1}^{t}(1 + r_t^i)$$

STEP2 (Gatev et al., 2006): Compute the distance between the two stocks in the pair over the formation period. The goal is to find a matching partner for each stocks that minimize the sum squared deviations between the two stock price.

$$D_{i,j} = \sum_{t=1}^{T_{fp}} \frac{\left(P_t^i - P_t^j\right)^2}{T_{fp}}, \;\; for\ all\ pairs\ i, j$$

STEP2' (Schizas et al., 2011): The goal is the same, but they use the average absolute distance between stocks a and b instead of the sum squared deviation.

$$\Delta ab = \frac{1}{T_{tp}} \sum_{t=1}^{T_{tp}} \left|p_t^a - p_t^b\right|, \;\; for\ all\ pairs\ a, b$$

STEP3: Ranking the pairs based on their distance, and select the desired number of best pairs. The goal here is to create a portfolio composed of the top pairs with the smallest distance.

This three-step process is then repeated every month, in order to detect the best pairs for the coming trading period.

- **The co-integration approach**

This section will be a basic description of the method with the goal to have a general view about pairs trading methodologies, but will not go into the details. Indeed, recent study of Smith and Xu (2017) challenging the different methodologies and parameterization on a wide sample of stocks shows that this method isn't profitable nowadays, while the distance method still provides some small returns. Furthermore, they find that when using this approach, the optimal number of best pairs is 50. This conclusion does not suit us, because we will see in later sections that a too high number of pairs is counterproductive, as shown by Schizas et al. (2011). Furthermore, they also find that distance approach in the formation of the pairs is more profitable and significant in an economic and statistical point of view while the cointegration is not. This is the reason I will not use this methodology, but I wanted to describe it anyway.

The cointegration approach, as described by Gatev et al. (2006), Caldeira and Moura (2013) and Smith and Xu (2011), consist of identifying potential pairs that have the same order of integration and testing these pairs with the Augmented Dickey-Fuller (ADF) test. The goal being to find pairs whose spread are mean reverting. However, this method produces a high number of possible pairs with no possibilities to differentiate them. Then, the third step consists of ranking these potential pairs based on their Market Factor Spread (MFS) and selecting the X pairs with the lowest MFS.

2.1.2. Distance approach: Discussion about the parameters

In their research, Smith and Xu (2017) found that the parameterization of the strategies is much more important than it seems and have a great impact on the profitability of the strategy. Indeed, the parameterization used by Gatev et al. (2006) does not appear to be the optimal method most of the time, even if it is considered as a standard. They tested pairs trading strategy using different approaches and parameterization. They tested formation period of 9 and 12 months, and showed that the 9-month period doesn't yield more return than the 12-month. They suggest that a longer formation period could be beneficial for the profitability.

Schizas et al. (2011) also use a different parameter for the formation period. Instead of having a formation period of 12 months, they use a period of 120 trading days. By calibrating the model with a period two times smaller, they avoid excess over-lapping trading periods. They also use a different method to compute the distance (STEP2'), which they consider more robust to sudden and temporary large divergence and offer more trading opportunities.

According to Schizas et al (2011), the profitability of the strategy is impacted by the number of best pairs used during the trading period. But the profitability stays robust, whatever the number of pairs. In their study, they found that a larger number of pairs decrease the standard deviation of the portfolio, but also decrease the Sharpe ratio.

Note that even if the number of pairs selected is at the appreciation of the investors, Smith and Xu (2017) analysis about optimal Parameterization in pairs trading shows that the optimal number of top pairs for the distance method is 10 pairs. This is consistent with Schizas et al. (2011) finding about the negative relationship between the number of pairs selected and the return of the strategy, and with their optimal number of pairs of 10 using the distance approach.

2.2. Trading the best pairs: The trading period

2.2.1. Methodology

According to Gatev et al. (2006), Engelberg et al. (2009), Schizas et al. (2011) and Smith and Xu (2017) among others, once we have identified the pairs with the minimum historical price deviation, we can exploit their divergence during the trading period. This period consists in taking a long position on the cheapest stock and a short position on the most expensive. By doing so, when their normalized price will converge again, the pairs will generate a profit for the investor. Now, the question is: When do we open the long-short position and when do we close it?

These studies (Except Schizas et al., 2011, who use a multiple of their average absolute distance) agreed on opening and closing positions on a standard deviation basis. However, they diverge in the value of this so-called trigger. Gatev et al. (2006) open the position when the spread of the securities exceeds two standard deviations, based on the best practice.

$$Open\ pair\ when \left|P_t^i - P_t^j\right| > Trigger\ (i,j)\ x\ StdevD_{i,j}$$

The formula of the standard deviation, as described by Engelberg et al. (2009), being the following:

$$StdevD_{i,j} = \sqrt{\frac{1}{T_{fp} - 1} \sum_{t=1}^{T_m} \left[\left(P_t^i - P_t^j \right)^2 - D_{i,j} \right]^2}$$

When their prices cross, they close the positions and generate a profit.

$$Close\ pair\ when\ \left| P_t^a - P_t^b \right| \leq 0$$

If their prices never cross, the positions are closed anyway at the end of the trading period. Note that, according to Engelberg et al. (2009), the pair will be invested twice (or more) if a pair is eligible in two (or more) trading period. However, this is only pertinent when the trading period exceeds one month, as it is not possible to have overlapping trading period otherwise.

As mentioned previously, Schizas et al. (2011) use a different methodology to compute the distance between the stocks in a pair, so they also use a different method regarding the position opening of the selected pairs. Then, they open the pairs when:

$$Open\ pair\ when \quad \left| P_t^a - P_t^b \right| > trigger\ (a, b)\ x\ \Delta ab$$
$$Close\ pair\ when \quad \left| P_t^a - P_t^b \right| \leq 0$$

The two parameters of the trading session are then: The size of the period and the trigger.

2.2.2. Parameters analysis

Again, multiple studies (Engelberg et al. (2009), Schizas et al. (2011), Smith et al. (2017)) criticized the standardized character of the Gatev et al. (2006) methodology, because it seems to lack of rigorous justification. Their findings are described below and tend to provide an optimal framework for the trading period.

Engelberg et al. (2009) analysis shows that when a pair doesn't converge after 10 days, the probability that it will converge is really small. They show that the profitability of a "cream-skimming" strategy, which consist in keeping the trades open for 10 days maximum, yield higher returns than holding them for 6 months. However, the standard strategy (i.e. a holding period of maximum 6 months) yield higher returns per pair. The cream-skimming strategy yields a monthly alpha of 1.75% while the standard strategy yields only 0.70%, these two returns being statistically significant.

Furthermore, Schizas et al. (2011) analysis show that when trading on ETFs, the optimal trading period is 20 days. This finding is quite consistent with Engelberg et al. (2009) findings that if a pair doesn't converge after 10 days, they have a small probability to converge afterwards.

Last but not least, Schizas et al. (2011) analysis showed that the trigger (i.e. the multiple of the standard deviation to open the trades) is the parameter with the greatest impact on the profitability. A higher trigger lead to an increased profitability per trade with only few trades, while a lower trigger lead to a lower profitability per trade with a lot of trades. They found that the optimal trigger when using the distance approach is two standard deviations with the top 5, 10 and 20 pairs, confirming the hypothesis of Gatev et al. (2006). For the cointegration approach, results are more mitigated, but they showed that lower triggers are more profitable when using this approach.

2.3. Computation of the returns

Given the multiple cash flows of the strategy and its dollar neutral structure, calculate the total return can be difficult. To overcome this problem, Gatev et al. (2006) calculated the return of the strategy using two measures: The return on committed capital and the fully invested return (or return on actual employed capital). The return on committed capital is the portfolio returns for all the pairs selected at the formation period while the fully invested return only takes into account the number of pairs used in the trading period. Then, the return on committed capital gives a more realistic measure of the return as it takes into account the opportunity costs of capital of not trading (if the pairs don't diverge enough). This measure is useful when we want to assess the performance of the fund. However, the fully invested capital give a more realistic measure of the profitability of the strategy in an academic point of view, because it takes into account only the trading profits.

The methodology of the fully-invested return is expressed in excess return because the long and short position mutually cancel the risk-free rate. It is described by Smith and Xu (2017) as follows, using Gatev et al. (2006) methodology:

If the return of one pair at time t is:

$$R_t(P^k) = R_t(l^k) - R_t(s^k)$$

Then, the return of the portfolio is the weighted average of all pairs:

$$R_t^{port} = \sum_{k=1}^{N_t^*} W_t^k R_t(p^k)$$

Where the weight at time t of pair k is the cumulative return of pair k divided by the sum of the cumulative returns of all pairs in the portfolio:

$$W_t^k = \frac{w_t^k}{\sum_{j=1}^{N_t^*} w_t^j}$$

And the cumulative return of pair k at time t being:

$$w_t^k = \begin{cases} [1 + R_{t-1}(p^k)]\ x\ [1 + R_{t-2}(p^k)]\ x \dots x \left[\ 1 + R_{d^k+1}(p^k)\right] & if\ t \geq d^k + 2 \\ 1 & if\ t = d^k + 1 \end{cases}$$

3. Profitability of the strategy

Gatev et al.'s (2006) study shows that pairs trading on U.S. equity generates an average annualized excess return of about 11% for their top pairs portfolio. The goal of their study was to know if the strategy was still profitable, given its high dissemination among hedge funds. They found that the strategy was still profitable, and that the general risk and return characteristics of the strategy was not affected. Furthermore, their research showed that pairs trading is robust to short-selling and transaction costs. Gatev et al. (2006) research shows that there are also diversification benefits of combining multiple pairs and that there is a negative relationship between the number of pairs and the standard deviation of the portfolio.

According to Schizas et al. (2011), the timing ability of the strategy is quite good, as the mean positive excess return being larger than the mean negative excess return. Their research also showed that the skewness of the strategy is positive most of the time, while most of the indices they studied have a negative skewness.

Surprisingly, these studies don't take the trading costs into account, even if they can have a huge impact on the profitability. Do and Faff (2012) made an analysis about the robustness of pairs trading regarding the trading costs. They found that on average, pairs trading is unprofitable when trading costs are taken into account, their monthly excess return dropping from 93bps to 12bps. However, they also showed that the best pairs still provide reasonable excess returns, even if they are not as big as in previous studies. A deeper analysis of the source of profitability and the impact of the trading costs will be done in this section.

3.1. Sources of profitability in pairs trading

3.1.1. Regarding stocks characteristics

According to Gatev et al. (2006), the majority of their top 20 pairs are large cap companies, and are mainly utilities. They explain that because, even if they represent a small proportion of their universe, *"utility stocks tend to have lower volatility and tend to be correlated with interest rate innovations and macro-economic events"* (Gatev et al., 2006). However, later studies have shown opposite conclusion regarding the size of the companies. According to Schizas, Thomakos & Wang (2011), the strategy seems to give better results for small caps group ($59m to $330m). They explain this because of the timing ability of the strategy in smaller markets. Indeed, they found that there is a higher percentage of pairs yielding a positive return within their small capitalization sample than in others. Engelberg et al. (2009) also find that the strategy is more profitable and that pairs converge faster when applied to smaller and less liquid stocks.

In the pairs studied by Engelberg et al. (2009), 44.38% are financial industry stocks, 22.52% are utilities stocks and 13.96% are manufacturing stocks. They explain this because the prices of these stocks are more affected by macro-economic information than other sectors. This is quite consistent with Gatev et al. (2006) findings about the profitability of the strategy in function of the industry. Furthermore, Yu and Webb (2014) also showed that there is an increased profitability when the pairs are composed of two stocks from the same industry, and proved that selecting two stocks that shares common characteristics improves the profitability of the strategy.

Engelberg et al. (2009) also find that *"pairs of mixed exchanges lead to more pairs trading profits and that this result is statistically significant"*. (Engelberg et al., 2009), which is consistent with

Schizas et al. (2011) findings, who suggests that international exposure may be a significant factor explaining the performance of the pairs trading strategy.

In their study about the factors impacting the profitability of the strategy, Engelberg et al. (2009) found two relationships between the liquidity and the profitability: the level of liquidity has a negative and persistent effect while the change in the liquidity has a positive but temporary effect. Indeed, the most illiquid pairs tend to outperform the most liquid one in their analysis, and this is even more relevant in stocks with small market capitalization. However, this is associated with a higher arbitrage risk.

3.1.2. Regarding macro-economic characteristics

Smith and Xu (2017) made a broader analysis, using different parameters and testing a larger number of top pairs. By doing so, they assume to find the sources of pairs trading profitability. They found that pairs trading works better and represent bigger profit opportunities in turbulent market conditions. This is consistent with Do and Faff (2012), who found that the profitability of pairs trading is higher during bear markets. They explain this because of the lower market efficiency during these periods, and allowing to exploit more inefficiencies in the price of the securities with this strategy. However, transaction costs are higher during these periods, which can have a high impact on the profitability of the strategy (Do and Faff, 2012).

3.1.3. Regarding news and information diffusion

Engelberg et al. (2009) found that the profit is negatively impacted when only one of the two stocks in the pairs is impacted by news. They explain this because it changes the risk characteristics of this stock while not impacting those of the other, creating divergence in the risk equilibrium between the two securities. Furthermore, they found that the profit of the strategy is impacted by the causes of the divergence between the two stocks. The return being higher when a news negatively affects the liquidity of only one stock for a short period. The return also increases when one stock reacts faster to news than the other, while both are affected by this news. On the other hand, profits are lower when the divergence is triggered by a news relative to only one stock and have any effect on the other. The profitability of the strategy is then related to the different reaction of these stocks to news, and thus affecting differently their liquidity. So, if both stocks react with the same timing and in the same manner (overreact or underreact), the strategy will not be profitable. As ETFs' returns react more to macro-economic news than stock specific news, they can provide large excess returns using pairs trading. Moreover, as they can share some common underlying stocks, lots of ETFs react in the same way to these news but with different amplitude. Which corresponds even more to the profitability factors of Engelberg et al. (2009)

In their research, Papadakis and Wysocki (2007) found that the profitability of the strategy is negatively impacted by earning announcement and analysts forecast. They explain this because some trades are open in reaction of these announcements, and not because inefficiencies, which can lead to a non-convergence of the prices. This is why it can be interesting to apply this strategy on ETFs, as their price is not impacted by single company events and idiosyncratic news. Furthermore, Chen, Chen and Li (2012) found that the strategy is more profitable when the stocks composing the pairs are not popular and followed by a small number of analysts, as it slow down the informational diffusion. This remark is consistent with Papadakis and Wysocki (2007).

Engelberg et al. (2009) also shows that idiosyncratic news creates a “fake” impression of trading opportunities. Indeed, this kind of news increase the divergence between the two stocks. However, they are less likely to converge because it changed the fundamental of one stock while not affecting the other. Then, these news increases the horizon and divergence risk that investors may face and reduce the profitability of the strategy.

3.2. Impact of trading costs

“One day later rule”: *“The one-day-later rule is employed to reduce the effects on calculated returns of bid-ask bounce associated with using daily closing stock prices”* (Smith and Xu, 2017, p.15). Indeed, as end of day price represent the price of the last trade, we can’t say if it was an ask or a bid price. Gatev et al. (2006), Engelberg et al. (2009) and Smith and Xu (2017) showed that when applying the one day later trading rule, strategy’s return is going downward drastically.

Furthermore, Smith and Xu (2017) reported that when the bid-ask bounce is taken into account, the cointegration approach does not yield positive excess returns after the 1980s while the distance method does on a risk-adjusted basis. Furthermore, their analysis suggests that the distance approach may not be profitable when we consider all trading and transaction costs, even if the returns are statistically significant.

As mentioned previously, Do & Faff (2012) showed that the profitability of the strategy is greatly impacted by the trading costs. They identified the explicit trading costs as: Two round-trip commission per trade (then four commissions), the short-selling fees and the market impact of each trade. The latter being hard to measure afterward, I will then only focus on the commission and short-selling fees.

According to Petajisto (2016), as ETFs are diversified portfolio, they tend to have smaller bid-ask spread because market makers don't have to offset the idiosyncratic risk that they would have with individual stocks. According to the studies mentioned above, pairs trading is really sensitive to trading costs and the one-day later rule showed a huge decreased in return when taking the bid-ask bounce into account. Applying the strategy on ETFs is then supposed to yield higher profit than with individual stocks of similar trading volume. However, Petajisto (2016) highlight that an active long-short strategy on ETFs price inefficiencies should not be played aggressively, as paying the full bid-ask spread too many times significantly reduces its profitability. This observation is consistent with the two standard deviation trigger mentioned by Gatev et al. (2006) and Schizas et al. (2011).

4. Risks in pairs trading

According to Smith and Xu (2017), even if the strategy is market-neutral, the returns are not risk free as their standard deviation is not equal to zero. Indeed, losses can occur if the prices of the stocks don't converge and the strategy will not always yield the same amount. Furthermore, investors proceeding such strategies are exposed to arbitrage risk (Gatev et al., 2006).

Moreover, according to Engelberg et al. (2009), convergence arbitrageurs face two kinds of risks: The divergence risk and the horizon risk. Divergence risks is the risk that, in addition to not converging, the pair will diverge by more than two standard deviations and then oblige the trader to wipe out the positions. The horizon risk, is the risk that the pair will not converge during the trading period, and then resulting in a loss at the end of the time horizon.

5. Motivation to use ETFs in pairs trading

The goal of the pairs trading strategy is to design the price behavior of stocks, in order to find pairs that are highly correlated and with prices that follow the same path. There are two main assumptions in pairs trading, as described by Schizas et al. (2011): the co-movement of the stocks and the mean reversion. These assumptions are important because the goal of the strategy is to exploit divergences in the price of the stocks, by taking a short the most expensive and long position if the cheapest, then making a profit when their price converge to their common fundamental value. While some studies (Do and Faff (2012); Smith and Xu (2017)) have shown that the strategy became less profitable nowadays, I wanted to test its profitability by using ETFs. During my research, I saw that a lot of trading platforms provided some empirical investigation about the strategy on ETFs and its profitability, but not that much of academic research. We saw in the previous sections of this thesis that the price of ETFs are not always efficient, and that some mispricings can exist (Ackaert and Tian (2008); Cheng, Massa and Zhang (2013); Petajisto (2016)). It starts to be interesting because of these mispricings. Indeed, there is a systemic and recurrent behavior in ETFs price linked to the high number of arbitrageurs in the market, who keeps the price of the fund close to its NAV with the creation and redemption process.

Then, pairs of ETF that tracks partially or completely the same underlying basket will be consistent with the assumptions of Schizas et al. (2011) mentioned above: Their price will move together because they are driven by their common underlying stocks., and their value will always converge to their NAV because of the arbitrage mechanisms specific to ETFs.

While most of the studies (Donninger (2016); Schizas et al. (2011); Yu and Webb (2016)) about the pairs trade on ETFs considers the product like a stock and then apply the strategy in the same way that it is done with stocks. They seem to not consider the inefficiencies in the prices, which can make this strategy even more robust and less risky. This can be explained because these studies were mainly focused on the strategy and less on the product. As my researches were first oriented towards ETFs, I discovered these inefficiencies and then I thought about a strategy to exploit them. This is this unconsidered characteristic of ETFs that distinguish this paper with others.

Furthermore, given the huge growth of the ETF market, there are now a lot of new products covering a large quantity of region and sectors. It is then possible to define a wider universe of ETFs and increase the probability of finding the bests pairs.

Last but not least, Yu and Webb (2014) argue that the strategy is less profitable when the price variations are explained by fundamental changes. As ETFs are tracking a basket of stocks, they are less exposed to idiosyncratic risk than traditional stocks. I assume that they offer a great investment opportunity with this strategy. Furthermore, ETFs can be sold short more easily than stocks because the uptick rule doesn't apply for them (Yu and Webb, 2014). This increase even more the potential of pairs trading with ETFs given its sensitivity to trading and transaction costs (Do & Faff (2012); Gatev et al. (2006); Petajisto (2016); Schizas et al. (2011); Smith and Xu (2017)).

The combination of all these characteristics unique to Exchange-Traded Funds, looks like ETFs have been created for this strategy. Indeed, most of the factors influencing negatively the profitability of the strategy, like idiosyncratic risks, bankruptcy risk and analysts forecast do not concern ETFs. Furthermore, they also have the characteristics that increases the profitability of pairs trading, like low transaction costs or exposure to different regions and time zones.

PART II

PROFITABILITY AND EMPIRICAL ANALYSIS

I. Data and universe

Given the huge growth of the ETF market these last years, it is now possible to define a larger universe compared to previous studies. For instance, Schizas et al. (2011) starts with a universe of 22 different ETFs while most of the studies about pairs trading on individual stocks work with sample of hundreds stocks. For the creation of my universe, I had two goals: the first one was to reach at least 150 ETFs to increase the combination of pairs compared to other studies. My second goal was to cover the period from 2005 to 2017, so I can cover multiple market conditions and assess the robustness of the strategy.

With these two goals in mind, I started with the Bloomberg ETF database. This database gives the complete list of ETFs available and allows to filter them with the desired parameters. It allowed me to get the list of all equity ETFs exchanged worldwide. I tried different filters to restrict my universe, based on the factors impacting the profitability described in the section II.3 of this thesis.

First, I deleted the exchange filter to have a universe of all equity ETFs traded worldwide, as Engelberg et al. (2009) and Schizas et al. (2011) argue that the strategy works better with international exposure. I also exclude ETFs with derivatives and leverage, as they may lead to wrong decision given their higher sensitivity to the underlying baskets and because I didn’t cover them in this thesis. While Gatev et al. (2006) study shows that pairs trading works better on large cap companies, Engelberg et al. (2009) and Schizas et al. (2011) argue that the strategy gives better results with the small cap group, with a market capitalization between \$59 million and \$330 million. I take both into account and exclude only micro-cap ETFs, with asset under management under 60 million. Third, Engelberg et al. (2009) also showed that stocks with small liquidity tend to provide a higher profitability. However, the strategy still needs some liquidity and volume. Given so, I decided to exclude only company with really low volume (< 50 000 shares) and those with less than 1000\$ traded the day I downloaded the data (July 3rd 2017). Last but not least, Do and Faff (2012), Gatev et al. (2006) and Smith and Xu (2017) among others showed that the strategy is highly sensitive to trading and transaction costs. That’s why I also excluded ETFs with an average spread above the average (0.4%) and ETFs with expense costs above average (0.46%).

This gives me the following universe:

Universe			
Filters	*Worldwide traded*	Unfiltered N° ETFs	*4715*
	No derivatives / No leverage	Filtered N° ETFs	*318*
	Asset under management > 60M		
	Today trade > 1000		
	30D volume > 50 000		
	Average spread < 0,4%		
	Average expense costs < 0,46%		

N° of ETFs with data		N° of possible pairs	
2005 <	*99*	2005-2007	*4851*
2007 <	*143*	2007-2010	*10153*
2010 <	*175*	2010-2017	*15225*

Table 3: Pairs Trading universe

The next step was to get the historical prices of these ETFs. I downloaded the daily end-of-day data based on the universe above, with a time horizon between January 3rd 2005 to June 30th 2017. All the data were downloaded from Bloomberg.

I finally get a universe of 318 ETFs based on these filters. However, some ETFs lack of historical data, which restrict even more my universe. After eliminating ETFs with no data, I finally get three different samples. From 2005-2008, I have 99 ETFs and 4851 possible pairs. This sample will be used to see the behavior of the strategy during good market conditions, but does not represent the current situation of the ETF market given its radical evolution since 2005. Then, I have a larger sample of 143 ETFs and 10.153 possible pairs covering the period 2007-2011. This one will be used to see the performance during turbulent market conditions. And in the last sample, I get 175 ETFs and finally reach my goal of more than 150 ETFs. It will provide a more realistic view on the current ETF market and on the performance during good market condition. This sample allows the construction of 15.225 possible pairs.

II. Methodology

1. Best pairs selection

As mentioned in the section III.2.1 of the first part, the cointegration approach for the selection of the best pairs seems to not yield returns anymore, while the distance method has decreased in profitability these last years. In this thesis, I will then use the distance method proposed by Gatev et al. (2006) and improve it with the different studies about optimal parameterizations (Engelberg et al. (2009); Schizas et al. (2011); Smith and Xu (2017)).

Concerning the normalization of the price, as there is no discussion about it, I will use Gatev et al. (2006) methodology and using the following formula:

$$p_t^i = \prod_{t=1}^{t}(1 + r_t^i)$$

For the second step, I have two possibilities: The squared sum of deviations between both stocks proposed by Gatev et al. (2006) or the average absolute distance proposed by Schizas et al. (2011). While Schizas et al. (2011) argue that their method allows for more trading opportunities and is less sensitive to sudden large price discrepancies, I will use Gatev et al. (2006) methodology. I chose this one because I don't lack of trading opportunities given my larger sample, and because Gatev et al. (2006) methodology seems to be approved by most of later studies. Given that, the distance between each stocks will be calculated with:

$$D_{i,j} = \sum_{t=1}^{T_{fp}} \frac{\left(P_t^i - P_t^j\right)^2}{T_{fp}}$$

Concerning the parameterization of the formation period, I will use a 360 trading days duration. In their analysis about pairs trading on ETFs, Schizas et al. (2011) used a 120 trading days' formation period, to avoid excess over-lapping period. But as Engelberg et al. (2009) and Schizas et al. (2011) shows that an optimal trading period is between 10 and 20 trading days, the problem of overlapping trading period isn't a concern. Moreover, Smith and Xu (2017) tested a 9-month and a 12-month formation period, and their results showed that the 12 months' formation period is more efficient than the 9 months' one. They suggest that a longer formation period can have a positive impact on the profitability. Furthermore, as I put a minimum volatility constraint, using a longer formation period could have a positive impact. By computing the distance over a longer time frame, there is a higher probability to find pairs that will converge, even if they have a high volatility in their spread. For these reasons, I assume that under my parametrization, a longer formation period could be optimal.

Then, I will select the 10 pairs with the smallest distance, as Schizas et al. (2011) and Smith and Xu (2017) analysis show that it is the optimal number of pairs when using the distance method. Nonetheless, we will see later in this part that using only the distance when working with ETFs lead to wrong decisions in the choice of the pairs. So I will also select the pairs with a constraint on the standard deviation of their distance. The goal is to exclude ETFs who cover the same underlying basket with small price-inefficiencies, which should improve the performance of the strategy. This will be discussed later in this thesis.

2. Trading parameters

For my trading period, I will use a 20 trading days duration. The model will then be recalibrated every four weeks. Indeed, Engelberg et al. (2009) shows that if a pair doesn't converge after 10 days, the probability that it will converge later is really small. Moreover, using this parameterization yield higher returns than the standard parameterization proposed by Gatev et al. (2006), as Schizas et al. (2011) analysis showed that this is the optimal duration of the trading period using the distance method.

Concerning the trigger (i.e. the multiple of the standard deviation that open a trade), I will use the two standard deviation proposed by Engelberg et al. (2009) and Gatev et al. (2006). Indeed, Schizas et al. (2011) confirmed that it is the optimal value when using the distance method with the top 10 pairs. Given that, my parameterization can be modeled as follow:

$$StdevD_{i,j} = \sqrt{\frac{1}{T_{fp} - 1} \sum_{t=1}^{T_m} \left[\left(P_t^i - P_t^j \right)^2 - D_{i,j} \right]^2}$$

$$Open\ pair\ when \quad \left|P_t^i - P_t^j\right| > 2\ \ x\ StdevD_{i,j} \qquad and\ if\ d_t \leq d_{TP} + 20$$

$$\text{if } \mathrm{P_t^i} > \mathrm{P_t^j}\ then\ \begin{cases} Short\ position\ on\ i \\ Long\ position\ on\ j \end{cases} and \tag{1}$$

$$\text{if } \mathrm{P_t^i} < \mathrm{P_t^j}\ then\ \begin{cases} Long\ position\ on\ i \\ Short\ position\ on\ j \end{cases} and \tag{2}$$

$$Close\ pair\ when\ \begin{cases} P_t^i - P_t^j \leq 0, & if\ (1)\ \ or\ \ d_t \geq d_{TP} + 20 \\ P_t^i - P_t^j \geq 0, & if\ (2)\ \ or\ \ d_t \geq d_{TP} + 20 \end{cases}$$

3. Computation of the return

3.1. Raw return

For the calculation of the return, I used the "fully-invested capital" methodology used by Gatev et al. (2006), Engelberg et al. (2009) and Smith and Xu (2017) among others. As mentioned in the section III.2.1, this methodology assesses the profitability of the trading activities. Then, the costs of not trading are not taken into account in this methodology. As I only want to know if the trading activity is profitable, this methodology is the most appropriate. Given that, I computed the returns as follow:

First, I computed the daily returns of each pairs with the different between the long and short stock:

$$R_t(P^k) = R_t(l^k) - R_t(s^k)$$

Then, for each day, I computed the cumulative return since the beginning of the trading period. This will be used to weights each pairs, for the calculation of the return of the portfolio.

$$w_t^k = \begin{cases} [1 + R_{t-1}(p^k)]\ x\ [1 + R_{t-2}(p^k)]\ x \ldots x\ \left[\ 1 + R_{d^k+1}(p^k)\right] & if\ t \geq d^k + 2 \\ 1 & if\ t = d^k + 1 \end{cases}$$

With these weights, I'm now able to compute the return of the portfolio as a whole with:

$$W_t^k = \frac{w_t^k}{\sum_{j=1}^{N_t^*} w_t^j}$$

And $$R_t^{port} = \sum_{k=1}^{N_t^*} W_t^k R_t(p^k)$$

This formula gives us the daily returns during the trading period. The last step consists in the calculation of the return for the total period. The raw cumulative returns for the trading period are then expressed as follow:

$$Cumulative\ return_{raw} = \prod_{t=1}^{20}(1 + R_t^{port})$$

Based on this raw return, it is now possible to compute the net return of the strategy by taking the trading costs into account. The methodology used for these costs is explained in the next section.

3.2. Trading costs

Given the sensitivity of the strategy to costs, an analysis of the complete cost spectrum when trading ETFs seem mandatory. As mentioned in the section III.3.2, there are five different costs when trading ETFs: the bid-ask spread, the commissions per trade, the short-selling fees, the expense ratio and market impact (Gastineau, 2017). However, market impact will not be considered in this section.

Regarding the bid-ask spread, multiple studies (Engelberg et al., 2009; Smith and Xu, 2017; Gatev et al., 2006) used the "one-day later rule" to avoid the bid-ask bounce, but I decided to not use it. As explained previously, I restricted the pairs selection to those with a minimum level of volatility in their distance. Given that, I assume that opening positions one day later will highly bias the results. Indeed, given the higher volatility in the pairs' distance compared to other studies, using the one-day later rule will certainly avoid the bid-ask bounce, but will also increase the probability to miss profit opportunities. At first, I wanted to use the last bid and last ask price of the day, but there are too many missing data in the time series. These data are therefore not usable. Instead, I will use a another measure by always paying the full average bid-ask spread of the securities. It will probably bias the results downward, but will strongly assess the robustness of the strategy if the profits are still positive. I assume that, on the long run, there is a 50% chance that the last trade is at the bid price and 50% at the ask price.

Probability distribution				
Probability	25%	25%	25%	25%
Position	Buy ask - Sell ask	Buy ask - Sell bid	Buy bid - Sell Ask	Buy bid - Sell bid
Spread paid	0	1	-1	0

Table 4: Bid-ask spread probability distribution

When we look at the probability distribution in the table above, we can see that using the last price gives us a mean bid-ask spread of 0. As the mean is null, I decided to pay the full bid-ask spread of each stock at the closing of the pairs. On average, I will then pay the bid-ask spread of the stocks while not affecting the timing capability of the strategy. (See table 16,17 and 18 in appendix for ETF's bid-ask spread and expense ratio)

Regarding broker's commissions, I made a comparative analysis of multiple online brokers to have a global view of this kind of costs. For these, I assume that the strategy is applied to a fund with $1 million of assets under management with no leverage, so $200.000 is allocated to each pair. Note that the percentages are either fixed, or represent the maximum fees per $200.000.

	Minimum $	Maximum $	Percentage	Timing
Charles Swab	4,95	-	0,002%	per trade
RobinHood	0	-	0,000%	per trade
OptionsXpress	4,95	-	0,002%	per trade
Wealthfront	0,25%	-		per year (account)
Betterment	0,25%	-		per year (account)
TD Ameritrade	6,95	-	0,003%	per trade
e*trade	4,95	6,95	0,003%	per trade
Fidelity	4,95	-	-	per trade
Interactive Brokers	4	29	0,100% (fixed)	per trade
Keytrade	7,5	24,95	0,012%	per trade
Lynx	5	9	0,005%	per trade
Suretrader	1,95 (>1M per month)	4,95 (<250k per month)	0,002%	per trade

Table 5: Online broker pricing comparison

Based on this comparison, I will use the average commission as the commissions for my trades. Given that, the commissions are 0.015% per trade, so 0.06% each time the pairs open.

Regarding short-selling fees, not all brokers disclose their margin fees. OptionsXpress charge a 7% fees per year, e*trade 8.25% and Ameritrade 7.75%. Borrowing costs are then 7.66% per year on average, or 0.0205% per day.

$$ShortSellingFees_{Daily} = (1 + ShortSellingFees_{Annual})^{\frac{1}{360}} - 1$$

For the ETF expense ratio, I downloaded on Bloomberg the average expense ratio of all the ETFs in my universe (table 16, 17 and 18 in appendix). Then, I computed the costs related to the expense ratio of the ETF on long position over the trading period, taking only days when the pairs are open into account. These values being on an annual basis on Bloomberg, I had to transform these costs on a daily basis with:

$$ExpRatio_{Daily} = (1 + ExpRatio_{Annual})^{\frac{1}{360}} - 1$$

III. Application of the trading strategy

1. Preliminary results

At first, I applied the strategy using no minimum volatility in the distance. The results I get were far away from the previous literature so I decided to look deeper at the variable of the model. I discovered that the pairs selected had no standard deviation (or at least less than 0,0001) and that they were composed of ETF covering the same index. At this moment, I realized that, as the strategy constructs pairs based on the smallest distance, the algorithm tends to pick the most price-efficient ETFs. Given that, using the strategy on ETF with the same rules than with stocks produces really small return before costs, and clearly negative returns when taking the costs into account. I assume here that using pairs trade strategy on a large sample of ETFs will exploit the price inefficiencies of the most efficient ETFs, which have no sense…

Based on these observations, I decided to change my methodology and to add a new parameter in the model: the volatility in the distance, measured by the standard deviation. While previous studies used the standard deviation as a signal to open and close pairs, I will also use the standard deviation as an indicator of the price efficiencies and so, an indicator of profit opportunities for the highest values. To do that, I selected the best pairs with the minimum distance metric described by Gatev et al. (2006), but I also added a constraint of minimum standard deviation. In my research, I tested seven different standard deviation constraint in order to find an optimal volatility requirement for the strategy. While this method would probably not been appropriate for stocks, I assume that it is not the case for ETFs. Because they have unique characteristics in their price behavior, increasing the volatility of the spread between the two stocks while still picking the ones with the smallest distance can create highly correlated pairs but with significant price divergence.

2. Historical performance analysis

2.1. Global

This section will analyze the performance of the strategy from May 25th 2006 to June 30th 2017 with the ETFs available in the three sub-periods. From a period to another, all the profit will be reinvested in the strategy with the new universe. The first sample goes from May 25th 2006 to May 16th 2008, the second from May 19th 2008 to May 20th 2011 and the last one from May 23rd 2011 to June 30th 2017. As the ETFs in the samples are selected with the same criteria, I can assess the performance of the strategy over the long run, even if they don't share the same universe. Indeed, more recent period has more ETFs available, and allow to create a larger number of pairs.

The following chart summarize the performance of the 7 different parameterizations with and without trading costs, and compare them to the performance of the S&P500.

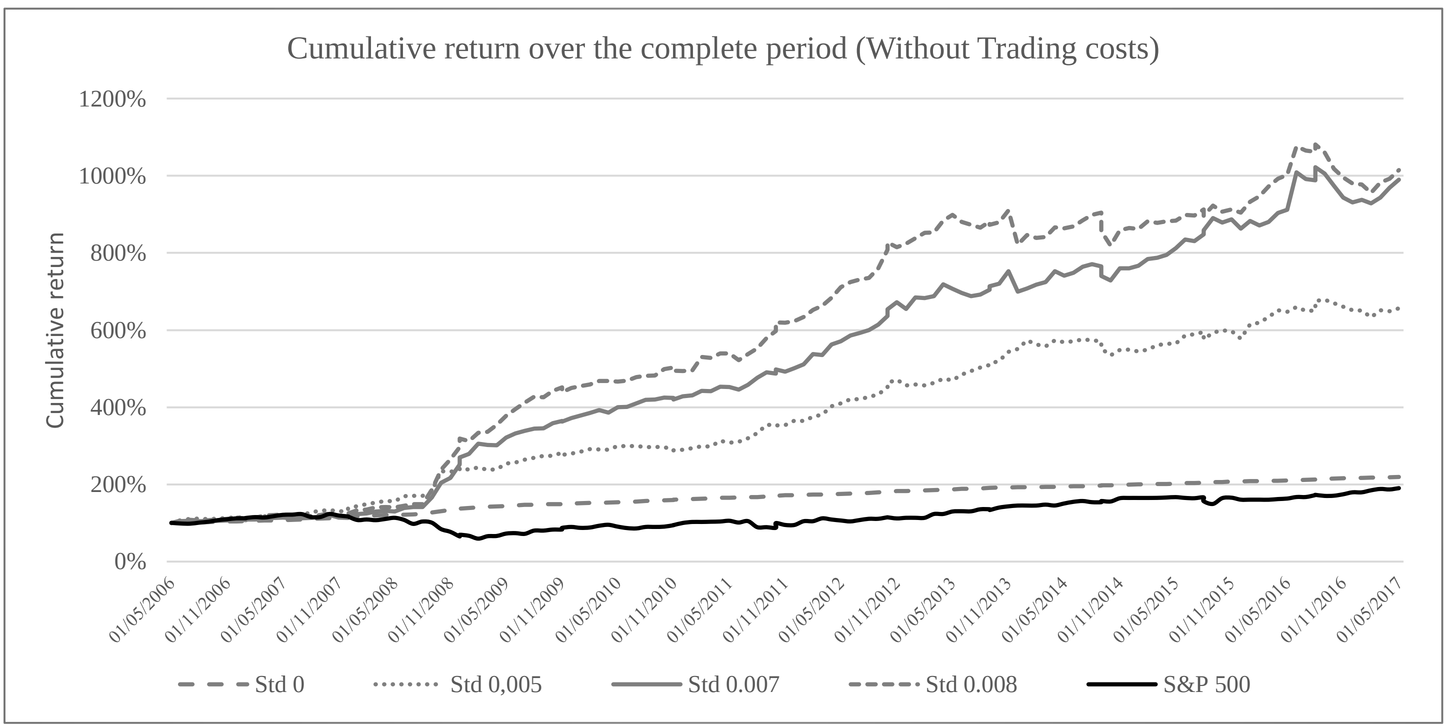

Figure 1: Cumulative return over the complete period without trading costs

2006-2017								
Parameterization	A	B	C	D	E	F	G	S&P500
Std Dev requirement	0	0,005	0,006	0,007	0,008	0,009	0,1	/
Cumulative return	2,1902	6,5708	9,5225	9,9025	10,1535	6,3829	7,8278	1,9011

Table 6: Strategies total return 2006-2017 without trading costs

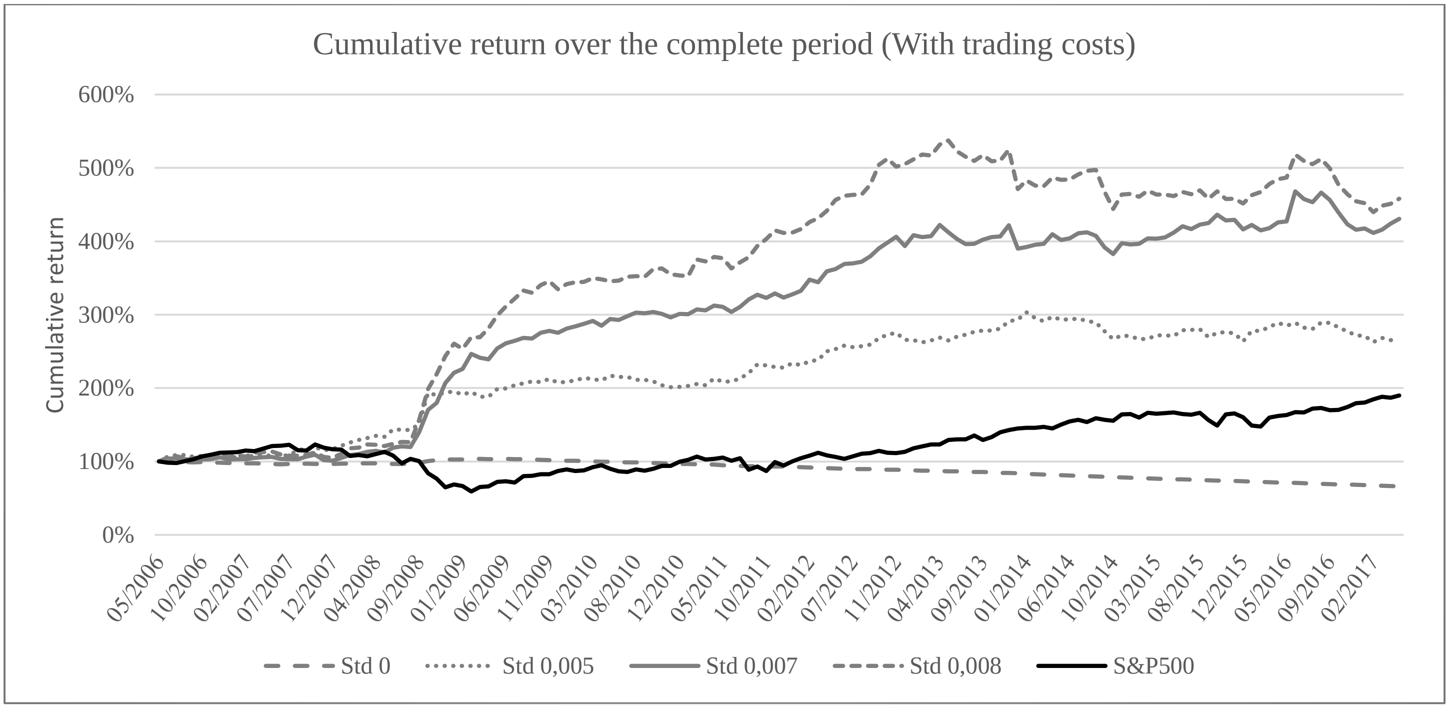

Figure 2: Cumulative return over the complete period with trading costs

2006-2017

Parameterization	A	B	C	D	E	F	G	S&P500
Std Dev requirement	0	0,005	0,006	0,007	0,008	0,009	0,1	/
Cumulative return	0,6593	2,6636	3,9592	4,3043	4,5817	2,9448	3,7548	1,9011

Table 7: Strategies total return 2006-2017 with trading costs

We can see that, except for the strategy with no restriction on the standard deviation, they all yield higher return than the S&P500.

Based on these four figures, we can clearly see that the strategy is highly profitable, even when taking the transaction costs into account. Among these 7 parameterizations, the standard deviation minimum requirement of 0.008 yield the higher return, whatever we take trading costs into account or not. However, its profitability drops after 2014 when taking transaction costs into account. This can be explained as the results of too high trading costs that are fixed under my preliminary assumptions. As the market is more efficient in the last periods, the bid-ask spread is probably lower than the average, as well as the short-selling costs. This will be analyzed in the next sections.

Furthermore, the strategy performed well during the market downturn of 2008-2009, which is consistent with Do and Faff (2012) and Smith and Xu (2017) assumptions about the profitability in turbulent markets.

2.2. By sample

In this section, I will analyze the performance of the strategy within the three different samples. The goal is to assess the robustness of the strategy trough different market condition. The first sample, covering the 2006 to 2008 period, will assess the performance of the strategy during bullish market. The second sample, covering 2008 to 2011, will show us the performance during the crisis and the following recovery period. The third sample, from 2011 to 2017 shows the performance with a larger universe and during a bullish market with really low volatility.

2.2.1. Sample 1: May 5th 2006 – May 16th 2008

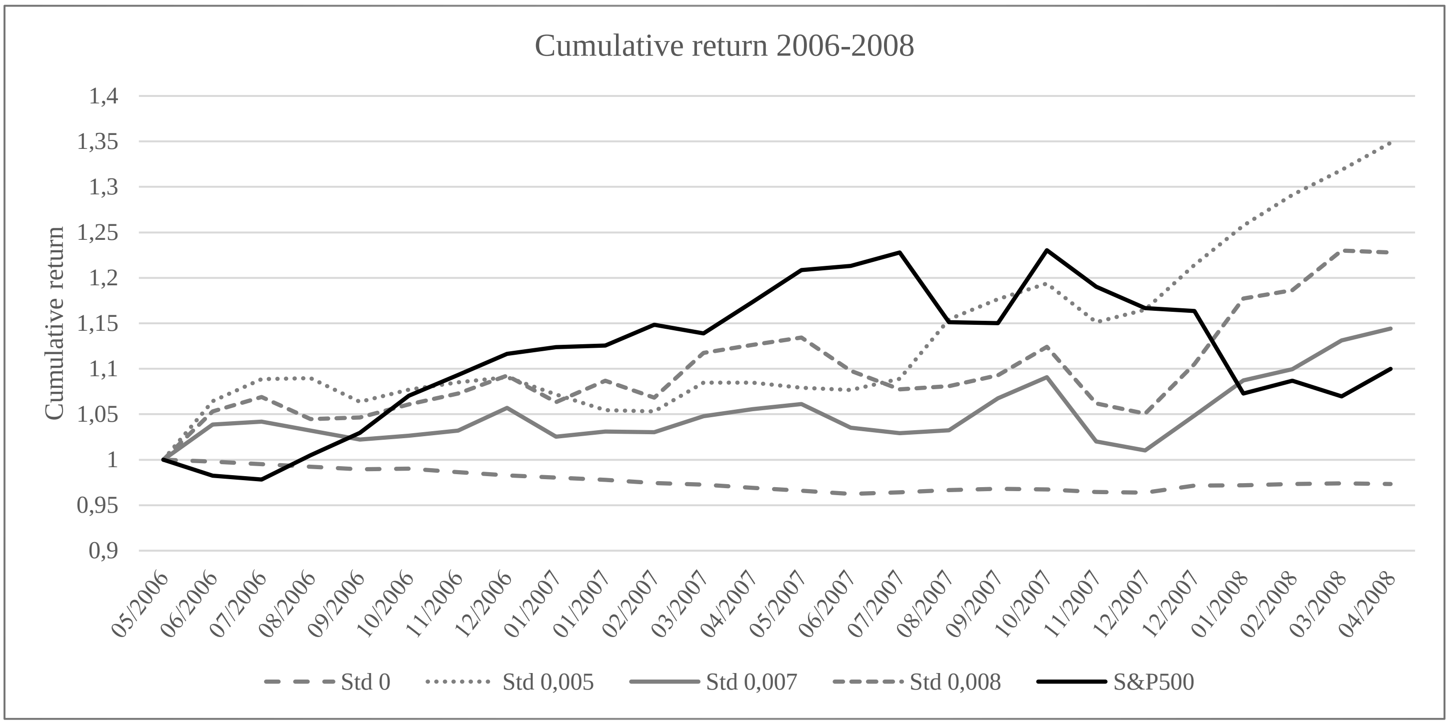

Figure 3: Strategies total return 2006-2008

2006-2008								
Parameterization	A	B	C	D	E	F	G	S&P500
Std Dev requirement	0	0,005	0,006	0,007	0,008	0,009	0,1	/
Cumulative return	0,9733	1,3486	1,2552	1,1443	1,2277	1,2685	1,2604	1,0999

Table 8: Strategies total return 2006-2008

In this sample, the universe was composed of 96 ETFs and then allow for 4 560 pairs. We can see in the chart above that the 7 different parameterization outperformed the S&P500 over the entire period. However, this performance mainly comes from the five last trading periods, the strategy showing less profitability than the S&P 500 during the 20 first periods.

The most performing parameterization during this period being the 0.005 minimum standard deviation requirement, with total return of 34,89% and so an annualized return of 16,14%.

2.2.2. Sample 2: May 19th 2008 – May 20th 2011

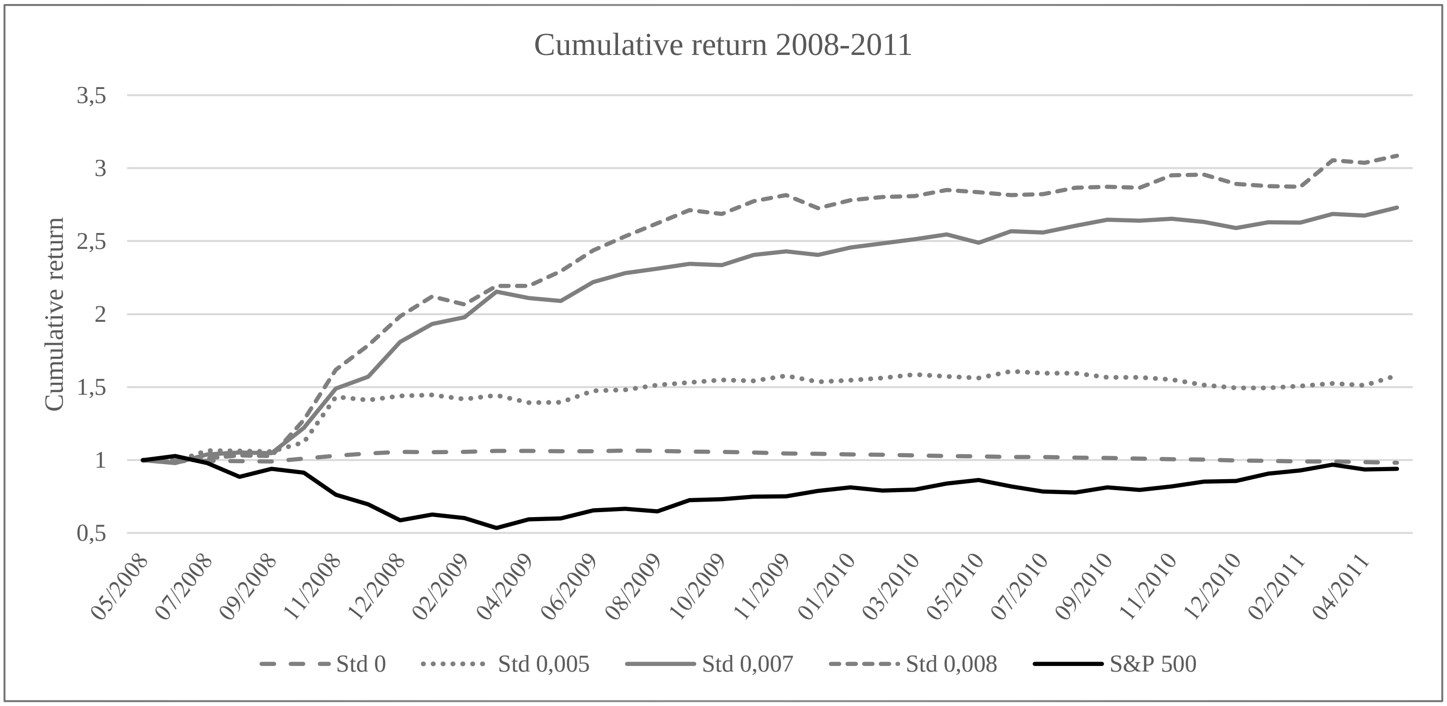

Figure 4: Strategies total return 2008-2011

2008-2011

Parameterization	A	B	C	D	E	F	G	S&P500
Std Dev requirement	0	0,005	0,006	0,007	0,008	0,009	0,1	/
Cumulative return	0,9820	1,5787	1,9733	2,7292	3,0843	1,9187	2,5858	0,9401

Table 9: Strategies total return 2008-2011

In this sample, the universe was composed of 142 ETFs and then allow for 10 011 pairs. There is no doubt that the strategy would have been highly profitable during this period. It performed particularly well during the subprime crisis. When the S&P 500 suffered huge losses, the strategy made huge profit. This can be explained by two reasons: during market turbulence, the market is less efficient and allow then for more trading opportunities using this strategy. The second reason is that I made assumptions about the costs that is probably not consistent with those of this period. Indeed, the short-selling costs can increase if there is already a lot of people that want to sell assets

(Do and Faff, 2012), as it was the case during the subprime crisis. Furthermore, I assume that the bid-ask spread should have been higher during this period too. Then, this huge performance should be taken with caution, regarding the costs assumptions.

During this period, the most performing Parameterization being the 0.008 minimum standard deviation requirement, with a total return of 208,42% and so an annualized return of 45,56%.

2.2.3. Sample 3: May 23rd 2011 – June 30th 2017

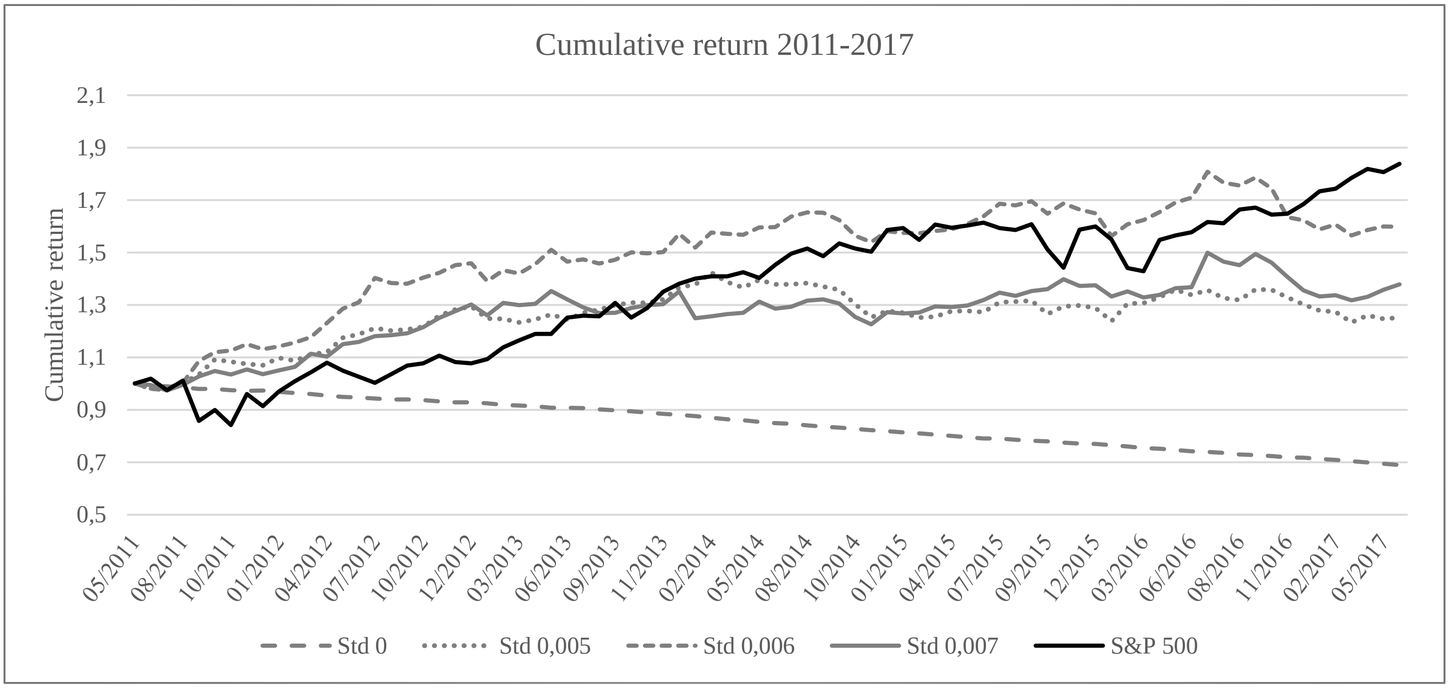

Figure 5: Strategies total return 2011-2017

2011-2017

Parameterization	A	B	C	D	E	F	G	S&P500
Std Dev requirement	0	0,005	0,006	0,007	0,008	0,009	0,1	/
Cumulative return	0,6897	1,2509	1,5983	1,3782	1,2099	1,2098	1,1520	1,8384

Table 10: Strategies total return 2011-2017

In this sample, the universe was composed of 169 ETFs and then allow for 14 196 pairs. On this sample, the results are more mitigated. At the end of the period, all Parameterization underperformed the S&P500 and performed poorly. The best performance being attributed to the 0.006 minimum standard deviation requirement, with a return of 59,88% and so an annualized return of 8.1%. This Parameterization outperformed the S&P500 in the majority of the period, but suffer losses during the 8 last periods and finally underperformed the benchmark. This can be explained by the fact that the market performed particularly well during this period, especially after trump elections. As the strategy yields better returns during turbulent market conditions, this is what was expected before the backtesting. However, other parameterization failed to produce positive returns after 2014.

2.3. Per year

Per year performance (With trading costs)

Parameterization	A	B	C	D	E	F	G	S&P500
Std Dev requirement	0	0,005	0,006	0,007	0,008	0,009	0,01	/
2007	-0,92%	13,31%	10,99%	2,24%	3,93%	7,75%	3,26%	3,53%
2008	5,69%	60,69%	66,00%	110,82%	135,64%	57,56%	88,74%	-40,79%
2009	-1,53%	6,89%	20,34%	27,18%	31,10%	29,64%	40,14%	29,72%
2010	-4,30%	-3,33%	3,17%	7,05%	3,47%	0,97%	7,00%	11,51%
2011	-4,37%	15,92%	18,08%	8,96%	16,58%	12,31%	13,19%	0,62%
2012	-4,53%	13,64%	21,82%	20,07%	22,65%	13,92%	11,12%	12,75%
2013	-5,25%	10,32%	9,19%	-0,85%	-6,69%	-9,62%	-3,37%	28,13%
2014	-7,03%	-7,74%	3,69%	1,45%	-1,36%	1,57%	-2,45%	13,71%
2015	-6,08%	-2,57%	-0,73%	5,12%	-2,81%	4,34%	-3,58%	-2,76%
2016	-6,76%	3,23%	1,63%	-0,01%	0,65%	2,94%	5,65%	11,94%
Mean per year	-3,51%	11,04%	15,42%	18,20%	20,31%	12,14%	15,97%	6,84%
Standard deviation	3,61%	18,23%	18,52%	32,05%	40,14%	18,02%	27,12%	18,75%

Table 11:Strategies performance per year

The table above presents the results of the strategy per year. Based on these results, the 0.008 minimum standard deviation requirement yield the highest return, with an average return of 20,31% per year and a standard deviation of 40,14%. The volatility may seem really high, but is mainly driven by the huge performance of 2008 and we will see in the next section that the results are highly skewed, meaning that the standard deviation overestimates the risks of the strategy. However, this Parameterization is the optimal one only in 2008 and 2012, so I can’t conclude that this is the optimal parameterization by only looking at the returns. I assume that the ratio and statistical analysis of the next section would answer this question.

3. Ratio and statistics

In this section, a deeper analysis of the parameterization will be done. As we can’t only use the performance analysis to determine which parameterization is the optimal, we need to look deeper in the results with the ratio and other statistical analysis. I assume here that the Sortino-Satchell ratio and performance analysis combined with the skewness and kurtosis analysis can give us a more precise view on the performance of the strategy. The goal is then to define, based on these ratios and statistics, the optimal parameterization.

For the complete period, during which the investors recalibrate the universe with the new ETFs available data in 2008 and in 2011, I get the following statistics based on the return of each trading period (4 weeks). Note that, unlike other studies about pairs trade, I will not use the Sharpe ratio as a measure of performance. Indeed, as mentioned by Farinelli, Ferreira, Rossello, Thoeny and Tibiletti (2007), Sharpe ratio can be a misleading indicator when the returns are not normally distributed. Instead, as their research suggests that this is a more robust indicator of the risks when evaluating hedge fund strategies, I will use the Sortino-Satchell ratio (Sortino and Satchell, 2001).

PARAMETERIZATION STATISTICS

Parameterization	A	B	C	D	E	F	G	S&P500
StdDev requirement	0	0,005	0,006	0,007	0,008	0,009	0,01	/
Mean per period	-0,29%	0,73%	1,00%	1,08%	1,14%	0,80%	0,98%	0,55%
Standard deviation	0,42%	3,16%	3,02%	3,49%	4,06%	3,10%	3,33%	4,45%
Skewness	3,087	4,484	1,370	2,526	3,025	1,784	2,456	-0,715
Kurtosis	12,833	36,483	5,848	12,215	17,403	9,648	11,169	3,601
Sortino-Satchell ratio	-2,811	0,449	0,494	0,579	0,505	0,348	0,560	0,086
Maximum rise	2,03%	27,81%	16,72%	22,09%	26,96%	19,09%	20,75%	14,02%
Maximum drawdown	-0,80%	-4,05%	-6,44%	-7,53%	-10,20%	-7,74%	-6,58%	-16,64%
Negative performance	123	58	51	49	51	51	58	44
Positive performance	20	85	92	94	92	92	85	78
Percentage positive	13,99%	59,44%	64,34%	65,73%	64,34%	64,34%	59,44%	63,93%

Table 12: Parameterization statistics

Based on these statistics, we can already exclude parameterizations A, B, F and G according to Markowitz mean-variance efficient portfolio selection (Markowitz, 1952). Indeed, these parameterizations offer lower return for a higher level of risk than other Parameterization… Making them inefficient from Markowitz point of view. Given that, the optimal Parameterization must be C, D or E.

When looking at the other statistics, we see that parameterization D seems to be the optimal parameterization for the strategy. Indeed, even if D have a lower skewness and kurtosis than E, this parameterization has a higher Sortino-Satchell ratio and is then less exposed to the downside risks for only 6 basis points lower return per period. Moreover, this parameterization yields more often positive return than parameterization F.

In light of this analysis, I can conclude that on a risk-reward basis, the optimal minimum standard deviation requirement using the distance method with ETFs is 0.007. In the next section, I will analyze in depth this parameterization.

4. Optimal Parameterization analysis

4.1. Correlation analysis

Now we know the optimal parameterization, this section will be an in depth analysis of the strategy's risk and return characteristics over time. First, when we look at the one year rolling correlation with the S&P 500, we can see that the trailing correlation is highly volatile, with an average correlation with the S&P 500 being slightly negative, which is consistent with previous studies about pairs trading. Moreover, we can observe that the correlation drops below zeros during market downturn, confirming the idea that the strategy performs well in turbulent market conditions. Last but not least, the trailing correlation goes positive during good market conditions, confirming the market-neutrality of the strategy.

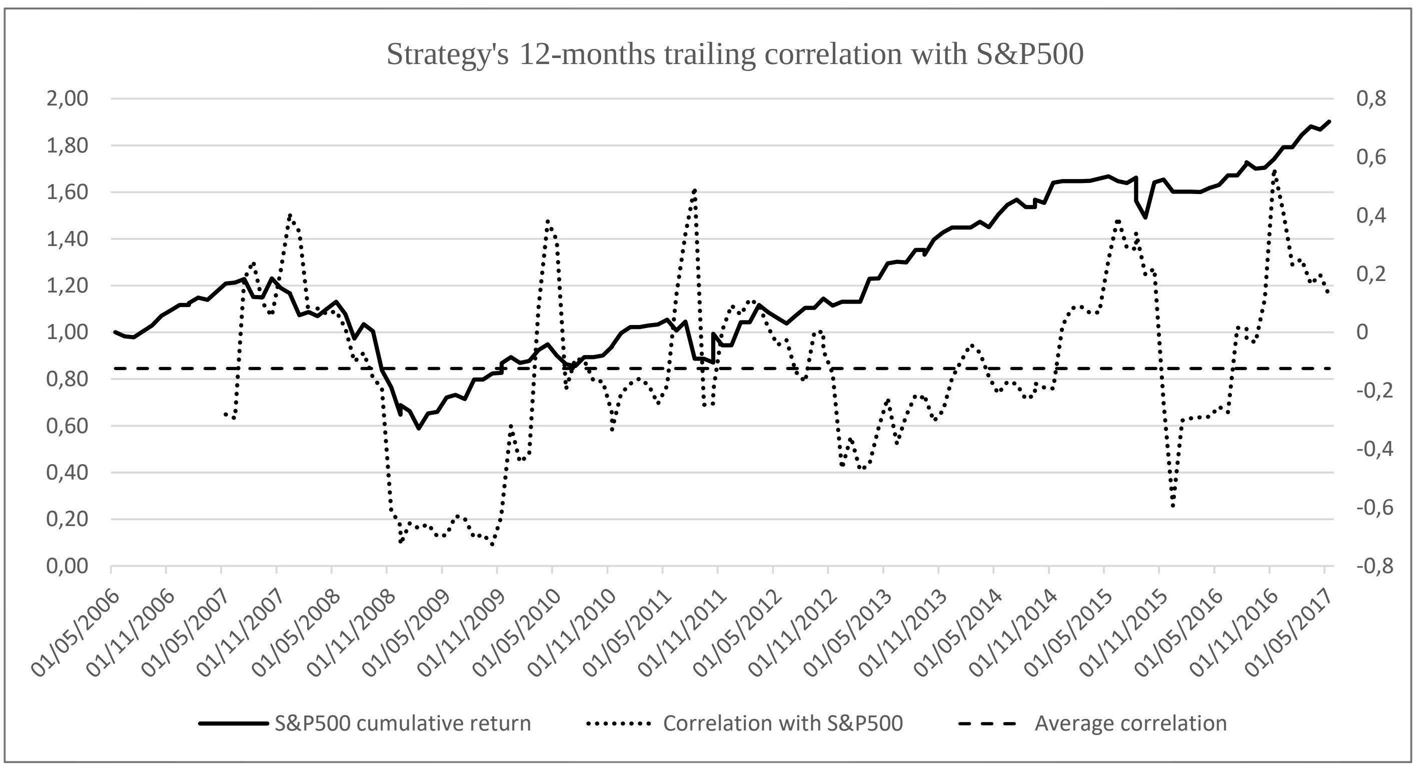

Figure 6: Strategy's 12-months trailing correlation with S&P500

When looking only at the performance of the strategy, one might believe that the strategy is positively correlated with the volatility of the market. Indeed, as the strategy is based on the spread between two correlated assets, a higher volatility in the market could potentially allow for more trading opportunities. However, as we can see on the chart below, this is not always the case. The strategy is slightly positively correlated with the VIX, but the rolling correlation is highly volatile.

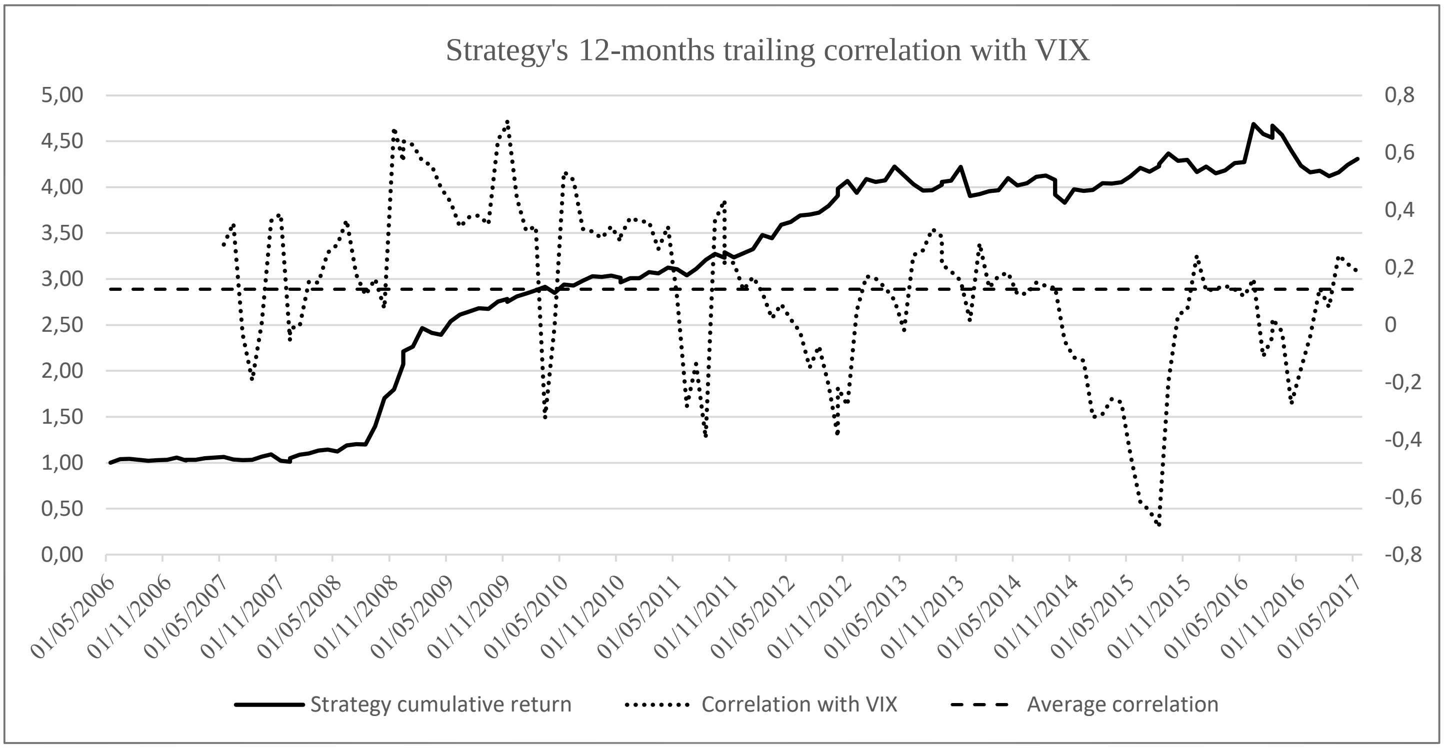

Figure 7: Strategy's 12-months trailing correlation with VIX

The strategy performed well during high volatility market conditions, confirmed here by the high correlation around 2008-2009. However, the correlation drops and goes below zero after 2014. We can see that during low volatility market conditions, the strategy performed poorly but still yield positive return. Then, as with the correlation with the S&P500, we can’t conclude any direct link between the implied volatility and the performance of the strategy.

4.2. Sub-period statistics analysis

In this section, I will analyze the statistics of the performance in four different sub-periods. The goal is to analyze the performance over a smaller time frame, but also to see the behavior of the strategy under different market conditions. Then the first one will show us the performance during good market conditions, from May 2006 to June 2008. The second is the opposite and cover highly turbulent market conditions, from June 2008 to May 2011. The third assess the performance during a recovery period, with middle to low level of volatility from May 2011 to April 2014. And the last one analyzes the performance during good market conditions with low volatility, from April 2014 to June 2017.

STATISTICS PER SUB-PERIOD

	Sub-period 1		Sub-period 2		Sub-period 3		Sub-period 4	
	Strategy	S&P500	Strategy	S&P500	Strategy	S&P500	Strategy	S&P500
Mean per trading period	0,67%	0,33%	2,68%	0,14%	0,76%	0,95%	0,15%	0,71%
Standard deviation	2,49%	3,15%	5,10%	6,24%	2,40%	4,67%	2,45%	2,57%
Skewness	-0,517	-0,716	2,390	-0,822	-1,031	-0,202	1,229	0,695
Kurtosis	1,415	0,915	5,947	1,047	2,253	3,893	4,341	4,300
Sortino-Satchell ratio	0,182	-0,004	3,577	-0,017	0,325	0,238	-0,009	0,316
Maximum profit	5,93%	6,95%	22,09%	11,77%	4,68%	14,02%	9,69%	10,07%
Maximum loss	-6,49%	-7,79%	-2,24%	-16,64%	-7,53%	-15,16%	-3,92%	-6,00%
Positive performance	18	15	25	23	28	17	23	23
Negative performance	9	11	13	12	10	11	17	10
Percentage positive	66,67%	57,69%	65,79%	65,71%	73,68%	60,71%	57,50%	69,70%

Table 13: Statistics per sub-period

As we can see on the table above, this analysis shows a different picture of the performance. While the performance analysis over the complete back-testing timeframe was really attractive, these results are mainly driven by the huge performance of the second sub-sample. However, even if its profitability drops during the sub-period 3 and 4, the strategy still outperforms the S&P500 on a risk-reward basis during the period 1, 2 and 3. Note that during sub-period 3, the strategy yields slightly lower return than the S&P500 but have a lower volatility and a higher Sortino-Satchell ratio, being then more efficient on a risk-adjusted basis.

This sub-period analysis shows us that, even if the strategy yielded little return these last years, it still provides positive return. Given that the strategy works particularly well during turbulent market conditions, I would not expect much of it during good market conditions. Pairs trading seems to be a good strategy when an investor expects an economic downturn, and wants to make money when other investors will lose theirs. By assuming some small profit when the economy goes well, and investors can earn big returns when everything goes wrong. The timing for the implementation of the strategy is then a matter of importance, even if the investor faces small risk of losses.

IV. One step ahead

With regard to the previous analysis, I wanted to test the effect of diversification with an ETF tracking the S&P500. Indeed, the strategy tends to produce low returns when the market goes well. So I assume that on a risk-adjusted basis, allocating a fraction of the portfolio to the strategy and another to the S&P500 could yield more stable and potentially more efficient returns. I will test 9 different allocations, from 10% to 90% on the S&P500 with the 0.007 minimum standard deviation requirement.

ALLOCATION STATISTICS

Allocation	A	B	C	D	E	F	G	H	I	Strategy
Percentage to S&P500	10%	20%	30%	40%	50%	60%	70%	80%	90%	/
Mean per period	1,02%	0,97%	0,92%	0,87%	0,81%	0,76%	0,71%	0,65%	0,60%	1,08%
Standard deviation	3,00%	2,59%	2,30%	2,17%	2,25%	2,50%	2,89%	3,36%	3,89%	3,49%
Skewness	2,218	1,730	1,125	0,656	0,463	0,329	0,096	-0,193	-0,472	2,526
Kurtosis	10,422	7,546	4,175	2,035	1,671	1,815	2,030	2,436	2,994	12,215
Sortino-Satchell ratio	0,585	0,591	0,578	0,524	0,452	0,345	0,238	0,164	0,114	0,579
Maximum rise	18,22%	14,34%	10,63%	8,70%	7,94%	9,16%	10,37%	11,59%	12,80%	22,09%
Maximum drawdown	-6,64%	-5,84%	-5,52%	-5,19%	-5,99%	-7,83%	-9,66%	-11,49%	-13,33%	-7,53%
Negative performance	48	46	44	46	45	47	51	52	49	49
Positive performance	95	97	99	97	98	96	92	91	94	94
Percentage positive	66,43%	67,83%	69,23%	67,83%	68,53%	67,13%	64,34%	63,64%	65,73%	65,73%

Table 14: Strategy allocation statistics

When looking at this preliminary analysis, we can see that increasing the proportion allocated to the S&P500 reduce the volatility of the return, until 40% allocated. So we can see here that diversification has a positive effect on the risk, until a certain threshold. However, when looking at the Sortino-Satchell ratio, we can see that the diversification effect of the allocation C and D is not on the loss side. Based on these preliminary analyses, allocating 20% of the portfolio to the S&P500 provides the most efficient return on a risk-adjusted basis.

Now, let's give a look at the performance in the different sub-period to see if the diversification has a positive effect on the performance during the different state of the economy.

STATISTICS PER SUB-PERIOD

	Sub-period 1		Sub-period 2		Sub-period 3		Sub-period 4	
	Diversified	Strategy	Diversified	Strategy	Diversified	Strategy	Diversified	Strategy
Mean per trading period	0,58%	0,65%	2,17%	2,68%	0,80%	0,76%	0,26%	0,15%
Standard deviation	1,96%	2,45%	3,47%	5,10%	2,04%	2,40%	2,02%	2,45%
Skewness	-1,149	-0,493	2,106	2,390	-0,861	-1,031	1,362	1,229
Kurtosis	2,764	1,524	4,561	5,947	1,330	2,253	4,942	4,341
Sortino-Satchell ratio	0,145	0,168	4,045	3,633	0,438	0,325	0,102	-0,009
Maximum profit	3,81%	5,93%	14,34%	22,09%	4,30%	4,68%	8,24%	9,69%
Maximum loss	-5,84%	-6,49%	-1,25%	-2,24%	-5,74%	-7,53%	-3,09%	-3,92%
Positive performance	9	9	9	13	10	10	18	17
Negative performance	18	18	29	25	28	28	22	23
Percentage positive	66,67%	66,67%	76,32%	65,79%	73,68%	73,68%	55,00%	57,50%

Table 15: Allocation statistics per sub-period

In the table above, we can see that allocating one small part to the S&P500 have a good effect on the risk-adjusted return of the strategy. Indeed, except for the sub-period 1 where the Sortino-Satchell ratio slightly decreases, the effect on all other periods is positive. Now, the strategy shows less volatile returns for a small cut in the overall performance. Moreover, the performance is now more robust to the different state of the economy, as we can see in the statistics during the sub-period 3 and 4 whose produces higher return. This analysis shows us that a small diversification has a good impact on the strategy, making it more reliable over the long run while still provide some reasonable returns, especially during market downturn.

V. Statistical analysis of the results

To conclude the second part of this thesis, I will see if the results provided in the previous analysis are statistically significant. I will then test three different hypotheses. The first one will indicate if the strategy yields positive results, as the previous literature are mitigated about its profitability. The second hypothesis will assess if the strategy yields higher return than passive investing. Indeed, famous investors like Warren Buffet assess that most of the time, hedge funds tend to underperforms passive investing over the long run and this assumption is one of the factors making ETFs so popular nowadays. The third hypothesis will indicate if the strategy using diversification with the S&P500 is more profitable than investing in the strategy only. Then, the hypotheses are the following:

H1: Pairs trading with ETFs generates positive excess return.

H2: Pairs trading with ETFs generates more return than passive investing on the S&P500.

H3: The portfolio composed of the strategy and an ETF tracking the S&P500 yield higher risk-adjusted return than the portfolio composed only of the strategy.

1. Hypothesis 1: Pairs trading with ETFs generate positive excess return

My analysis showed that the strategy yields an average excess return of 1,08% per trading period of 4 weeks with a standard deviation of 3,49%. After the statistical test, it appears that these results are strongly statistically significant at the 1% significance level.

2. Hypothesis 2: Pairs trading with ETFs generate more return than passive investing on the S&P500

When passive investing in an ETF covering the S&P500 would have produced an average return of 0.55% per trading period with a standard deviation of 4,45%, the strategy produced a return of 1,08% with a standard deviation of 3,49%. Then, the strategy has a higher excess return and a lower standard deviation than passive investing. However, these results are not statistically significant at the 5% significance level. Unfortunately, statistical tests support the superiority of the strategy only at the 10% significance level, which is not enough to conclude that the profitability is higher.

3. Hypothesis 3: A diversified portfolio composed of the strategy and an ETF tracking the S&P500 generate a higher risk-adjusted return than the portfolio composed only of the strategy.

For this hypothesis, I used the yearly Sortino-Satchell ratio of the diversified strategy and the classic strategy. The diversified strategy yields an average return per period of 0.97% with a standard deviation of 2,59% while the classic strategy yields 1.08% with a standard deviation of 3.49%, with Sortino-Satchell ratios of respectively 0.591 and 0.579. The diversified strategy has then a higher risk-adjusted return than the classic strategy. However, these results are not statistically significant at the 5% significance interval. The diversified strategy yields higher risk-adjusted return only at the 15% significance level, which is not enough to conclude that the profitability is higher.

CONCLUSION

Exchange-traded funds are one of the most innovative financial products of this last decade. With their unique characteristics, they extend the trading opportunities offered to investors and allow to build new trading strategies that were not possible before. On the other hand, pairs trading is a well-known strategy used by hedge fund, but the profitability of the strategy seems to decrease nowadays. Many studies and investors tried to assess its profitability, and most of them agree on the fact that this profitability is lower than in the past. However, only few studies tested this strategy using exchange-traded funds. For this reason, I wanted to test by myself how profitable the strategy would have been in the last ten years, and if it is possible to generate profit nowadays using different parameterizations.

To answer this question, it is worth emphasizing how I produced this profitability analysis. After readings about exchange-traded funds, I realized that ETFs' prices were sometimes inefficient. Regarding this discovery, I first wanted to exploit these inefficiencies and I started to study how pairs trading works. Once I knew how to produce returns using this strategy, I created the universe based on the sources of profitability highlighted by the previous literature and I implemented the algorithm using Matlab.

After the first run of the algorithm, I realized that it was not possible to exploit these inefficiencies using the classic methodology… Indeed, when using the classic pairs-trading algorithm, the strategy tends to pick ETFs covering the same underlying basket and the most price-efficient of them, which have no sense. Then, I chose to insert some constraints in the model. As the model picks the most price-efficient ETFs, I needed to exclude them. I decided to use a minimum volatility in the distance as a constraint, and I tested 7 different parameters regarding this volatility: 0, 0.005, 0.006, 0.007, 0.008, 0.009 and 0.01. Then, the algorithm would pick pairs of ETFs that have the lower historical distance, but with a standard deviation of their distance higher or equal to the parameterizations mentioned above.

By doing so, the strategy produces substantially higher returns with all these parameterization, except for the 0 minimum standard deviation requirement, which is the classic pairs trading method. Based on the performance statistics of these parameterizations, I concluded that using a minimum volatility requirement of 0.007 was the optimal one on a risk-adjusted basis. It yields an average excess return per trading periods (four weeks) of 1,08% with a standard deviation of 3,49%, these results being statistically significant at the 1% significance level and even at lower significance level. Given so, my analysis concluded that pairs trading using exchange-traded funds yield positive excess return.

Then, I compared these results to those of the S&P500 to know if the strategy outperformed the S&P500 and so, generate more return than investing in an ETF tracking the S&P500. My analysis showed that the strategy outperformed the benchmark over the 10 year back testing period. However, most of the return were produced during the 2008 financial crisis and the strategy outperformed the benchmark only 4 years out of the 10. The strategy yields on average 53 basis points more than the S&P500, but these results are not statistically significant at the 1% significance level, being significant only at the 10% significance level. So I cannot conclude that the strategy yields higher return than the S&P500.

I finished with a third hypothesis, assuming that the strategy would yield a higher risk-adjusted return when combining it with an ETF tracking the S&P500, increasing its diversification and counterbalancing its low profitability during good market conditions. I tested 9 different allocations and found the optimal allocation on a risk-adjusted basis. The investors would then allocate 80% to the strategy and 20% to the ETF S&P500 of his choice. By doing so, the risk adjusted return increased from 0.579 to 0.591, based on the Sortino-Satchel ratio. However, these results are not statistically significant at the 1% significance level, being significant only at the 15% level. Then, I cannot conclude that diversification using an ETF S&P500 increases the risk-adjusted return.

Based on these analyses, it is clear that pairs trading with ETF is a profitable strategy over the long run and especially during turbulent market conditions. However, its profitability indeed decreased these last years while still remaining positive. Given that, for an investor that is pessimistic about the future of the market, it can be a great opportunity to implement pairs trading using ETFs. Indeed, by implementing this strategy, an investor faces small risk of losses by assuming low profitability, but can expect really high returns when everybody will lose their money. Furthermore, my algorithm does not allow to open a pair if it has been closed the same day, which bias the profitability of the strategy downward and could allow for even more profit in real-life application.

Finally, I chose one optimal Parameterization in this thesis and made an analysis of its profitability and its correlation with VIX and S&P500 during different periods. However, each parameterization could be the optimal one, depending of the year. My correlation analysis with the S&P500 and the VIX hasn’t shown any link, even if it’s clear that the strategy works better during turbulent market conditions and so, high volatility period. This part of the profitability then remains unsolved, and could be an interesting subject for further researches. Moreover, as I used end-of-day data, I had to use the two-standard deviation trigger. But, I saw that pairs often fluctuate more than two standard deviations. An implementation with intraday data could then allow to increase the trigger to more than two standard deviations, offering potentially higher profit. Then, making these analysis using intraday data could also be interesting for further researches.

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APPENDICES

Table 16: ETFs in the universe 1 (2006-2008)

Name	Expense Ratio(Daily)	Bid-ask spread	Picked in pair	Geo Focus	Stock exchange	Underlying assets
Consumer Discretionary Select	0,00036%	0,01138%	1	U.S.	NYSE Arca	Consumer Discretionary
Consumer Staples Select Sector	0,00036%	0,01832%	9	U.S.	NYSE Arca	Consumer Staples
Daiwa ETF-TOPIX	0,00029%	0,06684%	1	Japan	Tokyo	Large-cap
Energy Select Sector SPDR Fund	0,00036%	0,01563%	4	U.S.	NYSE Arca	Energy
Financial Select Sector SPDR F	0,00036%	0,04070%	10	U.S.	NYSE Arca	Financial
Guggenheim S&P 500 Equal Weigh	0,00094%	0,05870%	3	U.S.	NYSE Arca	Large-cap
Health Care Select Sector SPDR	0,00036%	0,01273%	8	U.S.	NYSE Arca	Health Care
Industrial Select Sector SPDR	0,00036%	0,01490%	2	U.S.	NYSE Arca	Industrials
iShares Cohen & Steers REIT ET	0,00083%	0,06033%	5	U.S.	NYSE Arca	Real Estate
iShares Core FTSE 100 UCITS ET	0,00019%	0,02965%	7	U.K.	London	United Kingdom
iShares Core S&P 500 ETF	0,00011%	0,00720%	0	U.S.	NYSE Arca	Large-cap
iShares Core S&P 500 Index ETF	0,00026%	0,04103%	8	U.S.	Toronto	US
iShares Core S&P Mid-Cap ETF	0,00019%	0,01489%	1	U.S.	NYSE Arca	Mid-cap
iShares Core S&P Small-Cap ETF	0,00019%	0,01583%	6	U.S.	NYSE Arca	Small-cap
iShares Core S&P Total US Stoc	0,00008%	0,04136%	2	U.S.	NYSE Arca	Broad Market
iShares Core S&P U.S. Growth E	0,00014%	0,09079%	6	U.S.	NYSE Arca	Broad Market
iShares Core S&P U.S. Value ET	0,00014%	0,10101%	4	U.S.	NYSE Arca	Broad Market
iShares Core S&P/TSX Capped Co	0,00016%	0,09167%	4	Canada	Toronto	Broad Market
iShares FTSE 250 UCITS ETF GBP	0,00094%	0,11054%	2	U.K.	London	United Kingdom
iShares MSCI EAFE ETF	0,00079%	0,01552%	8	International	NYSE Arca	International
iShares NAFTRAC ISHRS	0,00062%	0,06990%	0	Mexico	Mexico	Large-cap
iShares Russell 1000 ETF	0,00039%	0,01015%	1	U.S.	NYSE Arca	Large-cap
iShares Russell 1000 Growth ET	0,00051%	0,00917%	3	U.S.	NYSE Arca	Large-cap
iShares Russell 1000 Value ETF	0,00051%	0,00889%	2	U.S.	NYSE Arca	Large-cap
iShares Russell 2000 ETF	0,00051%	0,00746%	1	U.S.	NYSE Arca	Small-cap
iShares Russell 2000 Growth ET	0,00062%	0,05388%	4	U.S.	NYSE Arca	Small-cap
iShares Russell 2000 Value ETF	0,00062%	0,03968%	5	U.S.	NYSE Arca	Small-cap
iShares Russell 3000 ETF	0,00051%	0,02950%	3	U.S.	NYSE Arca	Broad Market
iShares Russell Mid-Cap ETF	0,00051%	0,03656%	3	U.S.	NYSE Arca	Mid-cap
iShares Russell Mid-Cap Growth	0,00062%	0,05178%	3	U.S.	NYSE Arca	Mid-cap
iShares Russell Mid-Cap Value	0,00062%	0,04137%	4	U.S.	NYSE Arca	Mid-cap
iShares S&P 100 ETF	0,00051%	0,01832%	2	U.S.	NYSE Arca	Large-cap
iShares S&P 500 Growth ETF	0,00046%	0,01773%	11	U.S.	NYSE Arca	Large-cap
iShares S&P 500 UCITS ETF USD	0,00019%	0,03609%	1	U.S.	London	US
iShares S&P 500 Value ETF	0,00046%	0,01152%	1	U.S.	NYSE Arca	Large-cap
iShares S&P Mid-Cap 400 Growth	0,00062%	0,06646%	2	U.S.	NYSE Arca	Mid-cap
iShares S&P Mid-Cap 400 Value	0,00062%	0,07278%	3	U.S.	NYSE Arca	Mid-cap
iShares S&P Small-Cap 600 Grow	0,00062%	0,10143%	2	U.S.	NYSE Arca	Small-cap

iShares S&P Small-Cap 600 Valu	0,00062%	0,10200%	8	U.S.	NYSE Arca	Small-cap
iShares S&P/TSX 60 Index ETF	0,00046%	0,05429%	11	Canada	Toronto	Broad Market
iShares Select Dividend ETF	0,00092%	0,01292%	10	U.S.	NYSE Arca	Broad Market
iShares SMI CH	0,00083%	0,04493%	6	Switzerland	SIX Swiss Ex	Large-cap
iShares Transportation Average	0,00099%	0,04953%	4	U.S.	NYSE Arca	Industrials
iShares U.S. Basic Materials E	0,00099%	0,04902%	2	U.S.	NYSE Arca	Materials
iShares U.S. Consumer Services	0,00099%	0,05361%	3	U.S.	NYSE Arca	Consumer Discretionary
iShares U.S. Energy ETF	0,00099%	0,02951%	8	U.S.	NYSE Arca	Energy
iShares U.S. Financial Service	0,00099%	0,04446%	10	U.S.	NYSE Arca	Financial
iShares U.S. Healthcare ETF	0,00099%	0,04259%	7	U.S.	NYSE Arca	Health Care
iShares U.S. Industrials ETF	0,00099%	0,05222%	6	U.S.	NYSE Arca	Industrials
iShares U.S. Real Estate ETF	0,00099%	0,01302%	5	U.S.	NYSE Arca	Real Estate
iShares US Consumer Goods ETF	0,00099%	0,05397%	2	U.S.	NYSE Arca	Consumer Staples
iShares US Financials ETF	0,00099%	0,03562%	8	U.S.	NYSE Arca	Financial
iShares US Technology ETF	0,00099%	0,04095%	2	U.S.	NYSE Arca	Technology
iShares US Telecommunications	0,00099%	0,11225%	7	U.S.	NYSE Arca	Communications Sector
iShares US Utilities ETF	0,00099%	0,05760%	12	U.S.	NYSE Arca	Utilities
Listed Index Fund 225	0,00056%	0,05307%	0	Japan	Tokyo	Large-cap
Listed Index Fund TOPIX	0,00023%	0,06683%	3	Japan	Tokyo	Large-cap
LYXOR CAC 40 DR UCITS ETF	0,00062%	0,04615%	12	France	EN Paris	Large-cap
Lyxor EURO STOXX 50 DR UCITS E	0,00051%	0,04621%	11	Eurozone	EN Paris	Eurozone
Materials Select Sector SPDR F	0,00036%	0,01900%	5	U.S.	NYSE Arca	Materials
Nikkei 225 Exchange Traded Fun	0,00055%	0,05152%	0	Japan	Tokyo	Large-cap
PowerShares QQQ Trust Series 1	0,00051%	0,00734%	10	U.S.	NASDAQ GM	Large-cap
Satrix 40	0,00103%	0,23258%	1	South Africa	Johannesburg	Large-cap
SPDR Dow Jones Industrial Aver	0,00044%	0,00635%	10	U.S.	NYSE Arca	Large-cap
SPDR Dow Jones REIT ETF	0,00062%	0,06192%	6	U.S.	NYSE Arca	Real Estate
SPDR EURO STOXX 50 ETF	0,00071%	0,02605%	7	Eurozone	NYSE Arca	Eurozone
SPDR S&P MidCap 400 ETF Trust	0,00062%	0,01563%	2	U.S.	NYSE Arca	Mid-cap
SPDR S&P/ASX 200 Fund	0,00048%	0,06307%	12	Australia	ASE	Broad Market
SPDR S&P/ASX 200 Listed Proper	0,00094%	0,21434%	5	Australia	ASE	Real Estate
SPDR S&P500 ETF Trust	0,00025%	0,00422%	1	U.S.	NYSE Arca	Large-cap
SPDR Straits Times Index ETF	0,00073%	0,32636%	11	Singapore	Singapore	Large-cap
Technology Select Sector SPDR	0,00036%	0,01833%	5	U.S.	NYSE Arca	Technology
TOPIX Exchange Traded Fund	0,00029%	0,06224%	0	Japan	Tokyo	Large-cap
Tracker Fund of Hong Kong Ltd	0,00026%	0,19601%	10	Hong Kong	Hong Kong	Large-cap
Utilities Select Sector SPDR F	0,00036%	0,01928%	19	U.S.	NYSE Arca	Utilities
Vanguard Consumer Discretionar	0,00026%	0,05076%	2	U.S.	NYSE Arca	Consumer Discretionary
Vanguard Consumer Staples ETF	0,00026%	0,03902%	3	U.S.	NYSE Arca	Consumer Staples
Vanguard Energy ETF	0,00026%	0,05341%	5	U.S.	NYSE Arca	Energy
Vanguard Extended Market ETF	0,00021%	0,08925%	6	U.S.	NYSE Arca	Broad Market
Vanguard Financials ETF	0,00026%	0,01870%	7	U.S.	NYSE Arca	Financial
Vanguard Growth ETF	0,00016%	0,03062%	3	U.S.	NYSE Arca	Large-cap
Vanguard Health Care ETF	0,00026%	0,05283%	6	U.S.	NYSE Arca	Health Care
Vanguard Industrials ETF	0,00026%	0,06553%	7	U.S.	NYSE Arca	Industrials

Vanguard Information Technolog	0,00026%	0,04191%	3	U.S.	NYSE Arca	Technology
Vanguard Large-Cap ETF	0,00016%	0,02402%	2	U.S.	NYSE Arca	Large-cap
Vanguard Materials ETF	0,00026%	0,05634%	4	U.S.	NYSE Arca	Materials
Vanguard Mid-Cap ETF	0,00016%	0,03986%	2	U.S.	NYSE Arca	Mid-cap
Vanguard REIT ETF	0,00031%	0,01277%	3	U.S.	NYSE Arca	Real Estate
Vanguard Small-Cap ETF	0,00016%	0,04206%	4	U.S.	NYSE Arca	Small-cap
Vanguard Small-Cap Growth ETF	0,00019%	0,08736%	9	U.S.	NYSE Arca	Small-cap
Vanguard Small-Cap Value ETF	0,00019%	0,05943%	6	U.S.	NYSE Arca	Small-cap
Vanguard Telecommunication Ser	0,00026%	0,11904%	12	U.S.	NYSE Arca	Communications Sector
Vanguard Total Stock Market ET	0,00011%	0,00844%	4	U.S.	NYSE Arca	Broad Market
Vanguard Utilities ETF	0,00026%	0,04919%	10	U.S.	NYSE Arca	Utilities
Vanguard Value ETF	0,00016%	0,01374%	4	U.S.	NYSE Arca	Large-cap
XACT OMXS30	0,00026%	0,07676%	15	Sweden	Stockholm	Large-cap

Table 17: ETFs in the universe 2 (2008-2011)

Name	Expense Ratio(Daily)	Bid-ask spread	Picked in pair	Geo Focus	Stock exchange	Underlying assets
Accion Ibex 35 ETF FI Cotizado	0,00079%	0,14941%	2	Spain	Soc.Bol SIBE	Large-cap
Amundi ETF CAC 40 UCITS ETF DR	0,00062%	0,06000%	3	France	EN Paris	Large-cap
Consumer Discretionary Select	0,00036%	0,01138%	9	U.S.	NYSE Arca	Consumer Discretionary
Consumer Staples Select Sector	0,00036%	0,01832%	3	U.S.	NYSE Arca	Consumer Staples
Daiwa ETF-TOPIX	0,00029%	0,06684%	13	Japan	Tokyo	Large-cap
Energy Select Sector SPDR Fund	0,00036%	0,01563%	6	U.S.	NYSE Arca	Energy
Financial Select Sector SPDR F	0,00036%	0,04070%	3	U.S.	NYSE Arca	Financial
First Trust Morningstar Divide	0,00103%	0,04102%	15	U.S.	NYSE Arca	Large-cap
Guggenheim S&P 500 Equal Weigh	0,00094%	0,05870%	5	U.S.	NYSE Arca	Financial
Guggenheim S&P 500 Equal Weigh	0,00094%	0,05870%	2	U.S.	NYSE Arca	Technology
Guggenheim S&P 500 Equal Weigh	0,00094%	0,05870%	2	U.S.	NYSE Arca	Large-cap
Guggenheim S&P 500 Pure Growth	0,00083%	0,02710%	4	U.S.	NYSE Arca	Large-cap
Guggenheim S&P 500 Pure Value	0,00083%	0,03151%	1	U.S.	NYSE Arca	Large-cap
Guggenheim S&P Midcap 400 Pure	0,00083%	0,17405%	4	U.S.	NYSE Arca	Mid-cap
Health Care Select Sector SPDR	0,00036%	0,01273%	3	U.S.	NYSE Arca	Health Care
Huatai-PineBridge SSE Dividend	0,00000%	0,04761%	0	China	Shanghai	Broad Market
Industrial Select Sector SPDR	0,00036%	0,01490%	2	U.S.	NYSE Arca	Industrials
iShares Cohen & Steers REIT ET	0,00083%	0,06033%	0	U.S.	NYSE Arca	Real Estate
iShares Core FTSE 100 UCITS ET	0,00019%	0,02965%	9	U.K.	London	United Kingdom
iShares Core S&P 500 ETF	0,00011%	0,00720%	5	U.S.	NYSE Arca	Large-cap
iShares Core S&P 500 Index ETF	0,00026%	0,04103%	7	U.S.	Toronto	US
iShares Core S&P Mid-Cap ETF	0,00019%	0,01489%	0	U.S.	NYSE Arca	Mid-cap
iShares Core S&P Small-Cap ETF	0,00019%	0,01583%	16	U.S.	NYSE Arca	Small-cap
iShares Core S&P Total US Stoc	0,00008%	0,04136%	5	U.S.	NYSE Arca	Broad Market
iShares Core S&P U.S. Growth E	0,00014%	0,09079%	4	U.S.	NYSE Arca	Broad Market
iShares Core S&P U.S. Value ET	0,00014%	0,10101%	4	U.S.	NYSE Arca	Broad Market
iShares Core S&P/TSX Capped Co	0,00016%	0,09167%	5	Canada	Toronto	Broad Market
iShares Euro Dividend UCITS ET	0,00094%	0,14922%	11	Eurozone	London	Eurozone
iShares FTSE 250 UCITS ETF GBP	0,00094%	0,11054%	3	U.K.	London	United Kingdom
iShares MSCI EAFE ETF	0,00079%	0,01552%	7	International	NYSE Arca	International
iShares MSCI EAFE Growth ETF	0,00094%	0,16379%	5	International	NYSE Arca	International
iShares MSCI EAFE Value ETF	0,00094%	0,07385%	7	International	NYSE Arca	International
iShares MSCI Europe ex-UK UCIT	0,00094%	0,10524%	4	European Reg. ex UK	London	European Reg. ex UK

iShares NAFTRAC ISHRS	0,00062%	0,06990%	1	Mexico	Mexico	Large-cap
iShares Russell 1000 ETF	0,00039%	0,01015%	5	U.S.	NYSE Arca	Large-cap
iShares Russell 1000 Growth ET	0,00051%	0,00917%	3	U.S.	NYSE Arca	Large-cap
iShares Russell 1000 Value ETF	0,00051%	0,00889%	4	U.S.	NYSE Arca	Large-cap
iShares Russell 2000 ETF	0,00051%	0,00746%	10	U.S.	NYSE Arca	Small-cap
iShares Russell 2000 Growth ET	0,00062%	0,05388%	4	U.S.	NYSE Arca	Small-cap
iShares Russell 2000 Value ETF	0,00062%	0,03968%	10	U.S.	NYSE Arca	Small-cap
iShares Russell 3000 ETF	0,00051%	0,02950%	10	U.S.	NYSE Arca	Broad Market
iShares Russell Mid-Cap ETF	0,00051%	0,03656%	7	U.S.	NYSE Arca	Mid-cap
iShares Russell Mid-Cap Growth	0,00062%	0,05178%	3	U.S.	NYSE Arca	Mid-cap
iShares Russell Mid-Cap Value	0,00062%	0,04137%	7	U.S.	NYSE Arca	Mid-cap
iShares S&P 100 ETF	0,00051%	0,01832%	2	U.S.	NYSE Arca	Large-cap
iShares S&P 500 Growth ETF	0,00046%	0,01773%	2	U.S.	NYSE Arca	Large-cap
iShares S&P 500 UCITS ETF USD	0,00019%	0,03609%	5	U.S.	London	US
iShares S&P 500 Value ETF	0,00046%	0,01152%	4	U.S.	NYSE Arca	Large-cap
iShares S&P Mid-Cap 400 Growth	0,00062%	0,06646%	10	U.S.	NYSE Arca	Mid-cap
iShares S&P Mid-Cap 400 Value	0,00062%	0,07278%	1	U.S.	NYSE Arca	Mid-cap
iShares S&P Small-Cap 600 Grow	0,00062%	0,10143%	20	U.S.	NYSE Arca	Small-cap
iShares S&P Small-Cap 600 Valu	0,00062%	0,10200%	12	U.S.	NYSE Arca	Small-cap
iShares S&P/TSX 60 Index ETF	0,00046%	0,05429%	4	Canada	Toronto	Broad Market
iShares Select Dividend ETF	0,00092%	0,01292%	6	U.S.	NYSE Arca	Broad Market
iShares SMI CH	0,00083%	0,04493%	13	Switzerland	SIX Swiss Ex	Large-cap
iShares Transportation Average	0,00099%	0,04953%	11	U.S.	NYSE Arca	Industrials
iShares U.S. Basic Materials E	0,00099%	0,04902%	4	U.S.	NYSE Arca	Materials
iShares U.S. Consumer Services	0,00099%	0,05361%	8	U.S.	NYSE Arca	Consumer Discretionary
iShares U.S. Energy ETF	0,00099%	0,02951%	19	U.S.	NYSE Arca	Energy
iShares U.S. Financial Service	0,00099%	0,04446%	7	U.S.	NYSE Arca	Financial
iShares U.S. Healthcare ETF	0,00099%	0,04259%	4	U.S.	NYSE Arca	Health Care
iShares U.S. Home Construction	0,00099%	0,03044%	6	U.S.	NYSE Arca	Consumer Discretionary
iShares U.S. Industrials ETF	0,00099%	0,05222%	3	U.S.	NYSE Arca	Industrials
iShares U.S. Medical Devices E	0,00099%	0,06152%	9	U.S.	NYSE Arca	Health Care
iShares U.S. Oil & Gas Explora	0,00099%	0,07895%	8	U.S.	NYSE Arca	Energy
iShares U.S. Oil Equipment & S	0,00099%	0,14536%	2	U.S.	NYSE Arca	Energy
iShares U.S. Real Estate ETF	0,00099%	0,01302%	4	U.S.	NYSE Arca	Real Estate
iShares UK Dividend UCITS ETF	0,00094%	0,15053%	11	U.K.	London	United Kingdom
iShares US Aerospace & Defense	0,00099%	0,07659%	5	U.S.	NYSE Arca	Industrials
iShares US Consumer Goods ETF	0,00099%	0,05397%	7	U.S.	NYSE Arca	Consumer Staples
iShares US Financials ETF	0,00099%	0,03562%	4	U.S.	NYSE Arca	Financial
iShares US Regional Banks ETF	0,00099%	0,05227%	7	U.S.	NYSE Arca	Financial
iShares US Technology ETF	0,00099%	0,04095%	3	U.S.	NYSE Arca	Technology
iShares US Telecommunications	0,00099%	0,11225%	1	U.S.	NYSE Arca	Communications Sector

iShares US Utilities ETF	0,00099%	0,05760%	3	U.S.	NYSE Arca	Utilities
Listed Index Fund 225	0,00056%	0,05307%	12	Japan	Tokyo	Large-cap
Listed Index Fund TOPIX	0,00023%	0,06683%	11	Japan	Tokyo	Large-cap
LYXOR CAC 40 DR UCITS ETF	0,00062%	0,04615%	6	France	EN Paris	Large-cap
Lyxor EURO STOXX 50 DR UCITS E	0,00051%	0,04621%	6	Eurozone	EN Paris	Eurozone
Materials Select Sector SPDR F	0,00036%	0,01900%	3	U.S.	NYSE Arca	Materials
Nikkei 225 Exchange Traded Fun	0,00055%	0,05152%	11	Japan	Tokyo	Large-cap
Powershares FTSE RAFI US 1000	0,00092%	0,05043%	5	U.S.	NYSE Arca	Large-cap
PowerShares QQQ Trust Series 1	0,00051%	0,00734%	3	U.S.	NASDAQ GM	Large-cap
PowerShares S&P 500 Quality Po	0,00071%	0,05184%	3	U.S.	NYSE Arca	Large-cap
Psagot Sal TA Banks	0,00103%	0,13168%	2	Israel	Tel Aviv	Financial
Satrix 40	0,00103%	0,23258%	3	South Africa	Johannesburg	Large-cap
SPDR Dow Jones Industrial Aver	0,00044%	0,00635%	1	U.S.	NYSE Arca	Large-cap
SPDR Dow Jones REIT ETF	0,00062%	0,06192%	3	U.S.	NYSE Arca	Real Estate
SPDR EURO STOXX 50 ETF	0,00071%	0,02605%	4	Eurozone	NYSE Arca	Eurozone
SPDR MSCI ACWI ex-US ETF	0,00073%	0,08678%	7	International	NYSE Arca	International
SPDR S&P Bank ETF	0,00083%	0,02453%	2	U.S.	NYSE Arca	Financial
SPDR S&P Biotech ETF	0,00083%	0,04407%	3	U.S.	NYSE Arca	Health Care
SPDR S&P Dividend ETF	0,00083%	0,04289%	8	U.S.	NYSE Arca	Large-cap
SPDR S&P Homebuilders ETF	0,00083%	0,02714%	29	U.S.	NYSE Arca	Consumer Discretionary
SPDR S&P Insurance ETF	0,00083%	0,06496%	8	U.S.	NYSE Arca	Financial
SPDR S&P Metals & Mining ETF	0,00083%	0,03518%	2	U.S.	NYSE Arca	Materials
SPDR S&P MidCap 400 ETF Trust	0,00062%	0,01563%	2	U.S.	NYSE Arca	Mid-cap
SPDR S&P Oil & Gas Equipment &	0,00083%	0,10387%	3	U.S.	NYSE Arca	Energy
SPDR S&P Oil & Gas Exploration	0,00083%	0,03197%	7	U.S.	NYSE Arca	Energy
SPDR S&P Pharmaceuticals ETF	0,00083%	0,11762%	5	U.S.	NYSE Arca	Health Care
SPDR S&P Regional Banking ETF	0,00083%	0,01909%	2	U.S.	NYSE Arca	Financial
SPDR S&P Retail ETF	0,00083%	0,02685%	8	U.S.	NYSE Arca	Consumer Discretionary
SPDR S&P Semiconductor ETF	0,00083%	0,09310%	2	U.S.	NYSE Arca	Technology
SPDR S&P/ASX 200 Fund	0,00048%	0,06307%	1	Australia	ASE	Broad Market
SPDR S&P/ASX 200 Listed Proper	0,00094%	0,21434%	2	Australia	ASE	Real Estate
SPDR S&P500 ETF Trust	0,00025%	0,00422%	3	U.S.	NYSE Arca	Large-cap
SPDR Straits Times Index ETF	0,00073%	0,32636%	1	Singapore	Singapore	Large-cap
Technology Select Sector SPDR	0,00036%	0,01833%	1	U.S.	NYSE Arca	Technology
TOPIX Exchange Traded Fund	0,00029%	0,06224%	10	Japan	Tokyo	Large-cap
Tracker Fund of Hong Kong Ltd	0,00026%	0,19601%	3	Hong Kong	Hong Kong	Large-cap
Utilities Select Sector SPDR F	0,00036%	0,01928%	2	U.S.	NYSE Arca	Utilities
Vanguard Consumer Discretionar	0,00026%	0,05076%	7	U.S.	NYSE Arca	Consumer Discretionary
Vanguard Consumer Staples ETF	0,00026%	0,03902%	5	U.S.	NYSE Arca	Consumer Staples
Vanguard Dividend Appreciation	0,00021%	0,01545%	7	U.S.	NYSE Arca	Large-cap
Vanguard Energy ETF	0,00026%	0,05341%	7	U.S.	NYSE Arca	Energy

Vanguard Extended Market ETF	0,00021%	0,08925%	7	U.S.	NYSE Arca	Broad Market
Vanguard Financials ETF	0,00026%	0,01870%	8	U.S.	NYSE Arca	Financial
Vanguard FTSE Emerging Markets	0,00062%	0,19988%	2	International	NYSE Arca	Emerging Markets
Vanguard FTSE Europe ETF	0,00026%	0,01823%	4	European Region	NYSE Arca	European Region
Vanguard FTSE Pacific ETF	0,00026%	0,02484%	15	Asian Pacific Region	NYSE Arca	Asian Pacific Region
Vanguard Growth ETF	0,00016%	0,03062%	4	U.S.	NYSE Arca	Large-cap
Vanguard Health Care ETF	0,00026%	0,05283%	7	U.S.	NYSE Arca	Health Care
Vanguard High Dividend Yield E	0,00021%	0,01508%	4	U.S.	NYSE Arca	Large-cap
Vanguard Industrials ETF	0,00026%	0,06553%	3	U.S.	NYSE Arca	Industrials
Vanguard Information Technolog	0,00026%	0,04191%	2	U.S.	NYSE Arca	Technology
Vanguard Large-Cap ETF	0,00016%	0,02402%	5	U.S.	NYSE Arca	Large-cap
Vanguard Materials ETF	0,00026%	0,05634%	6	U.S.	NYSE Arca	Materials
Vanguard Mid-Cap ETF	0,00016%	0,03986%	0	U.S.	NYSE Arca	Mid-cap
Vanguard Mid-Cap Growth ETF	0,00019%	0,04540%	2	U.S.	NYSE Arca	Mid-cap
Vanguard Mid-Cap Value ETF	0,00019%	0,04513%	5	U.S.	NYSE Arca	Mid-cap
Vanguard REIT ETF	0,00031%	0,01277%	4	U.S.	NYSE Arca	Real Estate
Vanguard Small-Cap ETF	0,00016%	0,04206%	7	U.S.	NYSE Arca	Small-cap
Vanguard Small-Cap Growth ETF	0,00019%	0,08736%	11	U.S.	NYSE Arca	Small-cap
Vanguard Small-Cap Value ETF	0,00019%	0,05943%	10	U.S.	NYSE Arca	Small-cap
Vanguard Telecommunication Ser	0,00026%	0,11904%	1	U.S.	NYSE Arca	Communications Sector
Vanguard Total Stock Market ET	0,00011%	0,00844%	6	U.S.	NYSE Arca	Broad Market
Vanguard Utilities ETF	0,00026%	0,04919%	0	U.S.	NYSE Arca	Utilities
Vanguard Value ETF	0,00016%	0,01374%	2	U.S.	NYSE Arca	Large-cap
WisdomTree US LargeCap Dividen	0,00069%	0,03594%	3	U.S.	NYSE Arca	Large-cap
WisdomTree US MidCap Dividend	0,00090%	0,08553%	4	U.S.	NYSE Arca	Mid-cap
WisdomTree US SmallCap Dividen	0,00090%	0,15452%	3	U.S.	NYSE Arca	Small-cap
XACT OMXS30	0,00026%	0,07676%	7	Sweden	Stockholm	Large-cap

Table 18: ETF in the universe 3 (2011-2017)

Name	Expense Ratio(Daily)	Bid-ask spread	Picked in pair	Geo Focus	Stock exchange	Underlying assets
Accion Ibex 35 ETF FI Cotizado	0,00079%	0,14941%	8	Spain	Soc.Bol SIBE	Large-cap
Amundi ETF CAC 40 UCITS ETF DR	0,00062%	0,06000%	7	France	EN Paris	Large-cap
BMO MSCI EAFE Hedged to CAD In	0,00058%	0,31063%	5	International	Toronto	International
BMO S&P 500 Hedged to CAD Inde	0,00029%	0,04900%	14	U.S.	Toronto	US
BMO S&P/TSX Capped Composite I	0,00016%	0,09865%	18	Canada	Toronto	Broad Market
Consumer Discretionary Select	0,00036%	0,01138%	8	U.S.	NYSE Arca	Consumer Discretionary
Consumer Staples Select Sector	0,00036%	0,01832%	14	U.S.	NYSE Arca	Consumer Staples
Daiwa ETF-TOPIX	0,00029%	0,06684%	20	Japan	Tokyo	Large-cap
Energy Select Sector SPDR Fund	0,00036%	0,01563%	5	U.S.	NYSE Arca	Energy
Financial Select Sector SPDR F	0,00036%	0,04070%	5	U.S.	NYSE Arca	Financial
First Trust Morningstar Divide	0,00103%	0,04102%	6	U.S.	NYSE Arca	Large-cap
Guggenheim S&P 500 Equal Weigh	0,00094%	0,05870%	17	U.S.	NYSE Arca	Financial
Guggenheim S&P 500 Equal Weigh	0,00094%	0,05870%	9	U.S.	NYSE Arca	Technology
Guggenheim S&P 500 Equal Weigh	0,00094%	0,05870%	2	U.S.	NYSE Arca	Large-cap
Guggenheim S&P 500 Pure Growth	0,00083%	0,02710%	7	U.S.	NYSE Arca	Large-cap
Guggenheim S&P 500 Pure Value	0,00083%	0,03151%	21	U.S.	NYSE Arca	Large-cap
Guggenheim S&P Midcap 400 Pure	0,00083%	0,17405%	21	U.S.	NYSE Arca	Mid-cap
Health Care Select Sector SPDR	0,00036%	0,01273%	14	U.S.	NYSE Arca	Health Care
Huatai-PineBridge SSE Dividend	0,00000%	0,04761%	8	China	Shanghai	Broad Market
Industrial Select Sector SPDR	0,00036%	0,01490%	12	U.S.	NYSE Arca	Industrials
iShares Cohen & Steers REIT ET	0,00083%	0,06033%	11	U.S.	NYSE Arca	Real Estate
iShares Core FTSE 100 UCITS ET	0,00019%	0,02965%	7	U.K.	London	United Kingdom
iShares Core MSCI Japan IMI UC	0,00051%	0,13442%	17	Japan	London	Japan
iShares Core S&P 500 ETF	0,00011%	0,00720%	1	U.S.	NYSE Arca	Large-cap
iShares Core S&P 500 Index ETF	0,00026%	0,04103%	13	U.S.	Toronto	US
iShares Core S&P Mid-Cap ETF	0,00019%	0,01489%	6	U.S.	NYSE Arca	Mid-cap
iShares Core S&P Small-Cap ETF	0,00019%	0,01583%	10	U.S.	NYSE Arca	Small-cap
iShares Core S&P Total US Stoc	0,00008%	0,04136%	3	U.S.	NYSE Arca	Broad Market
iShares Core S&P U.S. Growth E	0,00014%	0,09079%	4	U.S.	NYSE Arca	Broad Market
iShares Core S&P U.S. Value ET	0,00014%	0,10101%	3	U.S.	NYSE Arca	Broad Market
iShares Core S&P/TSX Capped Co	0,00016%	0,09167%	8	Canada	Toronto	Broad Market
iShares Euro Dividend UCITS ET	0,00094%	0,14922%	9	Eurozone	London	Eurozone
iShares FTSE 250 UCITS ETF GBP	0,00094%	0,11054%	27	U.K.	London	United Kingdom
iShares MSCI EAFE ETF	0,00079%	0,01552%	6	International	NYSE Arca	International
iShares MSCI EAFE Growth ETF	0,00094%	0,16379%	13	International	NYSE Arca	International
iShares MSCI EAFE Value ETF	0,00094%	0,07385%	3	International	NYSE Arca	International

iShares MSCI Europe ex-UK UCIT	0,00094%	0,10524%	9	European Reg. ex UK	London	European Reg. ex UK
iShares MSCI Europe UCITS ETF	0,00083%	0,07843%	4	European Region	London	European Region
iShares NAFTRAC ISHRS	0,00062%	0,06990%	12	Mexico	Mexico	Large-cap
iShares Russell 1000 ETF	0,00039%	0,01015%	2	U.S.	NYSE Arca	Large-cap
iShares Russell 1000 Growth ET	0,00051%	0,00917%	2	U.S.	NYSE Arca	Large-cap
iShares Russell 1000 Value ETF	0,00051%	0,00889%	5	U.S.	NYSE Arca	Large-cap
iShares Russell 2000 ETF	0,00051%	0,00746%	17	U.S.	NYSE Arca	Small-cap
iShares Russell 2000 Growth ET	0,00062%	0,05388%	11	U.S.	NYSE Arca	Small-cap
iShares Russell 2000 Value ETF	0,00062%	0,03968%	13	U.S.	NYSE Arca	Small-cap
iShares Russell 3000 ETF	0,00051%	0,02950%	1	U.S.	NYSE Arca	Broad Market
iShares Russell Mid-Cap ETF	0,00051%	0,03656%	2	U.S.	NYSE Arca	Mid-cap
iShares Russell Mid-Cap Growth	0,00062%	0,05178%	2	U.S.	NYSE Arca	Mid-cap
iShares Russell Mid-Cap Value	0,00062%	0,04137%	7	U.S.	NYSE Arca	Mid-cap
iShares Russell Top 200 Growth	0,00051%	0,14711%	5	U.S.	NYSE Arca	Large-cap
iShares S&P 100 ETF	0,00051%	0,01832%	3	U.S.	NYSE Arca	Large-cap
iShares S&P 500 Growth ETF	0,00046%	0,01773%	4	U.S.	NYSE Arca	Large-cap
iShares S&P 500 UCITS ETF USD	0,00019%	0,03609%	4	U.S.	London	US
iShares S&P 500 Value ETF	0,00046%	0,01152%	4	U.S.	NYSE Arca	Large-cap
iShares S&P Mid-Cap 400 Growth	0,00062%	0,06646%	7	U.S.	NYSE Arca	Mid-cap
iShares S&P Mid-Cap 400 Value	0,00062%	0,07278%	6	U.S.	NYSE Arca	Mid-cap
iShares S&P Small Cap 600 UCIT	0,00094%	0,30269%	10	U.S.	London	US
iShares S&P Small-Cap 600 Grow	0,00062%	0,10143%	11	U.S.	NYSE Arca	Small-cap
iShares S&P Small-Cap 600 Valu	0,00062%	0,10200%	9	U.S.	NYSE Arca	Small-cap
iShares S&P/TSX 60 Index ETF	0,00046%	0,05429%	16	Canada	Toronto	Broad Market
iShares Select Dividend ETF	0,00092%	0,01292%	5	U.S.	NYSE Arca	Broad Market
iShares SMI CH	0,00083%	0,04493%	16	Switzerland	SIX Swiss Ex	Large-cap
iShares Transportation Average	0,00099%	0,04953%	18	U.S.	NYSE Arca	Industrials
iShares U.S. Basic Materials E	0,00099%	0,04902%	13	U.S.	NYSE Arca	Materials
iShares U.S. Consumer Services	0,00099%	0,05361%	6	U.S.	NYSE Arca	Consumer Discretionary
iShares U.S. Energy ETF	0,00099%	0,02951%	9	U.S.	NYSE Arca	Energy
iShares U.S. Financial Service	0,00099%	0,04446%	6	U.S.	NYSE Arca	Financial
iShares U.S. Healthcare ETF	0,00099%	0,04259%	10	U.S.	NYSE Arca	Health Care
iShares U.S. Home Construction	0,00099%	0,03044%	3	U.S.	NYSE Arca	Consumer Discretionary
iShares U.S. Industrials ETF	0,00099%	0,05222%	9	U.S.	NYSE Arca	Industrials
iShares U.S. Medical Devices E	0,00099%	0,06152%	10	U.S.	NYSE Arca	Health Care
iShares U.S. Oil & Gas Explora	0,00099%	0,07895%	10	U.S.	NYSE Arca	Energy
iShares U.S. Oil Equipment & S	0,00099%	0,14536%	12	U.S.	NYSE Arca	Energy
iShares U.S. Real Estate ETF	0,00099%	0,01302%	20	U.S.	NYSE Arca	Real Estate
iShares U.S. Small Cap Index E	0,00085%	0,04420%	10	U.S.	Toronto	US
iShares UK Dividend UCITS ETF	0,00094%	0,15053%	6	U.K.	London	United Kingdom

iShares UK Property UCITS ETF	0,00094%	0,18422%	24	U.K.	London	Real Estate
iShares US Aerospace & Defense	0,00099%	0,07659%	11	U.S.	NYSE Arca	Industrials
iShares US Consumer Goods ETF	0,00099%	0,05397%	12	U.S.	NYSE Arca	Consumer Staples
iShares US Financials ETF	0,00099%	0,03562%	5	U.S.	NYSE Arca	Financial
iShares US Regional Banks ETF	0,00099%	0,05227%	20	U.S.	NYSE Arca	Financial
iShares US Technology ETF	0,00099%	0,04095%	13	U.S.	NYSE Arca	Technology
iShares US Telecommunications	0,00099%	0,11225%	11	U.S.	NYSE Arca	Communications Sector
iShares US Utilities ETF	0,00099%	0,05760%	13	U.S.	NYSE Arca	Utilities
Listed Index Fund 225	0,00056%	0,05307%	20	Japan	Tokyo	Large-cap
Listed Index Fund TOPIX	0,00023%	0,06683%	20	Japan	Tokyo	Large-cap
LYXOR CAC 40 DR UCITS ETF	0,00062%	0,04615%	10	France	EN Paris	Large-cap
Lyxor EURO STOXX 50 DR UCITS E	0,00051%	0,04621%	9	Eurozone	EN Paris	Eurozone
Materials Select Sector SPDR F	0,00036%	0,01900%	7	U.S.	NYSE Arca	Materials
MAXIS TOPIX ETF	0,00021%	0,06721%	16	Japan	Tokyo	Large-cap
Nikkei 225 Exchange Traded Fun	0,00055%	0,05152%	19	Japan	Tokyo	Large-cap
Nikko AM Singapore STI ETF	0,00083%	0,33131%	9	Singapore	Singapore	Large-cap
Oppenheimer Large Cap Revenue	0,00092%	0,13894%	2	U.S.	NYSE Arca	Large-cap
PowerShares FTSE RAFI Develope	0,00103%	0,20522%	3	International	NYSE Arca	International
Powershares FTSE RAFI US 1000	0,00092%	0,05043%	3	U.S.	NYSE Arca	Large-cap
PowerShares QQQ Trust Series 1	0,00051%	0,00734%	16	U.S.	NASDAQ GM	Large-cap
PowerShares S&P 500 Quality Po	0,00071%	0,05184%	9	U.S.	NYSE Arca	Large-cap
Psagot Sal TA Banks	0,00103%	0,13168%	5	Israel	Tel Aviv	Financial
Satrix 40	0,00103%	0,23258%	11	South Africa	Johannesburg	Large-cap
Schwab International Equity ET	0,00016%	0,03433%	13	International	NYSE Arca	International
Schwab U.S. Large-Cap Growth E	0,00011%	0,04580%	5	U.S.	NYSE Arca	Large-cap
Schwab U.S. Large-Cap Value ET	0,00011%	0,03810%	3	U.S.	NYSE Arca	Large-cap
Schwab US Broad Market ETF	0,00008%	0,03126%	2	U.S.	NYSE Arca	Broad Market
Schwab US Large-Cap ETF	0,00008%	0,02495%	1	U.S.	NYSE Arca	Large-cap
Schwab US Small-Cap ETF	0,00014%	0,05698%	12	U.S.	NYSE Arca	Small-cap
SPDR Dow Jones Industrial Aver	0,00044%	0,00635%	3	U.S.	NYSE Arca	Large-cap
SPDR Dow Jones REIT ETF	0,00062%	0,06192%	15	U.S.	NYSE Arca	Real Estate
SPDR EURO STOXX 50 ETF	0,00071%	0,02605%	8	Eurozone	NYSE Arca	Eurozone
SPDR MSCI ACWI ex-US ETF	0,00073%	0,08678%	4	International	NYSE Arca	International
SPDR S&P Bank ETF	0,00083%	0,02453%	14	U.S.	NYSE Arca	Financial
SPDR S&P Biotech ETF	0,00083%	0,04407%	18	U.S.	NYSE Arca	Health Care
SPDR S&P Dividend ETF	0,00083%	0,04289%	5	U.S.	NYSE Arca	Large-cap
SPDR S&P Homebuilders ETF	0,00083%	0,02714%	18	U.S.	NYSE Arca	Consumer Discretionary
SPDR S&P Insurance ETF	0,00083%	0,06496%	27	U.S.	NYSE Arca	Financial
SPDR S&P International Dividen	0,00103%	0,29670%	2	International	NYSE Arca	International

SPDR S&P International Health	0,00094%	0,28744%	3	International	#N/A Field Not Applicable	Health Care
SPDR S&P Metals & Mining ETF	0,00083%	0,03518%	3	U.S.	NYSE Arca	Materials
SPDR S&P MidCap 400 ETF Trust	0,00062%	0,01563%	6	U.S.	NYSE Arca	Mid-cap
SPDR S&P Oil & Gas Equipment &	0,00083%	0,10387%	16	U.S.	NYSE Arca	Energy
SPDR S&P Oil & Gas Exploration	0,00083%	0,03197%	17	U.S.	NYSE Arca	Energy
SPDR S&P Pharmaceuticals ETF	0,00083%	0,11762%	7	U.S.	NYSE Arca	Health Care
SPDR S&P Regional Banking ETF	0,00083%	0,01909%	22	U.S.	NYSE Arca	Financial
SPDR S&P Retail ETF	0,00083%	0,02685%	15	U.S.	NYSE Arca	Consumer Discretionary
SPDR S&P Semiconductor ETF	0,00083%	0,09310%	29	U.S.	NYSE Arca	Technology
SPDR S&P/ASX 200 Fund	0,00048%	0,06307%	10	Australia	ASE	Broad Market
SPDR S&P/ASX 200 Listed Proper	0,00094%	0,21434%	11	Australia	ASE	Real Estate
SPDR S&P500 ETF Trust	0,00025%	0,00422%	1	U.S.	NYSE Arca	Large-cap
SPDR Straits Times Index ETF	0,00073%	0,32636%	8	Singapore	Singapore	Large-cap
Technology Select Sector SPDR	0,00036%	0,01833%	13	U.S.	NYSE Arca	Technology
TOPIX Exchange Traded Fund	0,00029%	0,06224%	21	Japan	Tokyo	Large-cap
Tracker Fund of Hong Kong Ltd	0,00026%	0,19601%	8	Hong Kong	Hong Kong	Large-cap
Utilities Select Sector SPDR F	0,00036%	0,01928%	6	U.S.	NYSE Arca	Utilities
Vanguard Australian Shares Ind	0,00036%	0,07306%	7	Australia	ASE	Broad Market
Vanguard Consumer Discretionar	0,00026%	0,05076%	4	U.S.	NYSE Arca	Consumer Discretionary
Vanguard Consumer Staples ETF	0,00026%	0,03902%	8	U.S.	NYSE Arca	Consumer Staples
Vanguard Dividend Appreciation	0,00021%	0,01545%	7	U.S.	NYSE Arca	Large-cap
Vanguard Energy ETF	0,00026%	0,05341%	8	U.S.	NYSE Arca	Energy
Vanguard Extended Market ETF	0,00021%	0,08925%	13	U.S.	NYSE Arca	Broad Market
Vanguard Financials ETF	0,00026%	0,01870%	16	U.S.	NYSE Arca	Financial
Vanguard FTSE All-World ex-US	0,00029%	0,02062%	2	International	NYSE Arca	International
Vanguard FTSE Developed Market	0,00019%	0,02432%	6	International	NYSE Arca	International
Vanguard FTSE Emerging Markets	0,00062%	0,19988%	9	International	NYSE Arca	Emerging Markets
Vanguard FTSE Europe ETF	0,00026%	0,01823%	10	European Region	NYSE Arca	European Region
Vanguard FTSE Pacific ETF	0,00026%	0,02484%	6	Asian Pacific Region	NYSE Arca	Asian Pacific Region
Vanguard Growth ETF	0,00016%	0,03062%	6	U.S.	NYSE Arca	Large-cap
Vanguard Health Care ETF	0,00026%	0,05283%	8	U.S.	NYSE Arca	Health Care
Vanguard High Dividend Yield E	0,00021%	0,01508%	4	U.S.	NYSE Arca	Large-cap
Vanguard Industrials ETF	0,00026%	0,06553%	9	U.S.	NYSE Arca	Industrials
Vanguard Information Technolog	0,00026%	0,04191%	10	U.S.	NYSE Arca	Technology
Vanguard Large-Cap ETF	0,00016%	0,02402%	1	U.S.	NYSE Arca	Large-cap
Vanguard Materials ETF	0,00026%	0,05634%	11	U.S.	NYSE Arca	Materials

Vanguard Mega Cap Growth ETF	0,00019%	0,04363%	8	U.S.	NYSE Arca	Large-cap
Vanguard Mega Cap Value ETF	0,00019%	0,08303%	9	U.S.	NYSE Arca	Large-cap
Vanguard Mid-Cap ETF	0,00016%	0,03986%	2	U.S.	NYSE Arca	Mid-cap
Vanguard Mid-Cap Growth ETF	0,00019%	0,04540%	6	U.S.	NYSE Arca	Mid-cap
Vanguard Mid-Cap Value ETF	0,00019%	0,04513%	2	U.S.	NYSE Arca	Mid-cap
Vanguard REIT ETF	0,00031%	0,01277%	9	U.S.	NYSE Arca	Real Estate
Vanguard Small-Cap ETF	0,00016%	0,04206%	9	U.S.	NYSE Arca	Small-cap
Vanguard Small-Cap Growth ETF	0,00019%	0,08736%	11	U.S.	NYSE Arca	Small-cap
Vanguard Small-Cap Value ETF	0,00019%	0,05943%	6	U.S.	NYSE Arca	Small-cap
Vanguard Telecommunication Ser	0,00026%	0,11904%	19	U.S.	NYSE Arca	Communications Sector
Vanguard Total Stock Market ET	0,00011%	0,00844%	1	U.S.	NYSE Arca	Broad Market
Vanguard Total World Stock ETF	0,00029%	0,01581%	12	Global	NYSE Arca	Global
Vanguard Utilities ETF	0,00026%	0,04919%	12	U.S.	NYSE Arca	Utilities
Vanguard Value ETF	0,00016%	0,01374%	2	U.S.	NYSE Arca	Large-cap
WisdomTree US LargeCap Dividen	0,00069%	0,03594%	5	U.S.	NYSE Arca	Large-cap
WisdomTree US MidCap Dividend	0,00090%	0,08553%	2	U.S.	NYSE Arca	Mid-cap
WisdomTree US SmallCap Dividen	0,00090%	0,15452%	11	U.S.	NYSE Arca	Small-cap
XACT OMXS30	0,00026%	0,07676%	4	Sweden	Stockholm	Large-cap

Table 19: Parameterization returns per trading period

Parameterization	A	B	C	D	E	F	G	S&P500
StdDev requirement	0	0,005	0,006	0,007	0,008	0,009	0,01	/
22/05/2006	0%	0%	0%	0%	0%	0%	0%	0%
19/06/2006	-0,20%	6,43%	5,47%	3,86%	5,31%	5,87%	6,27%	-1,74%
17/07/2006	-0,30%	2,28%	1,79%	0,33%	1,49%	0,51%	0,05%	-0,45%
14/08/2006	-0,25%	0,10%	-1,40%	-0,95%	-2,26%	-1,46%	0,03%	2,73%
11/09/2006	-0,30%	-2,40%	-1,32%	-0,95%	0,16%	-1,22%	-2,83%	2,47%
09/10/2006	0,08%	1,28%	1,25%	0,42%	1,39%	1,03%	1,92%	3,93%
06/11/2006	-0,40%	0,73%	1,09%	0,55%	1,14%	0,11%	0,53%	2,16%
04/12/2006	-0,37%	0,52%	1,11%	2,40%	1,82%	0,76%	0,66%	2,13%
01/01/2007	-0,22%	-1,73%	-3,16%	-2,98%	-2,66%	-1,12%	-1,22%	0,00%
29/01/2007	-0,28%	-1,61%	1,43%	0,55%	2,21%	2,89%	0,84%	0,82%
26/02/2007	-0,36%	-0,12%	0,48%	-0,07%	-1,73%	1,26%	2,51%	2,02%
26/03/2007	-0,18%	2,99%	5,29%	1,70%	4,62%	5,40%	3,12%	-0,82%
23/04/2007	-0,37%	0,01%	-0,55%	0,75%	0,79%	-1,58%	-4,01%	3,02%
21/05/2007	-0,32%	-0,52%	-0,80%	0,52%	0,70%	1,38%	-0,30%	2,98%
18/06/2007	-0,34%	-0,20%	-0,55%	-2,45%	-3,21%	-0,74%	1,34%	0,39%
16/07/2007	0,17%	1,14%	0,74%	-0,56%	-1,85%	0,54%	1,38%	1,21%
13/08/2007	0,26%	5,99%	0,41%	0,30%	0,32%	1,58%	1,68%	-6,23%
10/09/2007	0,14%	1,92%	0,67%	3,38%	1,12%	3,64%	3,39%	-0,08%
08/10/2007	-0,09%	1,47%	4,54%	2,20%	2,86%	0,31%	-1,57%	6,95%
05/11/2007	-0,28%	-3,55%	-6,44%	-6,49%	-5,54%	-7,63%	-6,58%	-3,25%
03/12/2007	-0,08%	1,20%	0,79%	-0,97%	-1,05%	-1,78%	-0,34%	-1,98%
31/12/2007	0,81%	4,20%	5,02%	3,78%	5,17%	2,84%	2,27%	-0,28%
28/01/2008	0,06%	3,58%	5,79%	3,72%	6,54%	5,20%	9,19%	-7,79%
25/02/2008	0,13%	2,68%	0,06%	1,11%	0,75%	2,26%	2,64%	1,32%
24/03/2008	0,06%	2,10%	1,82%	2,88%	3,68%	3,42%	2,11%	-1,60%
21/04/2008	-0,05%	2,29%	0,25%	1,17%	-0,18%	1,39%	1,31%	2,84%
19/05/2008	-0,38%	-1,00%	2,31%	-2,01%	-1,35%	2,11%	1,85%	2,77%
16/06/2008	-0,22%	7,56%	3,08%	5,93%	2,59%	1,03%	2,84%	-4,66%
14/07/2008	-0,15%	-0,29%	0,73%	1,32%	2,06%	0,45%	-2,23%	-9,69%
11/08/2008	-0,19%	-0,27%	-1,18%	-0,37%	-0,55%	-0,20%	-0,18%	6,27%
08/09/2008	1,98%	5,89%	16,72%	16,42%	24,13%	13,22%	14,75%	-2,88%
06/10/2008	2,03%	27,81%	12,31%	22,09%	26,96%	19,09%	20,75%	-16,64%
03/11/2008	1,32%	-1,60%	0,86%	5,48%	10,25%	-4,29%	-1,22%	-8,57%
01/12/2008	1,17%	2,09%	1,73%	15,18%	11,20%	2,92%	14,38%	-15,53%
29/12/2008	-0,17%	0,49%	8,81%	6,74%	6,88%	1,69%	1,73%	6,52%
26/01/2009	0,07%	-2,01%	7,99%	2,40%	-2,64%	-3,44%	-1,71%	-3,78%
23/02/2009	0,60%	1,85%	5,43%	8,89%	6,22%	7,62%	5,54%	-11,15%
23/03/2009	0,05%	-3,44%	-4,84%	-2,06%	0,02%	-0,63%	8,40%	10,71%

20/04/2009	-0,17%	0,10%	0,44%	-0,90%	4,55%	3,02%	4,53%	1,15%
18/05/2009	0,01%	5,60%	3,58%	6,15%	6,17%	5,91%	6,13%	9,29%
15/06/2009	0,37%	0,45%	2,96%	2,82%	3,98%	4,08%	3,22%	1,54%
13/07/2009	-0,29%	2,19%	-0,47%	1,35%	3,60%	1,24%	1,14%	-2,45%
10/08/2009	-0,35%	1,22%	1,40%	1,40%	3,39%	3,70%	2,75%	11,77%
07/09/2009	-0,13%	1,15%	-0,27%	-0,33%	-0,94%	-2,27%	-2,83%	0,00%
05/10/2009	-0,54%	-0,41%	1,88%	3,00%	3,22%	4,18%	3,58%	3,31%
02/11/2009	-0,47%	2,23%	-0,14%	0,99%	1,52%	1,34%	3,00%	0,23%
30/11/2009	-0,34%	-2,57%	0,29%	-1,04%	-3,22%	-0,37%	-0,52%	5,06%
28/12/2009	-0,34%	0,65%	0,97%	2,12%	2,05%	2,43%	1,55%	2,93%
25/01/2010	-0,16%	0,96%	0,26%	1,12%	0,77%	0,53%	1,46%	-2,75%
22/02/2010	-0,44%	1,63%	0,79%	1,20%	0,24%	1,28%	2,02%	1,02%
22/03/2010	-0,58%	-0,90%	0,66%	1,28%	1,46%	0,78%	1,55%	5,22%
19/04/2010	-0,21%	-0,74%	0,59%	-2,24%	-0,51%	-2,67%	-2,07%	2,72%
17/05/2010	-0,28%	2,95%	-0,33%	3,20%	-0,70%	-0,38%	1,86%	-5,06%
14/06/2010	-0,15%	-0,78%	0,36%	-0,37%	0,26%	-0,52%	-1,62%	-4,16%
12/07/2010	-0,38%	0,07%	1,44%	1,77%	1,52%	0,86%	0,50%	-1,00%
09/08/2010	-0,26%	-1,87%	-2,10%	1,60%	0,24%	1,40%	1,65%	4,55%
06/09/2010	-0,40%	-0,01%	-0,50%	-0,22%	-0,24%	0,93%	-0,31%	0,00%
04/10/2010	-0,39%	-0,88%	2,88%	0,47%	2,95%	1,24%	1,62%	0,82%
01/11/2010	-0,26%	-2,51%	-1,77%	-0,82%	0,21%	-0,84%	-0,27%	4,16%
29/11/2010	-0,50%	-1,28%	-0,30%	-1,53%	-2,19%	-1,12%	-0,96%	0,29%
27/12/2010	-0,38%	0,11%	1,25%	1,51%	-0,50%	-0,45%	1,47%	5,87%
24/01/2011	-0,36%	0,77%	-0,84%	-0,07%	-0,20%	-1,69%	-0,22%	2,65%
21/02/2011	-0,15%	1,20%	2,15%	2,21%	6,37%	6,14%	5,80%	0,00%
21/03/2011	-0,35%	-0,82%	-0,84%	-0,42%	-0,61%	0,01%	-0,80%	0,58%
18/04/2011	-0,38%	4,39%	2,97%	2,05%	1,59%	0,55%	1,17%	0,52%
16/05/2011	-0,58%	-2,05%	-1,88%	-0,54%	-0,45%	-1,46%	-2,15%	1,86%
13/06/2011	-0,49%	0,24%	-0,75%	-2,17%	-3,74%	-2,34%	-2,11%	-4,34%
11/07/2011	-0,43%	1,96%	2,98%	2,28%	2,28%	1,18%	2,73%	3,75%
08/08/2011	-0,52%	3,38%	8,25%	3,17%	1,97%	2,09%	2,34%	-15,16%
05/09/2011	-0,06%	5,46%	3,15%	2,06%	3,95%	0,45%	3,52%	0,00%
03/10/2011	-0,43%	-0,73%	0,54%	-1,30%	2,48%	2,97%	1,07%	-1,81%
31/10/2011	-0,34%	-0,80%	2,17%	1,87%	2,95%	2,84%	2,32%	14,02%
28/11/2011	0,10%	-0,50%	-1,73%	-1,70%	-0,85%	0,31%	-0,55%	-4,85%
26/12/2011	-0,47%	2,66%	1,00%	1,36%	0,08%	0,91%	-0,35%	0,00%
23/01/2012	-0,51%	-1,05%	1,29%	1,39%	1,22%	1,85%	1,23%	10,35%
20/02/2012	-0,30%	2,31%	1,84%	4,68%	2,20%	1,33%	1,95%	0,00%
19/03/2012	-0,64%	0,78%	4,47%	-1,06%	1,26%	1,30%	0,84%	7,12%
16/04/2012	-0,51%	4,87%	4,54%	4,31%	2,32%	-0,18%	0,22%	-2,85%
14/05/2012	-0,29%	1,11%	1,90%	0,81%	3,43%	2,99%	3,07%	-2,28%
11/06/2012	-0,36%	1,93%	7,01%	1,93%	1,21%	2,62%	2,33%	-2,20%
09/07/2012	-0,45%	-0,77%	-1,40%	0,27%	0,28%	0,86%	-2,51%	3,33%

06/08/2012	-0,02%	0,41%	-0,14%	0,59%	0,07%	2,43%	-1,50%	3,09%
03/09/2012	-0,24%	0,83%	1,65%	1,97%	2,94%	-0,76%	0,50%	0,00%
01/10/2012	-0,49%	3,43%	1,32%	2,89%	5,70%	1,02%	2,19%	3,60%
29/10/2012	-0,45%	1,85%	2,10%	2,02%	1,60%	1,28%	1,48%	0,00%
26/11/2012	0,09%	0,99%	0,46%	2,03%	-2,10%	0,01%	0,08%	-2,64%
24/12/2012	-0,46%	-3,58%	-4,66%	-3,15%	0,65%	-1,54%	0,85%	1,45%
21/01/2013	-0,60%	-0,11%	2,96%	3,79%	1,35%	0,61%	1,27%	0,00%
18/02/2013	-0,24%	-1,10%	-0,88%	-0,72%	1,27%	0,04%	-0,57%	0,00%
18/03/2013	-0,35%	0,91%	2,53%	0,41%	-0,23%	-1,45%	-0,63%	8,79%
15/04/2013	-0,58%	1,56%	3,78%	3,72%	2,86%	2,84%	1,78%	0,02%
13/05/2013	-0,12%	-1,54%	-2,98%	-2,34%	1,02%	0,85%	2,17%	5,24%
10/06/2013	-0,04%	2,05%	0,54%	-2,25%	-2,73%	-4,52%	-4,94%	0,55%
08/07/2013	-0,55%	0,96%	-1,05%	-1,72%	-1,38%	0,83%	3,38%	-0,14%
05/08/2013	-0,44%	1,33%	1,03%	0,07%	-1,14%	-0,52%	-0,45%	4,06%
02/09/2013	-0,34%	0,73%	1,88%	1,46%	1,51%	0,93%	0,16%	0,00%
30/09/2013	-0,56%	-0,06%	-0,27%	0,81%	-1,53%	-1,81%	0,74%	-1,50%
28/10/2013	-0,59%	1,02%	0,31%	0,30%	0,13%	0,04%	-1,15%	4,79%
25/11/2013	-0,37%	3,55%	4,66%	3,74%	2,88%	0,28%	0,59%	2,29%
23/12/2013	-0,60%	0,66%	-3,33%	-7,53%	-10,20%	-7,74%	-5,38%	1,42%
20/01/2014	-0,62%	3,40%	3,81%	0,53%	2,51%	0,94%	0,73%	0,00%
17/02/2014	-0,70%	-2,58%	-0,32%	0,75%	-1,46%	-2,05%	-3,32%	0,00%
17/03/2014	-0,51%	-1,47%	-0,24%	0,32%	-0,21%	1,04%	1,14%	1,69%
14/04/2014	-0,68%	2,10%	1,79%	3,35%	2,52%	3,30%	1,16%	-1,52%
12/05/2014	-0,59%	-1,24%	0,04%	-1,98%	-0,62%	-1,28%	-0,62%	3,61%
09/06/2014	-0,33%	0,06%	2,56%	0,56%	0,08%	0,44%	-0,56%	2,88%
07/07/2014	-0,61%	0,34%	0,99%	1,75%	1,40%	1,02%	-0,41%	1,35%
04/08/2014	-0,62%	-1,01%	-0,10%	0,35%	1,03%	0,52%	-0,22%	-1,95%
01/09/2014	-0,41%	-0,84%	-1,70%	-1,16%	0,22%	-0,59%	-0,76%	0,00%
29/09/2014	-0,55%	-4,05%	-3,68%	-3,92%	-5,95%	-3,57%	-1,45%	2,00%
27/10/2014	-0,65%	-3,87%	-1,55%	-2,25%	-5,07%	-0,41%	-0,32%	-0,82%
24/11/2014	-0,40%	1,92%	2,71%	3,79%	4,41%	3,03%	3,99%	5,49%
22/12/2014	-0,60%	-0,49%	-0,43%	-0,37%	0,27%	-0,62%	-1,66%	0,44%
19/01/2015	-0,56%	-1,47%	-0,06%	0,23%	-0,91%	1,82%	-0,56%	0,00%
16/02/2015	-0,58%	0,28%	0,55%	1,83%	1,81%	1,18%	1,61%	0,00%
16/03/2015	-0,62%	1,66%	0,40%	-0,11%	-1,07%	0,33%	0,54%	0,13%
13/04/2015	-0,57%	0,08%	1,26%	0,41%	-0,02%	-1,24%	-1,34%	0,54%
11/05/2015	-0,62%	-0,36%	1,82%	1,63%	-0,48%	-0,57%	-0,20%	0,62%
08/06/2015	0,05%	2,91%	2,93%	2,13%	1,23%	3,41%	0,09%	-1,24%
06/07/2015	-0,66%	0,20%	-0,32%	-0,94%	-0,68%	-0,82%	0,08%	-0,51%
03/08/2015	-0,41%	0,30%	0,94%	1,43%	1,15%	0,02%	0,37%	1,42%
31/08/2015	-0,38%	-3,87%	-2,82%	0,54%	-2,38%	-1,77%	-0,70%	-6,00%
28/09/2015	-0,59%	2,25%	2,36%	2,73%	2,19%	5,70%	2,12%	-4,58%
26/10/2015	-0,51%	0,32%	-1,37%	-1,83%	-2,26%	-3,02%	-1,49%	10,07%

23/11/2015	-0,19%	-0,71%	-0,92%	0,19%	0,09%	1,53%	-1,40%	0,74%
21/12/2015	-0,62%	-3,94%	-5,21%	-3,08%	-1,39%	-1,97%	-2,66%	-3,14%
18/01/2016	-0,53%	5,45%	2,88%	1,49%	2,44%	3,84%	2,27%	0,00%
15/02/2016	-0,80%	0,05%	0,95%	-1,77%	1,00%	-1,20%	-1,57%	0,00%
14/03/2016	-0,44%	1,80%	1,93%	0,76%	2,27%	1,41%	1,81%	-0,07%
11/04/2016	-0,60%	2,09%	2,22%	1,91%	1,43%	1,90%	3,96%	1,11%
09/05/2016	-0,62%	-1,36%	1,02%	0,25%	0,41%	2,17%	1,69%	0,82%
06/06/2016	-0,36%	1,28%	5,78%	9,69%	6,51%	9,56%	7,70%	2,46%
04/07/2016	-0,58%	-2,23%	-2,27%	-2,32%	-1,67%	-1,44%	-0,74%	0,00%
01/08/2016	-0,74%	-0,56%	-0,64%	-0,93%	-0,87%	-1,68%	-1,10%	2,91%
29/08/2016	-0,26%	3,11%	1,79%	2,94%	1,34%	1,95%	0,45%	0,44%
26/09/2016	-0,58%	-0,11%	-2,38%	-2,17%	-2,42%	-2,46%	-2,57%	-1,57%
24/10/2016	-0,62%	-2,18%	-6,23%	-3,74%	-4,48%	-5,46%	-0,73%	0,24%
21/11/2016	-0,28%	-2,05%	-0,80%	-3,67%	-2,76%	-1,75%	-2,70%	2,18%
19/12/2016	-0,57%	-1,78%	-2,08%	-1,71%	-2,06%	-3,09%	-2,43%	2,93%
16/01/2017	-0,63%	-0,34%	1,11%	0,37%	-0,59%	-0,15%	-0,01%	0,00%
13/02/2017	-0,67%	-3,13%	-2,55%	-1,43%	-2,63%	0,17%	-0,30%	2,90%
13/03/2017	-0,68%	2,14%	1,33%	1,00%	1,97%	0,47%	-0,25%	1,94%
10/04/2017	-0,67%	-1,04%	0,81%	2,05%	0,51%	-0,28%	1,33%	-0,69%
08/05/2017	-0,65%	0,33%	-0,01%	1,48%	1,60%	0,42%	0,30%	1,79%

Table 20: Diversified strategy return with different allocations to S&P500

	Portfolio allocation to the S&P500								
Allocation	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
22/05/2006	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
19/06/2006	3,30%	2,74%	2,18%	1,62%	1,06%	0,50%	-0,06%	-0,62%	-1,18%
17/07/2006	0,25%	0,17%	0,09%	0,02%	-0,06%	-0,14%	-0,22%	-0,30%	-0,38%
14/08/2006	-0,58%	-0,21%	0,15%	0,52%	0,89%	1,26%	1,63%	2,00%	2,36%
11/09/2006	-0,61%	-0,27%	0,08%	0,42%	0,76%	1,10%	1,44%	1,79%	2,13%
09/10/2006	0,77%	1,12%	1,47%	1,83%	2,18%	2,53%	2,88%	3,23%	3,58%
06/11/2006	0,71%	0,87%	1,03%	1,19%	1,35%	1,51%	1,67%	1,83%	2,00%
04/12/2006	2,37%	2,35%	2,32%	2,29%	2,26%	2,24%	2,21%	2,18%	2,15%
01/01/2007	-2,68%	-2,38%	-2,09%	-1,79%	-1,49%	-1,19%	-0,89%	-0,60%	-0,30%
29/01/2007	0,58%	0,60%	0,63%	0,66%	0,68%	0,71%	0,74%	0,76%	0,79%
26/02/2007	0,14%	0,35%	0,56%	0,77%	0,98%	1,19%	1,40%	1,61%	1,81%
26/03/2007	1,45%	1,20%	0,94%	0,69%	0,44%	0,19%	-0,06%	-0,32%	-0,57%
23/04/2007	0,98%	1,20%	1,43%	1,66%	1,89%	2,11%	2,34%	2,57%	2,79%
21/05/2007	0,77%	1,01%	1,26%	1,51%	1,75%	2,00%	2,24%	2,49%	2,74%
18/06/2007	-2,17%	-1,88%	-1,60%	-1,31%	-1,03%	-0,75%	-0,46%	-0,18%	0,11%
16/07/2007	-0,38%	-0,21%	-0,03%	0,15%	0,32%	0,50%	0,68%	0,85%	1,03%
13/08/2007	-0,35%	-1,01%	-1,66%	-2,31%	-2,97%	-3,62%	-4,27%	-4,93%	-5,58%
10/09/2007	3,03%	2,69%	2,34%	1,99%	1,65%	1,30%	0,96%	0,61%	0,26%
08/10/2007	2,67%	3,15%	3,62%	4,10%	4,57%	5,05%	5,52%	6,00%	6,47%
05/11/2007	-6,17%	-5,84%	-5,52%	-5,19%	-4,87%	-4,54%	-4,22%	-3,90%	-3,57%
03/12/2007	-1,07%	-1,17%	-1,27%	-1,37%	-1,48%	-1,58%	-1,68%	-1,78%	-1,88%
31/12/2007	3,37%	2,97%	2,56%	2,16%	1,75%	1,35%	0,94%	0,54%	0,13%
28/01/2008	2,57%	1,42%	0,27%	-0,88%	-2,04%	-3,19%	-4,34%	-5,49%	-6,64%
25/02/2008	1,13%	1,15%	1,17%	1,19%	1,21%	1,23%	1,26%	1,28%	1,30%
24/03/2008	2,43%	1,98%	1,54%	1,09%	0,64%	0,19%	-0,25%	-0,70%	-1,15%
21/04/2008	1,34%	1,50%	1,67%	1,84%	2,00%	2,17%	2,34%	2,50%	2,67%
19/05/2008	-1,53%	-1,05%	-0,58%	-0,10%	0,38%	0,86%	1,34%	1,81%	2,29%
16/06/2008	4,87%	3,81%	2,75%	1,69%	0,63%	-0,42%	-1,48%	-2,54%	-3,60%
14/07/2008	0,22%	-0,88%	-1,98%	-3,09%	-4,19%	-5,29%	-6,39%	-7,49%	-8,59%
11/08/2008	0,29%	0,96%	1,62%	2,29%	2,95%	3,61%	4,28%	4,94%	5,61%
08/09/2008	14,49%	12,56%	10,63%	8,70%	6,77%	4,84%	2,91%	0,98%	-0,95%
06/10/2008	18,22%	14,34%	10,47%	6,60%	2,73%	-1,15%	-5,02%	-8,89%	-12,76%
03/11/2008	4,07%	2,67%	1,26%	-0,14%	-1,55%	-2,95%	-4,36%	-5,76%	-7,17%
01/12/2008	12,11%	9,04%	5,97%	2,90%	-0,18%	-3,25%	-6,32%	-9,39%	-12,46%
29/12/2008	6,72%	6,70%	6,67%	6,65%	6,63%	6,61%	6,59%	6,56%	6,54%
26/01/2009	1,78%	1,16%	0,55%	-0,07%	-0,69%	-1,31%	-1,92%	-2,54%	-3,16%
23/02/2009	6,89%	4,88%	2,88%	0,88%	-1,13%	-3,13%	-5,13%	-7,14%	-9,14%
23/03/2009	-0,78%	0,49%	1,77%	3,05%	4,32%	5,60%	6,88%	8,15%	9,43%

20/04/2009	-0,69%	-0,49%	-0,28%	-0,08%	0,13%	0,33%	0,54%	0,74%	0,95%
18/05/2009	6,46%	6,78%	7,09%	7,41%	7,72%	8,03%	8,35%	8,66%	8,98%
15/06/2009	2,69%	2,56%	2,44%	2,31%	2,18%	2,05%	1,92%	1,80%	1,67%
13/07/2009	0,97%	0,59%	0,21%	-0,17%	-0,55%	-0,93%	-1,31%	-1,69%	-2,07%
10/08/2009	2,44%	3,47%	4,51%	5,55%	6,58%	7,62%	8,66%	9,70%	10,73%
07/09/2009	-0,30%	-0,26%	-0,23%	-0,20%	-0,16%	-0,13%	-0,10%	-0,07%	-0,03%
05/10/2009	3,03%	3,06%	3,09%	3,12%	3,16%	3,19%	3,22%	3,25%	3,28%
02/11/2009	0,91%	0,84%	0,76%	0,69%	0,61%	0,54%	0,46%	0,38%	0,31%
30/11/2009	-0,43%	0,18%	0,79%	1,40%	2,01%	2,62%	3,23%	3,84%	4,45%
28/12/2009	2,20%	2,28%	2,36%	2,45%	2,53%	2,61%	2,69%	2,77%	2,85%
25/01/2010	0,73%	0,35%	-0,04%	-0,43%	-0,81%	-1,20%	-1,59%	-1,98%	-2,36%
22/02/2010	1,18%	1,16%	1,15%	1,13%	1,11%	1,09%	1,08%	1,06%	1,04%
22/03/2010	1,67%	2,07%	2,46%	2,85%	3,25%	3,64%	4,04%	4,43%	4,82%
19/04/2010	-1,74%	-1,25%	-0,75%	-0,26%	0,24%	0,74%	1,23%	1,73%	2,22%
17/05/2010	2,37%	1,55%	0,72%	-0,10%	-0,93%	-1,76%	-2,58%	-3,41%	-4,23%
14/06/2010	-0,75%	-1,13%	-1,51%	-1,89%	-2,27%	-2,64%	-3,02%	-3,40%	-3,78%
12/07/2010	1,49%	1,22%	0,94%	0,66%	0,39%	0,11%	-0,17%	-0,44%	-0,72%
09/08/2010	1,89%	2,19%	2,48%	2,78%	3,07%	3,37%	3,66%	3,96%	4,25%
06/09/2010	-0,20%	-0,18%	-0,15%	-0,13%	-0,11%	-0,09%	-0,07%	-0,04%	-0,02%
04/10/2010	0,50%	0,54%	0,57%	0,61%	0,64%	0,68%	0,71%	0,75%	0,78%
01/11/2010	-0,32%	0,18%	0,68%	1,17%	1,67%	2,17%	2,67%	3,17%	3,67%
29/11/2010	-1,35%	-1,17%	-0,99%	-0,80%	-0,62%	-0,44%	-0,26%	-0,08%	0,10%
27/12/2010	1,95%	2,38%	2,82%	3,26%	3,69%	4,13%	4,57%	5,00%	5,44%
24/01/2011	0,20%	0,47%	0,75%	1,02%	1,29%	1,56%	1,83%	2,10%	2,38%
21/02/2011	1,99%	1,77%	1,55%	1,33%	1,11%	0,88%	0,66%	0,44%	0,22%
21/03/2011	-0,32%	-0,22%	-0,12%	-0,02%	0,08%	0,18%	0,28%	0,38%	0,48%
18/04/2011	1,90%	1,74%	1,59%	1,44%	1,29%	1,13%	0,98%	0,83%	0,67%
16/05/2011	-0,30%	-0,06%	0,18%	0,42%	0,66%	0,90%	1,14%	1,38%	1,62%
13/06/2011	-2,39%	-2,60%	-2,82%	-3,04%	-3,25%	-3,47%	-3,69%	-3,90%	-4,12%
11/07/2011	2,43%	2,57%	2,72%	2,87%	3,01%	3,16%	3,31%	3,45%	3,60%
08/08/2011	1,34%	-0,50%	-2,33%	-4,16%	-5,99%	-7,83%	-9,66%	-11,49%	-13,33%
05/09/2011	1,85%	1,65%	1,44%	1,24%	1,03%	0,82%	0,62%	0,41%	0,21%
03/10/2011	-1,35%	-1,40%	-1,45%	-1,50%	-1,55%	-1,60%	-1,65%	-1,71%	-1,76%
31/10/2011	3,08%	4,30%	5,51%	6,73%	7,94%	9,16%	10,37%	11,59%	12,80%
28/11/2011	-2,01%	-2,33%	-2,64%	-2,96%	-3,27%	-3,59%	-3,90%	-4,22%	-4,53%
26/12/2011	1,22%	1,09%	0,95%	0,82%	0,68%	0,54%	0,41%	0,27%	0,14%
23/01/2012	2,29%	3,18%	4,08%	4,97%	5,87%	6,77%	7,66%	8,56%	9,46%
20/02/2012	4,21%	3,74%	3,28%	2,81%	2,34%	1,87%	1,40%	0,94%	0,47%
19/03/2012	-0,24%	0,58%	1,40%	2,21%	3,03%	3,85%	4,67%	5,49%	6,31%
16/04/2012	3,59%	2,88%	2,16%	1,45%	0,73%	0,01%	-0,70%	-1,42%	-2,13%
14/05/2012	0,50%	0,19%	-0,12%	-0,43%	-0,73%	-1,04%	-1,35%	-1,66%	-1,97%
11/06/2012	1,52%	1,10%	0,69%	0,28%	-0,13%	-0,55%	-0,96%	-1,37%	-1,79%
09/07/2012	0,58%	0,88%	1,19%	1,49%	1,80%	2,10%	2,41%	2,71%	3,02%

06/08/2012	0,84%	1,09%	1,34%	1,59%	1,84%	2,09%	2,34%	2,59%	2,84%
03/09/2012	1,77%	1,58%	1,38%	1,18%	0,99%	0,79%	0,59%	0,39%	0,20%
01/10/2012	2,96%	3,03%	3,10%	3,18%	3,25%	3,32%	3,39%	3,46%	3,53%
29/10/2012	1,82%	1,62%	1,41%	1,21%	1,01%	0,81%	0,61%	0,40%	0,20%
26/11/2012	1,56%	1,10%	0,63%	0,16%	-0,31%	-0,77%	-1,24%	-1,71%	-2,18%
24/12/2012	-2,69%	-2,23%	-1,77%	-1,31%	-0,85%	-0,39%	0,07%	0,53%	0,99%
21/01/2013	3,41%	3,03%	2,65%	2,27%	1,90%	1,52%	1,14%	0,76%	0,38%
18/02/2013	-0,65%	-0,58%	-0,50%	-0,43%	-0,36%	-0,29%	-0,22%	-0,14%	-0,07%
18/03/2013	1,25%	2,09%	2,92%	3,76%	4,60%	5,44%	6,28%	7,12%	7,95%
15/04/2013	3,35%	2,98%	2,61%	2,24%	1,87%	1,50%	1,13%	0,76%	0,39%
13/05/2013	-1,58%	-0,82%	-0,06%	0,69%	1,45%	2,21%	2,97%	3,73%	4,49%
10/06/2013	-1,97%	-1,69%	-1,41%	-1,13%	-0,85%	-0,57%	-0,29%	-0,01%	0,27%
08/07/2013	-1,56%	-1,40%	-1,25%	-1,09%	-0,93%	-0,77%	-0,62%	-0,46%	-0,30%
05/08/2013	0,47%	0,87%	1,27%	1,67%	2,07%	2,47%	2,87%	3,27%	3,67%
02/09/2013	1,31%	1,17%	1,02%	0,88%	0,73%	0,58%	0,44%	0,29%	0,15%
30/09/2013	0,58%	0,35%	0,12%	-0,11%	-0,34%	-0,58%	-0,81%	-1,04%	-1,27%
28/10/2013	0,75%	1,20%	1,65%	2,10%	2,55%	2,99%	3,44%	3,89%	4,34%
25/11/2013	3,60%	3,45%	3,31%	3,16%	3,02%	2,87%	2,73%	2,58%	2,44%
23/12/2013	-6,64%	-5,74%	-4,85%	-3,95%	-3,06%	-2,16%	-1,27%	-0,37%	0,52%
20/01/2014	0,48%	0,42%	0,37%	0,32%	0,27%	0,21%	0,16%	0,11%	0,05%
17/02/2014	0,68%	0,60%	0,53%	0,45%	0,38%	0,30%	0,23%	0,15%	0,08%
17/03/2014	0,46%	0,59%	0,73%	0,87%	1,00%	1,14%	1,28%	1,41%	1,55%
14/04/2014	2,86%	2,38%	1,89%	1,40%	0,92%	0,43%	-0,06%	-0,54%	-1,03%
12/05/2014	-1,42%	-0,86%	-0,30%	0,26%	0,81%	1,37%	1,93%	2,49%	3,05%
09/06/2014	0,79%	1,02%	1,26%	1,49%	1,72%	1,95%	2,18%	2,42%	2,65%
07/07/2014	1,71%	1,67%	1,63%	1,59%	1,55%	1,51%	1,47%	1,43%	1,39%
04/08/2014	0,12%	-0,11%	-0,34%	-0,57%	-0,80%	-1,03%	-1,26%	-1,49%	-1,72%
01/09/2014	-1,04%	-0,93%	-0,81%	-0,70%	-0,58%	-0,46%	-0,35%	-0,23%	-0,12%
29/09/2014	-3,33%	-2,74%	-2,14%	-1,55%	-0,96%	-0,37%	0,23%	0,82%	1,41%
27/10/2014	-2,11%	-1,96%	-1,82%	-1,68%	-1,53%	-1,39%	-1,25%	-1,10%	-0,96%
24/11/2014	3,96%	4,13%	4,30%	4,47%	4,64%	4,81%	4,98%	5,15%	5,32%
22/12/2014	-0,29%	-0,21%	-0,13%	-0,05%	0,04%	0,12%	0,20%	0,28%	0,36%
19/01/2015	0,21%	0,18%	0,16%	0,14%	0,11%	0,09%	0,07%	0,05%	0,02%
16/02/2015	1,65%	1,46%	1,28%	1,10%	0,91%	0,73%	0,55%	0,37%	0,18%
16/03/2015	-0,09%	-0,06%	-0,04%	-0,02%	0,01%	0,03%	0,06%	0,08%	0,10%
13/04/2015	0,42%	0,44%	0,45%	0,46%	0,48%	0,49%	0,50%	0,51%	0,53%
11/05/2015	1,53%	1,43%	1,33%	1,22%	1,12%	1,02%	0,92%	0,82%	0,72%
08/06/2015	1,79%	1,46%	1,12%	0,78%	0,45%	0,11%	-0,23%	-0,56%	-0,90%
06/07/2015	-0,90%	-0,85%	-0,81%	-0,77%	-0,72%	-0,68%	-0,64%	-0,59%	-0,55%
03/08/2015	1,43%	1,43%	1,43%	1,42%	1,42%	1,42%	1,42%	1,42%	1,42%
31/08/2015	-0,11%	-0,77%	-1,42%	-2,08%	-2,73%	-3,38%	-4,04%	-4,69%	-5,35%
28/09/2015	2,00%	1,27%	0,54%	-0,20%	-0,93%	-1,66%	-2,39%	-3,12%	-3,85%
26/10/2015	-0,64%	0,55%	1,74%	2,93%	4,12%	5,31%	6,50%	7,69%	8,88%

23/11/2015	0,25%	0,30%	0,36%	0,41%	0,47%	0,52%	0,58%	0,63%	0,69%
21/12/2015	-3,09%	-3,09%	-3,10%	-3,10%	-3,11%	-3,11%	-3,12%	-3,12%	-3,13%
18/01/2016	1,34%	1,19%	1,04%	0,89%	0,74%	0,60%	0,45%	0,30%	0,15%
15/02/2016	-1,59%	-1,42%	-1,24%	-1,06%	-0,89%	-0,71%	-0,53%	-0,35%	-0,18%
14/03/2016	0,68%	0,59%	0,51%	0,43%	0,34%	0,26%	0,18%	0,09%	0,01%
11/04/2016	1,83%	1,75%	1,67%	1,59%	1,51%	1,43%	1,35%	1,27%	1,19%
09/05/2016	0,31%	0,36%	0,42%	0,48%	0,53%	0,59%	0,65%	0,70%	0,76%
06/06/2016	8,97%	8,24%	7,52%	6,80%	6,08%	5,35%	4,63%	3,91%	3,19%
04/07/2016	-2,09%	-1,86%	-1,62%	-1,39%	-1,16%	-0,93%	-0,70%	-0,46%	-0,23%
01/08/2016	-0,55%	-0,16%	0,22%	0,61%	0,99%	1,38%	1,76%	2,14%	2,53%
29/08/2016	2,69%	2,44%	2,19%	1,94%	1,69%	1,44%	1,19%	0,94%	0,69%
26/09/2016	-2,11%	-2,05%	-1,99%	-1,93%	-1,87%	-1,81%	-1,75%	-1,69%	-1,63%
24/10/2016	-3,34%	-2,94%	-2,54%	-2,15%	-1,75%	-1,35%	-0,95%	-0,55%	-0,15%
21/11/2016	-3,09%	-2,50%	-1,92%	-1,33%	-0,75%	-0,16%	0,42%	1,01%	1,59%
19/12/2016	-1,25%	-0,78%	-0,32%	0,14%	0,61%	1,07%	1,54%	2,00%	2,46%
16/01/2017	0,33%	0,30%	0,26%	0,22%	0,19%	0,15%	0,11%	0,07%	0,04%
13/02/2017	-1,00%	-0,56%	-0,13%	0,30%	0,74%	1,17%	1,60%	2,04%	2,47%
13/03/2017	1,09%	1,19%	1,28%	1,38%	1,47%	1,57%	1,66%	1,75%	1,85%
10/04/2017	1,78%	1,50%	1,23%	0,96%	0,68%	0,41%	0,13%	-0,14%	-0,41%
08/05/2017	1,51%	1,54%	1,57%	1,60%	1,64%	1,67%	1,70%	1,73%	1,76%

Table 21: Diversified strategy return per year

	Diversified strategy									
Trading period	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1	-2,38%	2,97%	6,70%	2,28%	2,38%	1,09%	-2,23%	-5,74%	-0,21%	-3,09%
2	0,60%	1,42%	1,16%	0,35%	0,47%	3,18%	3,03%	0,42%	0,18%	1,19%
3	0,35%	1,15%	4,88%	1,16%	1,77%	3,74%	-0,58%	0,60%	1,46%	-1,42%
4	1,20%	1,98%	0,49%	2,07%	-0,22%	0,58%	2,09%	0,59%	-0,06%	0,59%
5	1,20%	1,50%	-0,49%	-1,25%	1,74%	2,88%	2,98%	2,38%	0,44%	1,75%
6	1,01%	-1,05%	6,78%	1,55%	-0,06%	0,19%	-0,82%	-0,86%	1,43%	0,36%
7	-1,88%	3,81%	2,56%	-1,13%	-2,60%	1,10%	-1,69%	1,02%	1,46%	8,24%
8	-0,21%	-0,88%	0,59%	1,22%	2,57%	0,88%	-1,40%	1,67%	-0,85%	-1,86%
9	-1,01%	0,96%	3,47%	2,19%	-0,50%	1,09%	0,87%	-0,11%	1,43%	-0,16%
10	2,69%	12,56%	-0,26%	-0,18%	1,65%	1,58%	1,17%	-0,93%	-0,77%	2,44%
11	3,15%	14,34%	3,06%	0,54%	-1,40%	3,03%	0,35%	-2,74%	1,27%	-2,05%
12	-5,84%	2,67%	0,84%	0,18%	4,30%	1,62%	1,20%	-1,96%	0,55%	-2,94%
13	-1,17%	9,04%	0,18%	-1,17%	-2,33%	1,10%	3,45%	4,13%	0,30%	-2,50%
Average	-0,0018	0,0388	0,0231	0,0060	0,0060	0,0170	0,0065	-0,0012	0,0051	0,0004
Standard deviation	0,0236	0,0493	0,0253	0,0127	0,0204	0,0113	0,0190	0,0247	0,0084	0,0307
Sortino-Satchell ratio	-0,2585	29,2701	6,0934	0,5618	0,3353	1,3589	0,7236	-0,1395	0,8742	-0,1191

Figure 8: All parametrization total return over the complete period with trading costs

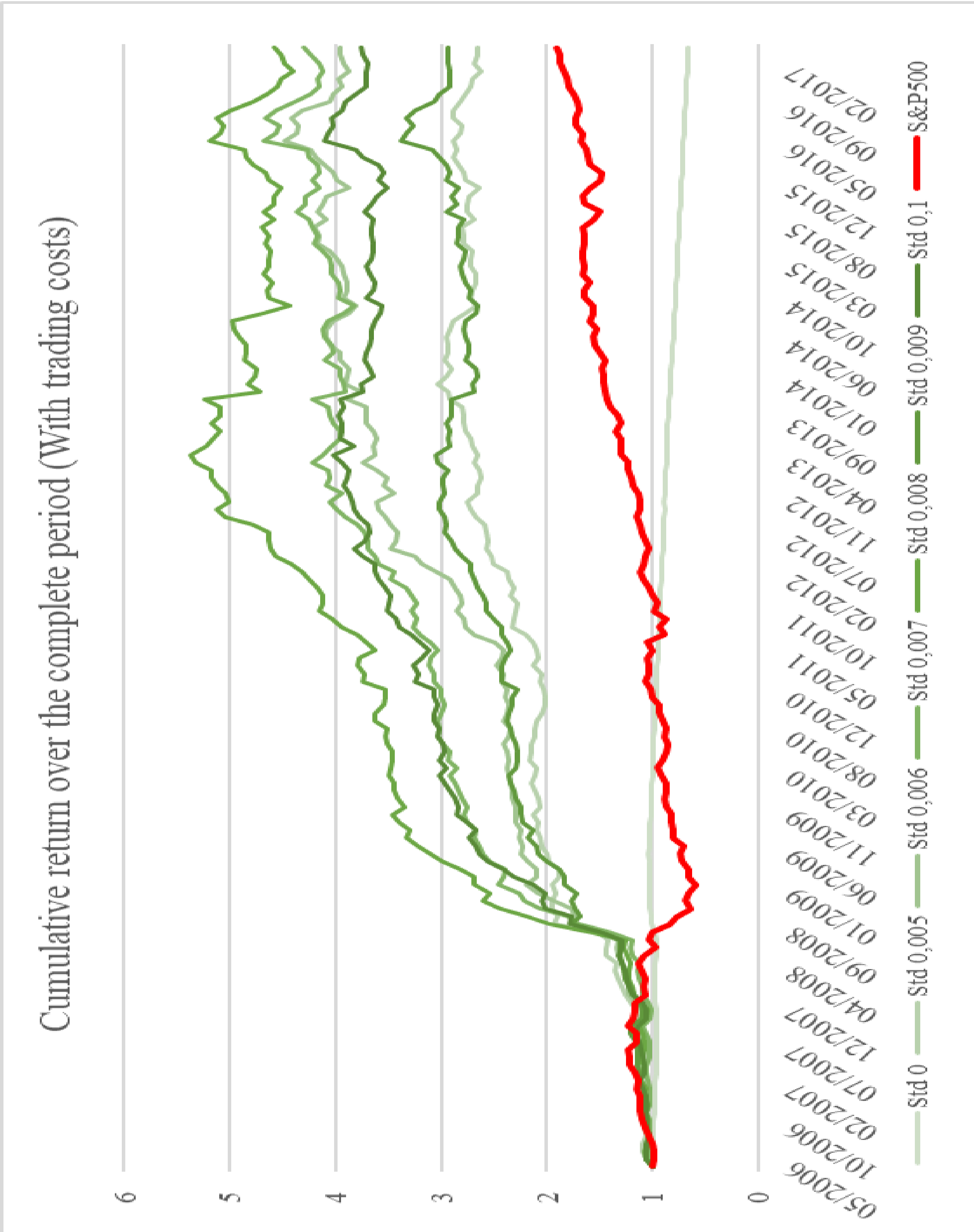


Figure 9: All parametrization total return over the complete period without trading costs

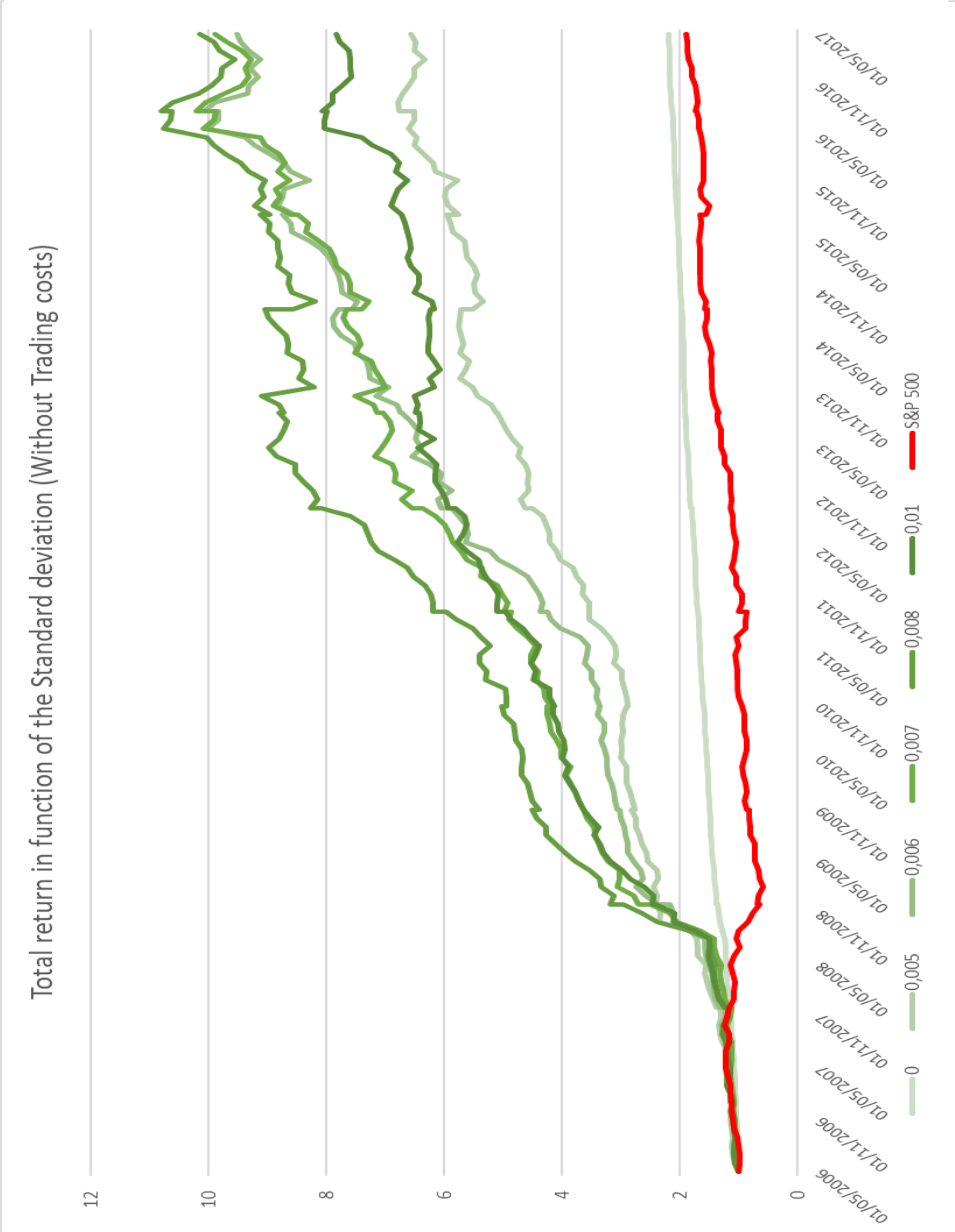


Figure 10: All parametrization total return from 2006 to 2008

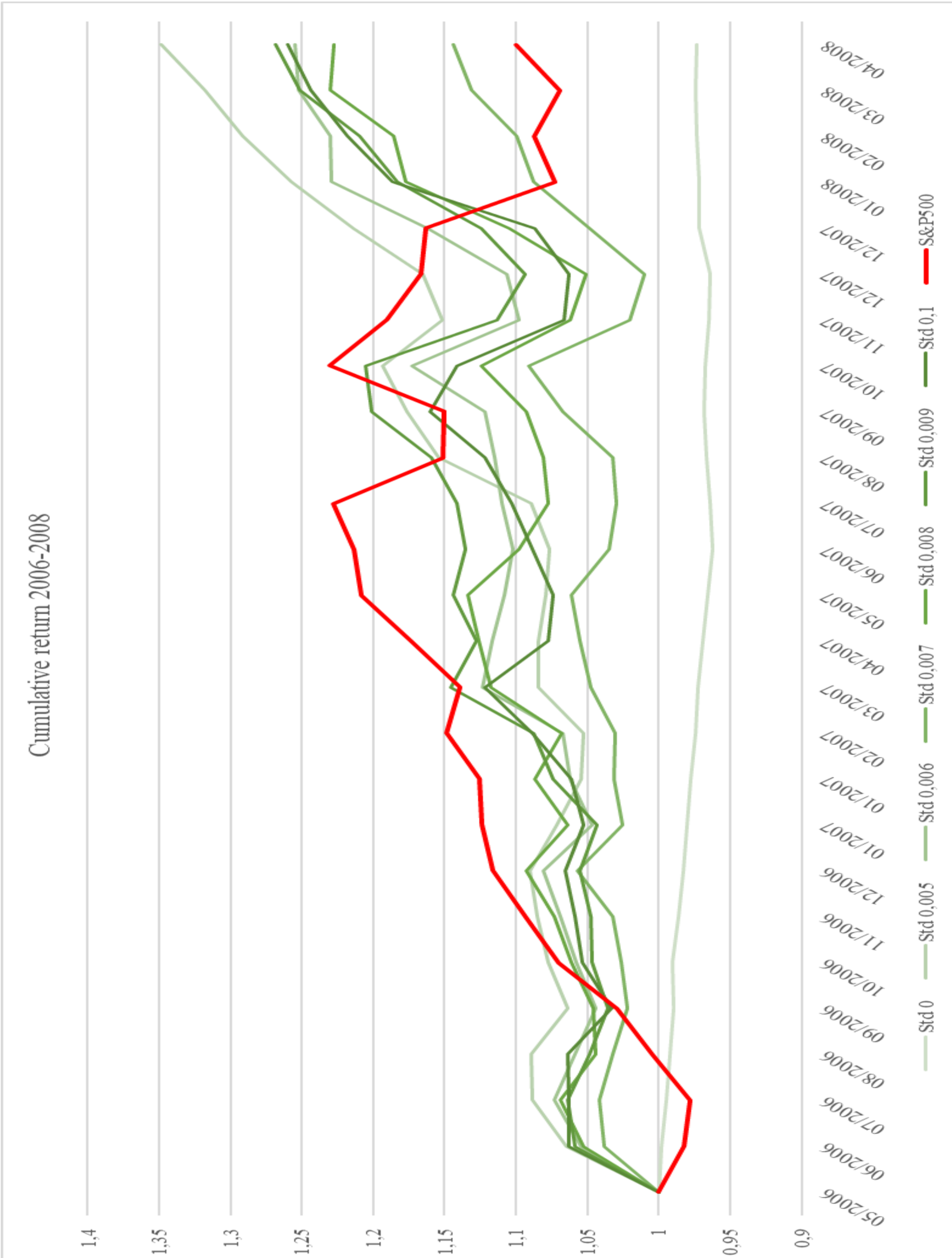


Figure 11: All parametrization total return from 2008 to 2011

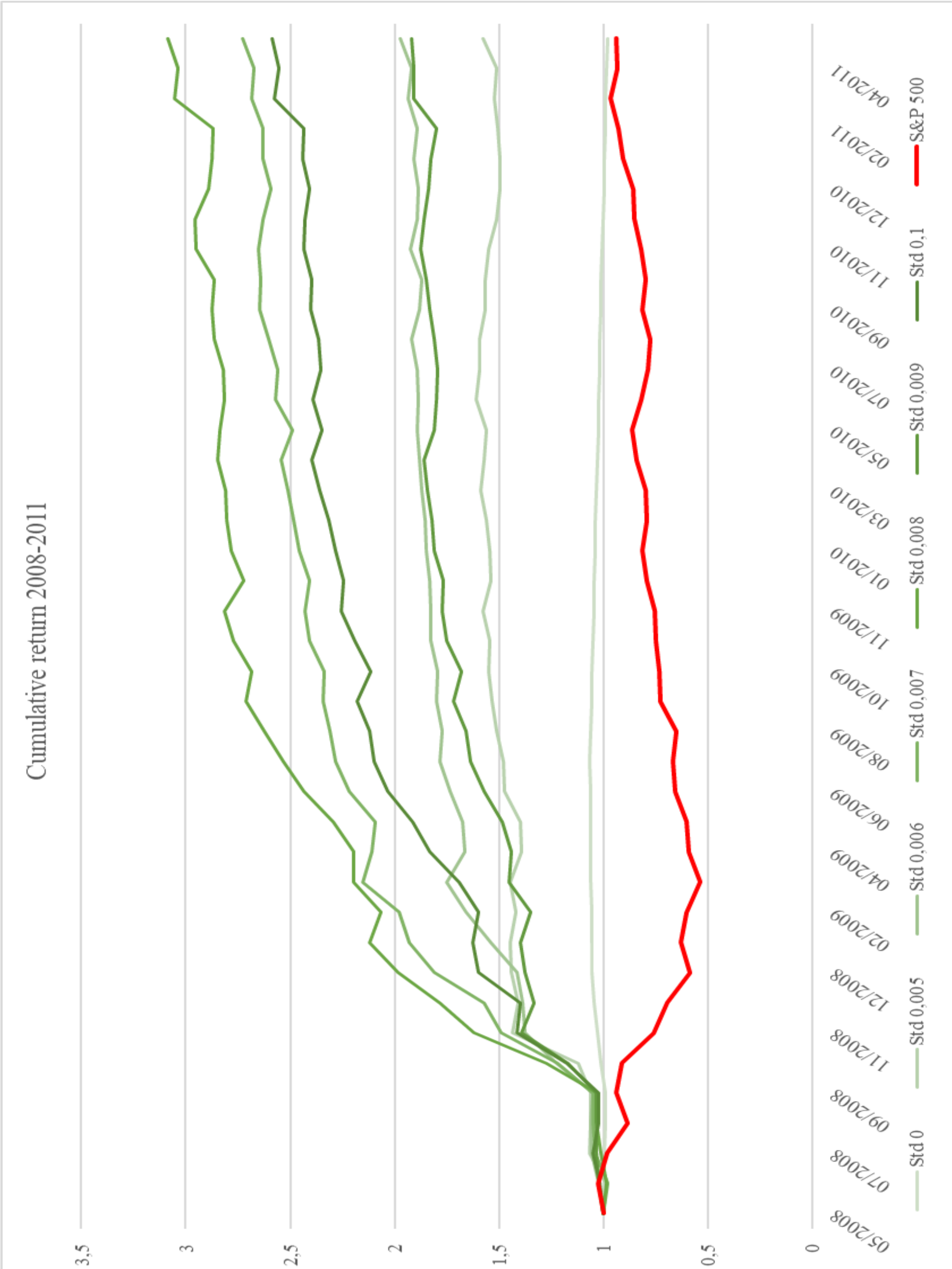
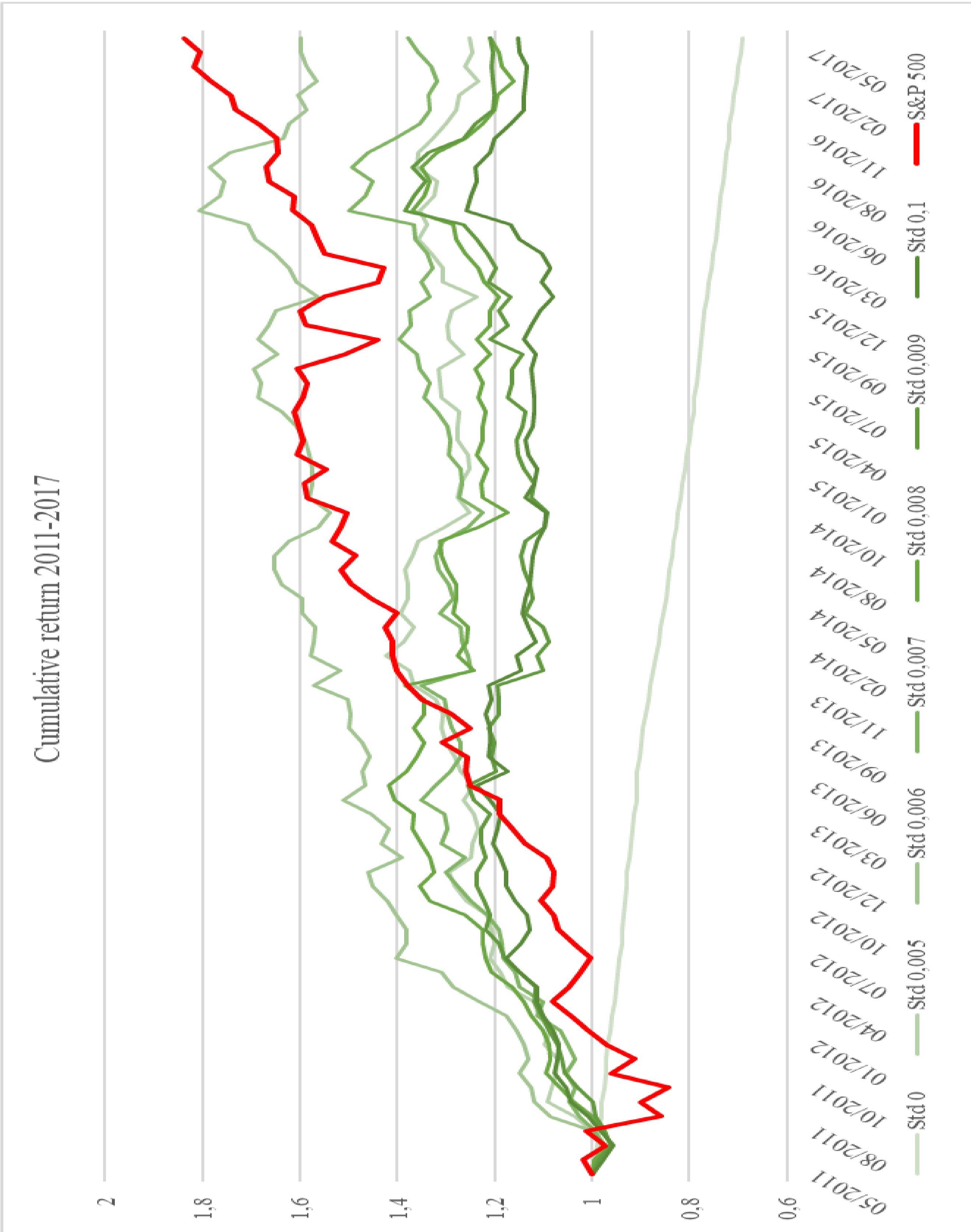


Figure 12: All parametrization total return from 2011 to 2017



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