LUND UNIVERSITY
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Statistical Arbitrage & Fund Performance

An Empirical Analysis of Fund Returns

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Abstract

Fund companies and banks argue that letting them manage one's money is a wise decision. They argue that they are able to create substantial growth in value for the investor without requiring any other input than a small fee and an amount to be invested. This essay tests this claim in a two folded analysis.

Time series data with historical value developments of 24 out of the 30 largest Swedish equity funds, along with the value development of the MSCI Sweden SEK stock market index, is used in the analysis. The first part of the analysis uses descriptive statistics of fund net returns and the benchmark index returns to assess whether or not fund managers are able to exploit statistical arbitrage opportunities in the Swedish equity market. It is concluded that fund managers are able to do this and consequently create average excess net returns that are greater than zero at an 80% confidence level.

The second part of the analysis investigates if it is really worth the cost of fees to let an actively managed fund take care of one's investment. The fact that fund managers are able to create positive excess returns is not good enough a reason to motivate fund investment on its own. It is investigated if the best three funds in the data set are able to outperform an active, but free, investment strategy that does not require financial sophistication. The investment strategy is based on a GARCH(2,1) model which is used to forecast the returns of the benchmark index and guide investment decisions. The second part of the analysis concludes that the funds are outperforming the proposed investment strategy on average, indicating that there is merit to the fund companies' claim; it is worth the cost of fees to have one's money looked after by an actively managed fund, given that the choice of fund is a well-informed decision.

KEYWORDS: Statistical Arbitrage, Fund Performance, Net Returns

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1. Introduction

Banks and fund companies often argue that a private investor should buy their funds as doing so lies in the person's own interest. Allegedly the investor will earn money, without actively doing anything. To a skeptical person this may sound as a rare arbitrage opportunity, since the concept of arbitrage can indeed be described as a money-for-nothing type of situation, in which an agent can exploit price gaps to create a profit. In this essay it will be explained why or perhaps why not there is merit to the fund companies' claim. Can an investor really earn money, in real terms rather than nominal, by simply investing a chosen amount in a fund and sitting back, waiting for the money to grow in value? And if this is case, is it really worth paying the required fees to have fund companies manage the investment? In order to answer these questions one will first need to determine whether or not fund managers are actually creating extra value, as compared to just investing in an equity index for free. In order to explain this, the concept of arbitrage is introduced and explained. It is also determined whether or not it is reasonable that arbitrage exists in the equity markets. Secondly, one will need to empirically determine if fund managers are skilled enough to capitalize off of these potential arbitrage opportunities. After all, if a private investor is going to earn money from buying the funds, net of fees, the fund's manager needs to be able to spot and exploit the market's statistical arbitrage opportunities well enough to create a substantial growth in the fund's value. Lastly, a comparison between the performance of professional fund managers and the performance of a rational, but financially uneducated, investor is made. This determines if the service provided by fund managers is actually worth its cost.

This essay will move on to explaining the concept of arbitrage and assessing whether or not it exists on equity markets. This assessment is based on an examination of some of the vast body of literature on the subject. After concluding that it is theoretically feasible for someone to observe arbitrage opportunities in equity markets it will be empirically investigated if fund managers are able to exploit these opportunities. Time-series data with the value development of 24 of the 30 largest Swedish equity funds, along with the value development of the underlying benchmark index, will be used to analyze the performance of actively managed funds. Since this essay means to determine if the decision to invest in funds is a wise one, the analysis determines if it is better to let a fund company manage one's money than just investing it by oneself. If a fund manager is consistently able to exploit the statistical arbitrage opportunities in the equity market, it is wise to let him or her manage one's investment, and if the manager is in fact outperforming the market index, one should be able to observe this as the manager's fund is yielding abnormal positive returns. Beating the market is exactly the point of actively managed funds. It is argued, at least by companies that manage funds actively, that the financial professionals analyzing the market will be able to spot and exploit situations of asset mispricing. From the private investor's perspective, letting a fund company invest one's money should hence result in more or less risk free profits. Whether or not this is the case is a very intriguing question and it is now explained how the data in this essay is treated in order to provide an answer to it.

The research purpose of the essay is two folded. The first part is an empirical investigation of the returns achieved by actively managed funds. Funds' historical returns are compared to the development of the benchmark index in order to determine if fund managers are able to exploit statistical arbitrage opportunities. Descriptive statistics regarding the funds' excess returns are used to settle this issue. It is concluded that fund managers are able to consistently beat the benchmark index, net of fees. The results from this part of the analysis are found in section 4.1**.**

The second part of the analysis aims at determining if it is worth paying the fees to have one's investment looked after by an actively managed fund. Good funds, in the sense that they create high returns, are beating index, but that does not automatically imply that they are a good option for an investor. If a private investor without extensive financial knowledge can create an investment strategy that generates as high returns as those achieved by funds, it is not an economically sound decision to pay a fund to manage one's money. In order to test this, an investment strategy which is purely empirical is created. It is based on a GARCH(2,1) time series model that is used to forecast the returns of the benchmark index. How this is done is explained in more detail in 4.2. The results from the second part of the analysis show that fund managers are in fact outperforming the proposed investment strategy, which indicates that fund investment is worth the cost of fees.

2. Background on Arbitrage

In this section the concepts of arbitrage and statistical arbitrage are explained. Previously published literature on the topic is reviewed and at the end of the section one finds a paragraph that briefly summarizes what can be concluded from the literature study. It is also clarified how these findings relate to the research question of determining whether or not a private investor will earn money, in real terms, by buying equity funds.

The definition of arbitrage has been formulated numerous times, but the essence of it is best explained by this "joke": A normal person and a financial mathematician are walking down the street. The normal person spots a $100 bill and attempts to pick it up. 'Don't try that!' says the mathematician 'if there really was a $100 bill there, somebody would've already picked it up!' The idea is that there can be no hundred dollar bills lying around, because if there were, somebody would immediately pick them up (Dalbaen and Schachermayer, 2006). As most of us know from experience, though, finding a couple of coins or a small bill on the sidewalk can happen, why Dalbaen and Schachermayer also provide an extension to the above joke that is better suited for a financial context: True arbitrage would imply that the average guy finds a money pump along the street.

The analogy lends itself to this essay quite well. After all, if one invests in an asset, say an equity fund, that person postpones some of his or her consumption for now but the fund will possibly generate high returns year after year, assuming that the fund companies and banks are correct in their claim. If one discounts the future returns generated by the fund, one can use the present value to determine whether or not the future earnings generated by fund will be worth the wait. If the fund's future values are discounted and the discounted value is higher than the invested amount, the person has found a $100 bill, so to speak. If an investor can find these $100 bills repeatedly, he or she has found a money pump. What is investigated in this section of the essay is whether or not it is feasible that somebody would be able to find something similar to a 'money pump'.

An elementary and well-known concept in finance is the law of one price. It states that arbitrage activity should eventually result in the prices of identical assets being equal, as unlimited risk-free profits could be made otherwise (Pasquariello, 2014). This clearly implies that there should be no arbitrage opportunities in the long run. The law of one price is however an old idea and it might be obsolete today. The number of recent papers and articles investigating the topic of stock market arbitrage is enormous, and the empirical results in many of these indicate that there are in fact arbitrage opportunities in the financial markets. More specifically, these papers conclude that there are statistical arbitrage opportunities and the concept of statistical arbitrage is explained here.

Fernholz and Maguire (2007) explain what the concept of statistical arbitrage actually is in a paper titled *The Statistics of Statistical Arbitrage*. The verbal explanation of the concept is that when the expected return of buying an asset, holding it for a given period of time, and then selling it is greater than zero, in net present value, a statistical arbitrage opportunity has presented itself. The key concept here, of course, is the expected return. The authors provide different portfolio strategies that are expected to yield positive returns, but all of them share one common feature. Using time series data for one entire day of trading on both the New York Stock Exchange (NYSE) and American Stock Exchange (NASDAQ), the authors estimate volatilities for different large-cap stocks and compare these sector-wise, i.e. the volatility of a car manufacturer's stock is compared to the stocks of other car manufacturers. For the sake of this explanation, let us assume that the volatility of one stock is greater than the volatility of the rest of the companies within a given sector, and that these companies' stocks are roughly equally volatile. The excess volatility is exploited to generate positive returns by selling the asset when its price is greater than the sector benchmark price, which is usually made up of a weighted average of all the sector stock prices, and re-buying the asset when its price is lower than the benchmark price. The authors find that the expected return of such strategies is indeed greater than zero, which supports the idea that there are statistical arbitrage opportunities on equity markets. They also conclude that implementing such a strategy is both data and software demanding, why it is not likely to ever be realized by most amateur investors.

Another paper that investigates statistical arbitrage on the American equities markets is written by Avellaneda and Lee (2009) and titled *Statistical Arbitrage in the US Equities Markets.* Their analysis is based on a similar idea to the one in performed by Fernholz and Maguire (2007). It is assumed that some individual stocks are idiosyncratically over-sensitive, meaning that they overreact to news affecting the market, as compared to other stocks within the same business sector. These overreactions result in periods of mispricing of the stock which can be exploited to generate positive returns. The authors find that stock prices are mean reverting, which gives rise to similar trading strategies as described by Fernholz and Maguire (2007) with the difference that Avellaneda and Lee follow a long/short-trading strategy instead of a buy, sell, and re-buy strategy. A merit of Avellaneda's and Lee's paper is that it discusses more extensively how an investor is supposed to find out whether or not the stock should be bought or "shorted". The most intuitively compelling suggestion is to regress the stock price on the price of exchange traded funds (ETFs), made up of stocks in the relevant business sector. The stock price and the price of the ETF are realistically assumed to be affected in the same direction by business related news. As the stock is idiosyncratically oversensitive the regression coefficient is > 1, i.e. the stock price varies more than the price of the ETF. When the price of the ETF increases, the stock is bought, and as soon as the price increase of the ETF flattens out or is reversed, a short position is taken in the stock. The authors find that such a trading strategy yields positive returns over time, again supporting the notion that there are statistical arbitrage opportunities on equities markets, but it is obviously not without risk. Since all stocks are associated with idiosyncratic risk the investor will lose every now and then, which means that the strategy requires a large financial buffer-zone to make sure that the investor can cope with temporary losses. The average return is however greater than zero over time. It should also be mentioned that the proposed trading strategy is sensitive to timing, so it requires much activity and monitoring from the investor.

The two papers described immediately above are obviously arguing that statistical arbitrage opportunities exist. This perhaps seems a bit contradictory to somebody who has studied the more classical ideas of efficient financial markets. Bondarenko (2003) offers an implicit explanation to this in his paper *Statistical Arbitrage and Securities P*rices. He argues that the possible existence of statistical arbitrage opportunities depends on whether or not investors are using historical information when evaluating future returns on investments. The arguments being made in the paper rely heavily on the concept of the pricing kernel, or stochastic discount factor, which is of fundamental importance in asset pricing theory. A brief explanation of the concept is provided here:

An asset is traded at time $t = 1, \dots, T$. The asset is assumed to be bought at $t = 0$. The asset's price at time $t = v_t$ and $I_t = v_0, \dots, v_t$ is the pricing history of the asset up until time *t*. Let x_t denote the payoff received when the asset is sold in period *t*. Then the pricing kernel, or stochastic discount factor, is any variable that satisfies $E[\bar{m}x_i] = v_i, \forall i \in [1, T]$, i.e. $\bar{m}$ is the pricing kernel.

Bondarenko argues that the functional form of the pricing kernel determines whether or not statistical arbitrage opportunities will exist or not when theoretical models regarding assets' prices are made. Bondarenko's conclusion suggests that when the pricing kernel is path independent, i.e. it depends only on the utility of the asset's payoff, $U(x_t)$, no statistical arbitrage opportunities may exist. This essentially means that every investor values an asset based on his or her expected utility. As everybody has different utility functions and x_t cannot be known in advance, trading strategies that yield expected returns > 0 over time cannot be formulated. The mathematical derivations of these arguments will not be formally explained or evaluated here since the purpose of this essay is not to determine the precise accuracy of Bondarenko's conclusions, but the paper has some interesting implications. As mentioned above, recent papers based on empirical research find that there may exist statistical arbitrage opportunities in equity markets. This can seem contradictive if one looks at some of the theory regarding financial assets, but theory may be misguiding in the sense that assumptions about investor behavior do not reflect reality.

Alexander and Dimitriu (2005) are testing portfolio management strategies that take historical prices of assets into account, i.e. strategies that are path dependent, in their paper *Indexing and Statistical Arbitrage*. They use historical data from the American S&P 100 index and use this price data to create portfolios that are cointegrated with some benchmark index. The basic idea of this purely statistical approach is that the cointegrated portfolio is mean reverting. Alexander and Dimitriu formulate a long-short-approach, very similar to the one Avellaneda and Lee use, but with different buy- or sell signals. Another difference between the two papers is that Avellaneda and Lee base the fact that stock prices are mean reverting, if the relevant benchmark index is found, on previous research findings, whereas Alexander and Dimitriu check statistically if the portfolio is cointegrated with the benchmark, and thus mean-reverting, using regression- and residual analysis. Alexander and Dimitriu use price spreads, the difference between the price of the index and the price of the portfolio. Let I_t denote the price of the index and P_t the price of the portfolio at time *t*. Then if $I_t - P_t > 0$, it is a buy-signal, meaning that a long position in the portfolio is taken, and when $I_t - P_t < 0$ a short position is taken. The results of the paper show the cointegrated portfolio generates expected returns that are greater than zero and statistically significant.

Most recent papers regarding statistical arbitrage opportunities show some evidence of their existence, at least when asset management strategies are empirically based. This, as has been mentioned, can seem quite unintuitive to somebody who believes in the theories regarding market efficiency. One of the reasons behind this phenomenon could be that investors are significantly limited in their ability to exploit arbitrage opportunities, e.g. by not being able to take short positions, why a mispriced asset can remain mispriced for a substantial period of time, as is argued by Ling, et al. (2014). This is connected to the efficient market hypothesis, which was originally formulated by Eugene Fama. The hypothesis is explained in a pedagogical way by Ausloos, et al., (2016) in their article *On the "Usual" Misunderstanding between Econophysics and Finance: Some Clarifications on Modelling Approaches and Efficient Market Hypothesis*. Fama's theory suggests that assets' prices are based on all available information, and that it should not be possible to consistently beat the market. Whether or not market participants have all information necessary to correctly value assets and make completely rational investment decisions is however something that has not yet been agreed upon. This issue is one of the reasons why the topic of arbitrage receives so much attention. There is no clear intuitive answer to the question.

Bidima and Rasonyi (2012) is one of the papers investigating the topic of stock market arbitrage. The authors investigate different trading strategies mathematically and find that even with very loose assumptions and restrictions one can find asymptotic arbitrage in the (very) long run. The paper is very mathematically involved why the details will not be explained here. It is more interesting to see that it can be shown mathematically that arbitrage might exist, and also that exploiting it may require a very long period of time. Perhaps longer than most peoples' investment horizons.

Doukas, Kim, and Pantzalis (2010) is another example of a paper that investigates the existence of arbitrage on the stock markets. The authors make a time series analysis of stock prices of American companies traded on the NYSE and NASDAQ. The goal of their investigation is to check if there is empirical evidence for arbitrage opportunities. For an arbitrage opportunity to arise the stock needs to be mispriced, and one of the merits of this paper is that the authors use more than one measurement of stock mispricing to check their results, ultimately making their conclusion more robust. They find that there appears to be arbitrage opportunities that persist over time, even when well informed, sophisticated traders can see that the stock is mispriced. Their explanation relies quite heavily on the idea of idiosyncratic risk, which arguably deters arbitrageurs from trying to exploit the arbitrage opportunity. If the stock is sensitive to non-market factors, its price can be very hard to predict. Even when it is obviously mispriced sophisticated investors cannot predict its next move, why they do not act on the opportunity to potentially earn money. Even arbitrageurs appear to be risk averse.

Cao and Han (2016) find results in line with Doukas's and Pantzalis's in a paper titled *Idiosyncratic Risk, Costly Arbitrage, and the Cross-Section of Stock Returns*. They investigate whether idiosyncratic risk can serve as a proxy for arbitrage costs. They investigate mispriced stocks with different idiosyncratic risk ranks and check how fast the price gaps of these stocks are eliminated. Indeed they find that price gaps of idiosyncratically volatile stocks are persistent. Quite likely due to arbitrageurs' risk aversion. Their measurement of idiosyncratic risk is calculated with the residuals from Fama's and French's three-factor-model for stock returns (Fama & French, 1992). The three-factor-model is a regression model formulated in the following way by Cao and Han:

$$\hat{r} = risk.free + \ \beta * (market\, r - risk.free) + b_2 * (Co.market\, cap - Big\, market\, cap.) + \\ + b_3 * (Company\, B.to\, M. - Low\, B.to\, M.)$$

The variables in the three factor model refer to the risk free rate of return, taken from government bonds, the market rate of return, which reflects the return of the stock market index, the difference between the company's market capitalizations and large-cap companies, and difference between company's book-to-market price ratio and the book-to-market price ratio of 'expensive' companies. The three-factor-model's residuals are saved and eventually used as measurements of idiosyncratic risk. The β in the above model is the conventional finance- β, measuring the ration between an asset's volatility and the asset's covariance with the market. Cao and Han also use different metrics for the price gap, giving their result an extra dimension of robustness.

Previous paragraphs touched on the subject that arbitrage opportunities might arise because people are not utilizing all available information. One could debate whether or not the information is available for ages, but Jin (2014) takes a slightly different and perhaps more pragmatic approach. It is basically stated that whether or not the information is available is perhaps not the most relevant thing to look at, since even if the information is available it would not be of any use unless investors pay attention to it. He checks this by investigating if stocks that receive more attention are less mispriced. Mispricing in this paper is determined within a large dataset of American stocks by taking the inverse of sizeadjusted one-, two-, and three-year buy-and-hold abnormal returns. The stocks' returns are compared to their industry benchmarks to determine whether or not they are abnormal. The amount of attention a stock receives is quantified using a dummy variable, which is equal to 1 if one or more analysts are actively following the stock and 0 otherwise. The attention-dummy, along with other controls, is included on the right hand side of a linear regression model with stock mispricing as dependent variable. The results show that stocks being followed by analysts are indeed less mispriced.

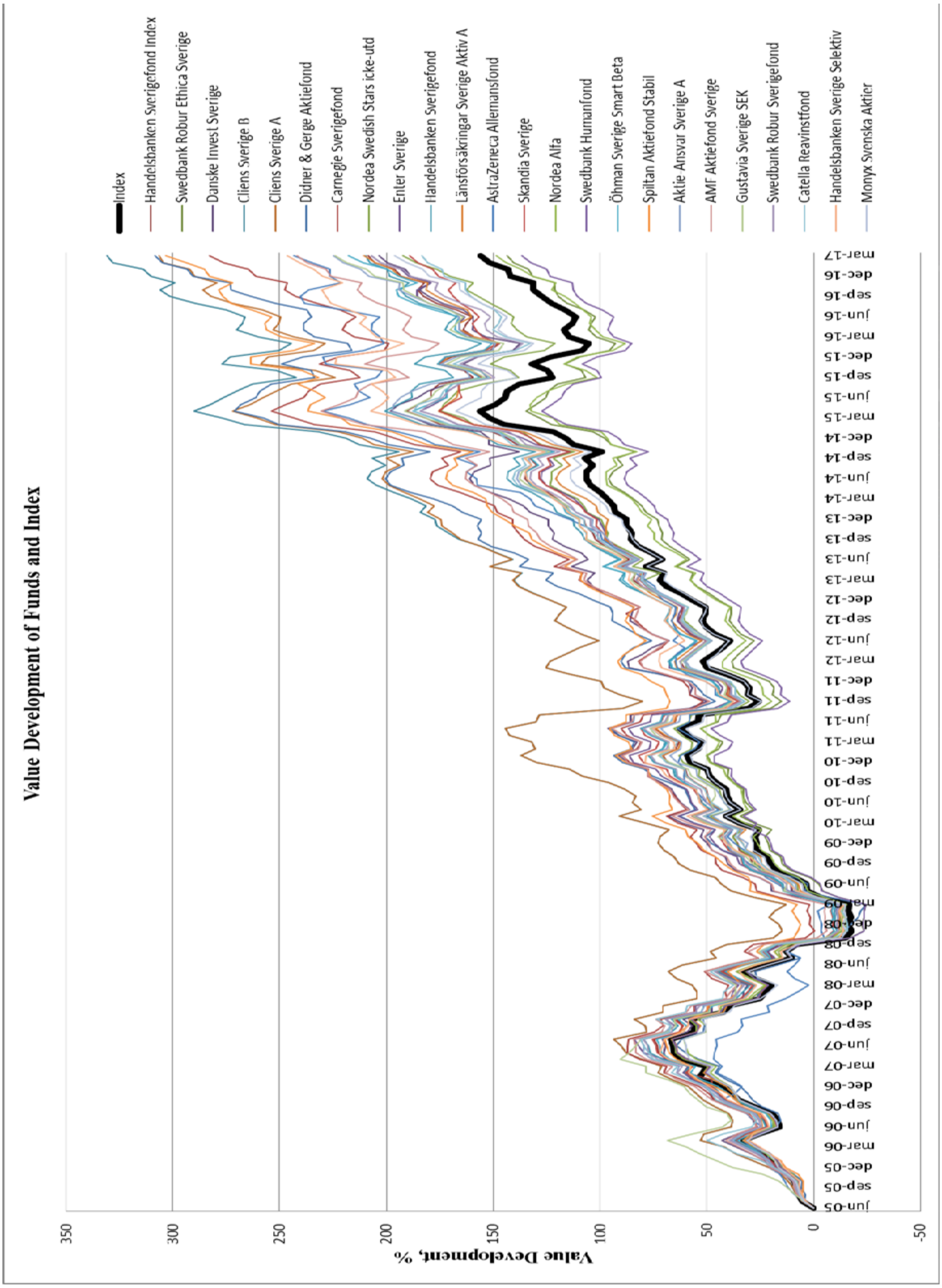
Several of the above described papers use different signals for, or measurements of, stock mispricing, which invites a reader to ask what definition of mispricing should be used. Chen, Lung, and Wang (2009) investigate different mispricing theories in their article *Stock Market Mispricing: Money Illusion or Resale Option?* They check, using regression models, which of the theories – the money illusion theory that relates mispricing to faulty inflation expectations, or the resale option which relates mispricing to investors' subjective expectations on dividend growth rates – that create the most suitable measurement of stock mispricing. The latter of the two theories split investors into two groups, one is more optimistic than the other, although which is which can change. This means that the ownership of a stock can shift, depending on which group is more optimistic. This raises stock turnover and gives rise to buy-and-sell strategies. Besides inflating the stock's value, it also results in greater volatility. They find that the different measurements of stock mispricing work better or worse during different time periods.

From the literature reviewed above one can conclude the following: Empirically, there appears to be evidence that statistical arbitrage opportunities exist. Classic theories such as the Efficient Market Hypothesis and the Law of One Price state that there should be no arbitrage opportunities, since asset prices allegedly reflect all available information. Studies, however, show that investors are not using all available information and that the risk aversion of investors can lead to persistent mispricing of stocks. An example of such a study is Jin (2014). Periods of assets mispricing are longer than suggested by classic theory, and the persistent mispricing situations can potentially be exploited by skillful and knowledgeable investors. This motivates the research question in this essay. There appears to be statistical arbitrage opportunities in the financial markets, and the question is whether professionals in the financial industry are skillful enough to exploit them over and over again. The fund companies and banks themselves argue that they are. If this is truly the case, fund investments should generate safe, positive returns for the average private investor.

3. Data

This section of the essay describes the data being analyzed and explains what transformations that are made. The data analyzed in the essay is taken from Morningstar's historical data of funds' value development. Historical data for 24 out of the 30 biggest Swedish equity funds are included in the data set along with the MSCI Sweden SEK stock market index. The time series contain monthly data that start in June 2005 and continue up until March 2017, resulting in 142 observed time periods for the 24 funds and the index, which yields 3550 total observations. Six out of the 30 biggest funds are excluded because data is only available for shorter time periods. A graphical illustration of the data is presented in figure 1 below.

Figure 1: Value Development of Funds & Index



The funds' value developments, depicted in the figure above, are transformed to fund returns. The fund companies' monthly fees (Morningstar, retrieved 2017-04) are then subtracted from the returns to generate time series with net fund returns. The descriptive statistics for all the funds' net returns and the index's returns are presented in table 1 below.

Table 1: Descriptive Statistics, Net Fund Returns, in %

Fund	Mean	Standard Error	Median	Skewness
Aktie-Ansvar Sverige A	0.816	0.372	1.360	-1.245
AMF Aktiefond Sverige	0.938	0.378	1.491	-1.135
AstraZeneca Allemansfond	0.863	0.313	1.297	-0.661
Carnegie Sverigefond	0.924	0.362	1.538	-1.121
Catella Reavinstfond	0.718	0.401	1.221	-1.321
Cliens Sverige A	0.970	0.369	1.736	-1.022
Cliens Sverige B	0.983	0.371	1.801	-1.014
Danske Invest Sverige	0.791	0.408	1.187	-0.537
Didner & Gerge Aktiefond	1.016	0.415	1.476	-0.198
Enter Sverige	0.757	0.391	1.324	-1.167
Gustavia Sverige SEK	0.819	0.404	1.487	-0.694
Handelsbanken Sverige Selektiv	0.814	0.357	1.315	-1.119
Handelsbanken Sverigefond	0.816	0.378	1.389	-1.097
Handelsbanken Sverigefond Index	0.845	0.376	1.352	-1.065
Index	0.770	0.381	1.170	-1.118
Länsförsäkringar Sverige Aktiv A	0.785	0.365	1.244	-1.072
Monyx Svenska Aktier	0.772	0.359	1.296	-1.065
Nordea Alfa	0.614	0.353	1.336	-1.226
Nordea Swedish Stars icke-utd	0.740	0.373	1.289	-0.979
Öhman Sverige Smart Beta	0.817	0.374	1.393	-1.014
Skandia Sverige	0.730	0.371	1.238	-1.187
Spiltan Aktiefond Stabil	0.918	0.283	1.154	-0.660
Swedbank Humanfond	0.717	0.386	1.260	-1.179
Swedbank Robur Ethica Sverige	0.632	0.387	1.189	-1.187
Swedbank Robur Sverigefond	0.796	0.388	1.441	-1.098

Note: Mean, Standard Error, and Median are measured in %

The stationarity of the time series with funds' net returns and the index returns are checked using Augmented Dickey-Fuller tests, and all the time series are stationary. The test results are presented in the following table:

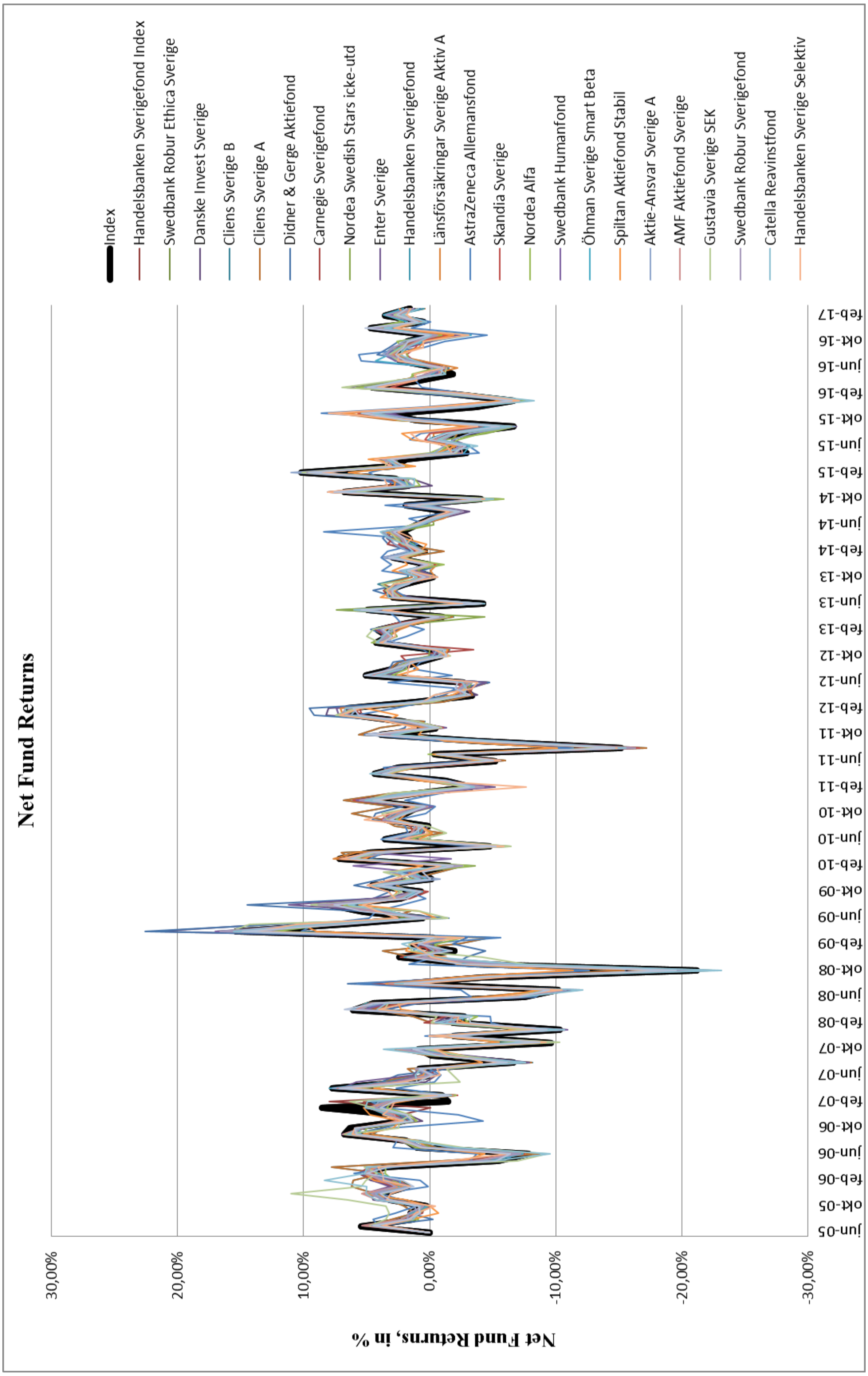
Table 2: Net Returns Stationarity Tests

Fund	t-Statistics	P-value
Aktie-Ansvar Sverige A	-8.683	0.000***
AMF Aktiefond Sverige	-8.911	0.000***
AstraZeneca Allemansfond	-10.106	0.000***
Carnegie Sverigefond	-9.222	0.000***
Catella Reavinstfond	-8.656	0.000***
Cliens Sverige A	-9.134	0.000***
Cliens Sverige B	-9.077	0.000***
Danske Invest Sverige	-8.814	0.000***
Didner & Gerge Aktiefond	-8.727	0.000***
Enter Sverige	-8.973	0.000***
Gustavia Sverige SEK	-8.207	0.000***
Handelsbanken Sverige Selektiv	-8.933	0.000***
Handelsbanken Sverigefond	-9.106	0.000***
Handelsbanken Sverigefond Index	-8.694	0.000***
Index	-9.128	0.000***
Länsförsäkringar Sverige Aktiv A	-9.171	0.000***
Monyx Svenska Aktier	-9.301	0.000***
Nordea Alfa	-9.252	0.000***
Nordea Swedish Stars icke-utd	-8.997	0.000***
Öhman Sverige Smart Beta	-9.170	0.000***
Skandia Sverige	-8.987	0.000***
Spiltan Aktiefond Stabil	-9.106	0.000***
Swedbank Humanfond	-8.704	0.000***
Swedbank Robur Ethica Sverige	-8.783	0.000***
Swedbank Robur Sverigefond	-8.843	0.000***

Note: The significance codes are the following: '*' implies significance at the 0,05 level, '**' signals significance at the 0,01 level, and '***' means that the parameter is significant at the 0,001 level. The null hypothesis is that the true parameter is equal to 0 for all parameters.

A graphical illustration of the funds' net returns and the index return is presented in figure 2 below.

Figure 2: Net Fund Returns & Index Returns



The figure shows net returns of included funds and the benchmark index. The returns are calculated net of fees. The returns of the index and the funds track very closely, why all lines are not completely visible.

4. Results

The empirical analysis in this essay is based mainly on methods outlined in Enders, 2015, but is also inspired by the papers *Rating Equity Funds against Return of Random Traders*, by Hung, et. al., 2014, and *The Index Fund Rationality Paradox*, 2010, by Boldin and Cici. Both these papers show that returns of funds tend to track returns of their underlying benchmark very closely. The funds analyzed in this essay are all benchmarked against the same stock market index, the MSCI Sweden SEK index, and all the funds are in fact linear combinations of this index. This fact, along with the papers mentioned just above and inspection of figure 2 in the Data section, motivate the strategy to compare fund returns to the underlying benchmark index in order to assess the funds' performances.

4.1 Fund Managers Ability to Exploit Statistical Arbitrage

The first step of the analysis is to investigate the historical returns achieved by the included funds. From an inspection of figure 1 it is clear that there are funds that underperform and consistently drag below the index, as well as there are funds that consistently outperform the index. Before a more detailed analysis of specific funds is made it is interesting to examine net fund returns in general. A graphical illustration of these numbers is found in figure 3 and statistical results regarding net fund returns in general are presented in table 3 below.

Figure 3: Distribution of Fund Net Returns

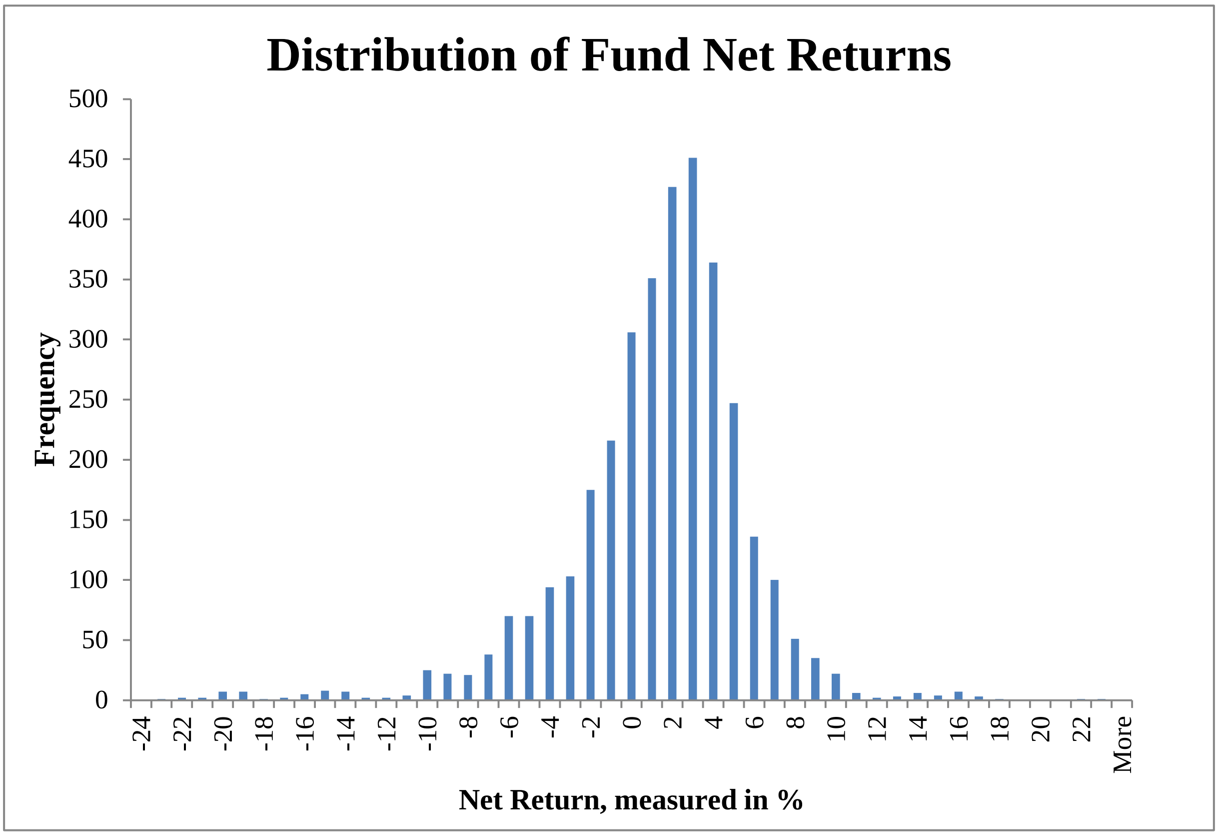


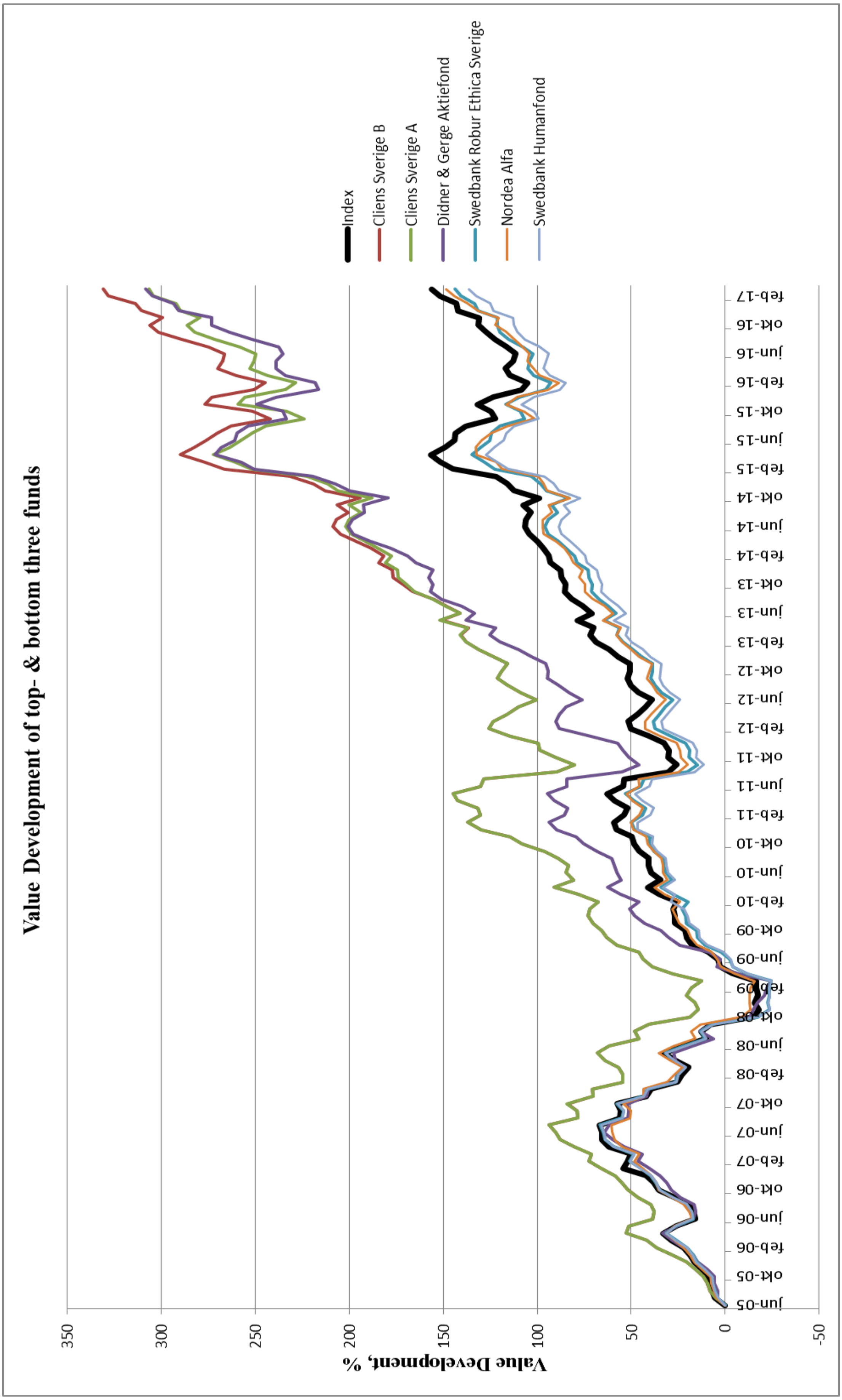
Table 3: Descriptive Statistics, Net Fund Returns

Descriptive Statistics, Net Fund Returns (in %)	
Mean	0.816
Median	1.377
Standard Error	0.076
Skewness	-0.996
CI, Lower Bound	0.667
CI, Upper Bound	0.965

Note: The confidence interval in the table is the 95% confidence level interval.

Just a quick glance at the numbers in the table above confirms that funds' net returns are significantly different from zero in general. This can be interpreted as fund investment being a good idea for the private investor, seeing as the average net return is significantly positive. The confidence interval ranges from roughly 0.67% to 0.97%. It is however the case that the performances of the different funds in the data vary to a great extent, so determining that fund investment is a good idea solely on these general numbers is a premature conclusion. As previously mentioned, there are a few funds that are consistently underperforming compared to the index, as well as there is a number of funds that are consistently outperforming the index, why the three best and the three worst funds are extracted from the data and analyzed on their own. Average monthly net returns are used to determine how good or bad the funds' performances have been, and the three funds with the highest average net returns are Didner & Gerge Aktiefond (1.016%), Cliens Sverige B (0.983%), and Cliens Sverige A (0.970%). The three funds with the lowest average net returns are Nordea Alfa (0.614%), Swedbank Robur Ethica Sverige (0.632%), and Swedbank Humanfond (0.717%). The historical value development of these six funds is depicted in figure 4 below.

Figure 4: Value Development of Best & Worst Three Funds



The figure shows the value development, measured in %, of the top- and bottom three funds as compared to the value development of the index. The top-three funds are distinctly above the index line whereas the bottom-three funds are trailing just below the index line.

The relevant statistics for these six funds are presented in table 4 below.

Table 4: Descriptive Statistics, Net Fund Returns of Best and Worst Funds

	Mean	Median	Standard Error	Skewness	CI, Lower Bound	CI, Upper Bound
Descriptive Statistics, Net Fund Returns, Best Three Funds (in %)						
Didner & Gerge Aktiefond	1.016	1.476	0.415	-0.198	0.196	1.837
Cliens Sverige B	0.983	1.801	0.371	-1.014	0.251	1.716
Cliens Sverige A	0.970	1.736	0.369	-1.022	0.240	1.670
Descriptive Statistics, Net Fund Returns, Worst Three Funds (in %)						
Swedbank Robur Ethica Sverige	0.632	1.189	0.387	-1.187	-0.133	1.397
Nordea Alfa	0.614	1.336	0.353	-1.226	-0.084	1.312
Swedbank Humanfond	0.717	1.260	0.387	-1.179	-0.047	1.481

Note: The confidence interval in the table is the 95% confidence level interval.

If an investor is primarily interested in the returns of funds, she/he will not invest in the worst three funds, but might find the top three interesting. The information regarding fund performance is publically available so it is reasonable that an investor will avoid the poorly performing funds. A graphical illustration of the net returns of the best three funds is found in figure 5 below.

Figure 5: Net Fund Returns, Best Three Funds

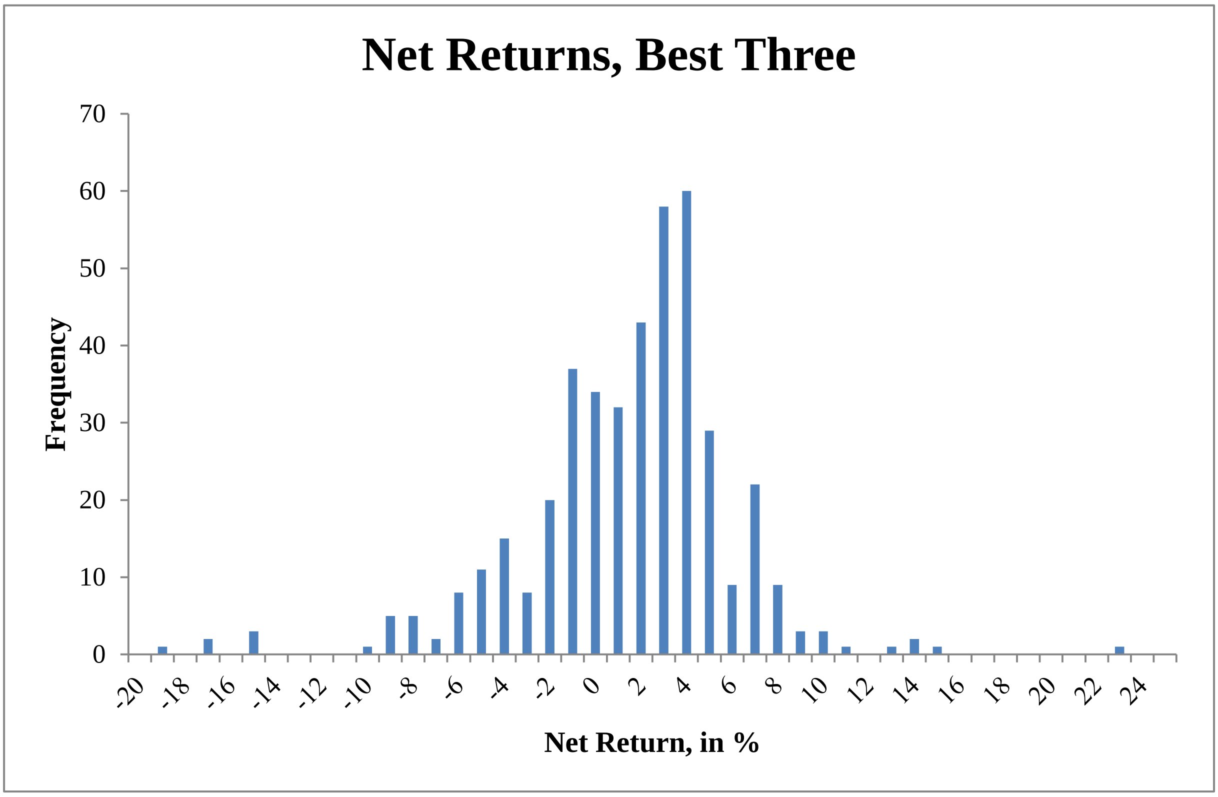


Table 5 below describes the excess net returns, $r_{et} = r_{ft} - r_{it}$, of the three best funds, where r_{ft} is the return achieved by the fund in period t and r_{it} refers to the return generated by passively owning the benchmark index portfolio in period t.

Table 5: Descriptive Statistics, Excess Net Returns, Best Three Funds

Descriptive Statistics, Excess Returns, Best Three Funds (in %)						
	Mean	**Median**	**Standard Error**	**Skewness**	**CI, Lower Bound**	**CI, Upper Bound**
Didner & Gerge Aktiefond	0.248	0.168	0.154	0.620	-0.056	0.552
Cliens Sverige B	0.215	-0.015	0.154	0.557	-0.100	0.530
Cliens Sverige A	0.202	-0.029	0.160	0.621	-0.115	0.518

Note: The confidence interval in the table is the 95% confidence level interval.

Based on the statistical analysis of the funds' excess net returns it is concluded that investing in a good fund, in the sense that the fund generates high returns, is a good idea for the investor, despite the excess net returns of the three best funds in our dataset not being significantly greater than zero at the 95% confidence level. However if one uses a different confidence level than the 95% limit, the confidence intervals will be narrower. One can find the new confidence level that pushes all of the lower bounds in table 5 above zero by solving the following equation:

$$0{,}00202 - t * 0{,}0016 = 0 \qquad (1)$$

The t-value that solves the equation is $1{,}2625 \approx 1{,}263$, which corresponds to a confidence interval at approximately an 80% confidence level. This means that the investor can be roughly 80% certain that the average excess net return from the fund is greater than zero. One should however note that the t-value that solves (1) in fact corresponds to the worst of the three best funds, so the confidence level is greater than 80% for the even better funds. This implies that in the long run, an investor will earn more money being invested in a good fund than he/she will earn being invested in the benchmark index. This is also confirmed by figure 4, which clearly shows that the best three funds have experienced a more rapid growth in value than the index. The fact that there are fund managers who, on average, beat the index at a confidence level of at least 80% implies that they can exploit some of the statistical arbitrage opportunities that exist in the equity market. They are able to identify companies that are mispriced and use this information to design funds that generate positive expected excess returns in the long run.

Based on the statistics of the first step of the analysis it is concluded that fund managers are consistently outperforming the market, which is clearly a requirement if it should be interesting for a rational investor to buy the fund. This answers the first part of the two-sided research purpose, namely whether or not an investor will earn money when investing in an equity fund. The results clearly show that the expected net return from fund investment is positive, given that a good fund is chosen.

4.2 Comparison between a Fictive Investor and the Best Three Funds

The second step of the analysis is to assess whether or not the fund managers are utilizing the statistical arbitrage opportunities that exist in in the equity market to a notable extent. If it is going to be interesting for an investor to buy the funds, their performance need to exceed what the investor can achieve by him/herself without a great deal of effort. This is tested by first creating a statistically sophisticated investment strategy which a fictive private investor could implement him- or herself, assuming that the investor is familiar with the relevant statistical and econometric concepts, and comparing this to the performance of the funds. If the funds are not outperforming this strategy there is obvious room for improvement on the behalf of the fund managers, but if the funds' average returns are significantly greater than the average return generated by the fictive investor, it is concluded that fund managers are capitalizing on market opportunities to create substantial positive excess returns.

The investment strategy that is used to emulate the behavior of the fictive, sophisticated investor is based on a time-series regression model fitted to the index series and it is now explained what motivates the choice of this model. Inspection of the graphs in figure 1 and figure 2 suggests that volatilities of neither funds' nor index's value developments are independent of time. There appears to be periods of higher and lower volatility that all funds are affected by. This is true for the funds' net returns as well, and since all the time series are tracking the index closely, it is likely that they follow roughly the same underlying process as the index.

It is described by Enders (2015) that models which account for volatility clustering are usually a good fit to financial data, specifically ARCH/GARCH models are commonly used. One will also find that the use of ARCH/GARCH models is very common in finance literature and research. A few examples are Engle (2001), Xekalaki and Degiannakis (2010), Berezka and Masliy (2016), and Ivrendi and Guloglu (2012). All of the above argue that ARCH/GARCH models suit financial data as volatility is typically not independent of time. Inspection of the graphs in the Data section also leads one to suspect that such a model should be used in this particular case. In order to test if a model from the ARCH family should be used, ARCH LM tests are performed. The test procedure is the following:

Step 1) Run the following regression:

$$r_t = \beta_1 + \beta_2 r_{t-1} + \cdots + \beta_{p+1} r_{t-p} + \varepsilon_t \qquad (2)$$

where p is the chosen lag order. What lag order to choose depends on the nature of the data and, to a great extent, common sense. In this particular case, the lag order was only set to equal 1. The observed fund returns are spread with one month intervals, and it is very unlikely that a fund's return today is significantly connected to the return that the fund achieved two months ago.

Step 2) The residuals are saved and used in an auxiliary regression:

$$e_t^2 = \alpha + \gamma_1 e_{t-1}^2 + \gamma_2 e_{t-2}^2 + \cdots + \gamma_k e_{t-k}^2 + u_t \qquad (3)$$

The lag order, k, is chosen by what seems reasonable. The coefficients are checked for significance and signal what lag order the ARCH model is likely to be. In the case of this essay's analysis, no significant coefficients are found for any values of k. This is troublesome to a certain degree, but the test should not be blindly trusted. One reason is that if the wrong lag order is chosen, the result of the test is very unlikely to be significant. Secondly, the ARCH LM test investigates ARCH terms only. The error terms in the real data generating process can follow a different structure, for example a GARCH process, which the test does not detect. Since there is no obvious model specification which is right for the data, various ARCH/GARCH models are fitted to the index's returns and the choice of model is based mainly on the models' BIC scores, as the BIC evaluates how likely the model is given the set of used parameters. Coefficient significance is also taken into consideration when two different models have similar BIC scores. The model selection is data driven and starts with a fairly simplistic ARCH(1) model. Other model variations include ARCH(2), GARCH(0,1), GARCH(1,1), GARCH(2,1), and GARCH(2,2). Higher lag orders are excluded as it does not make intuitive sense to include them. Since the observations are spread with one month intervals it does not make sense to include as much as three lags, which would imply that fund returns from three months back influence present returns to a notable extent. The structure of the different models' error terms are the following:

ARCH(1): $$h_t = a_0 + a_1 \varepsilon_{t-1}^2 \qquad (4)$$

ARCH(2): $$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 \qquad (5)$$

GARCH(0,1): $$h_t = a_0 + \beta_1 h_{t-1} \qquad (6)$$

GARCH(1,1): $$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (7)$$

GARCH(2,1): $$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \beta_1 h_{t-1} \qquad (8)$$

GARCH(2,2): $$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \beta_1 h_{t-1} + \beta_2 h_{t-2} \qquad (9)$$

Table 6 below presents the BIC scores of the examined model variations.

Table 6: BIC Scores of Examined Models

Model Type	BIC
ARCH(1)	**5.855**
ARCH(2)	**5.932**
GARCH(0,1)	**5.913**
GARCH(1,1)	**5.908**
GARCH(2,1)	**5.777**
GARCH(2,2)	**5.816**

When inspecting the BIC scores of the different ARCH/GARCH models it becomes evident that the GARCH(2,1) specification is the best fit to the index data, even though the differences are very small. The GARCH(2,1) model is formulated in the following way:

$$r_{it} = \delta_1 r_{it-1} + \varepsilon_t \tag{10}$$

$$\varepsilon_t = v_t \sqrt{h_t} \tag{11}$$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \beta_1 h_{t-1} \tag{12}$$

The dependent variable, r_{it}, represents the return of the benchmark index at time *t*. The intercept in the level equation is zero by construction since at the starting point all the time series with returns are naturally zero. The error term, ε_t, consists of a white-noise term, v_t, as well as an ARMA-term, h_t. The coefficient estimates of the GARCH(2,1) model are presented in table 7 below.

Table 7: Coefficient Estimates of GARCH(2,1)

Coefficient	Value
$\hat{\boldsymbol{\delta}}_{\mathbf{1}}$	0.244***
$\hat{\boldsymbol{a}}_{\mathbf{0}}$	2.987**
$\hat{\boldsymbol{a}}_{\mathbf{1}}$	-0.072***
$\hat{\boldsymbol{a}}_{\mathbf{2}}$	0.344***
$\hat{\boldsymbol{\beta}}_{\mathbf{1}}$	0.611***
BIC Score	5.932

Note: The significance codes are the following: '*' implies significance at the 0,05 level, '**' signals significance at the 0,01 level, and '***' means that the parameter is significant at the 0,001 level. The null hypothesis is that the true parameter is equal to 0 for all parameters.

The model is used to emulate the sophisticated investor's behavior. It is assumed here that the investor operates according to the following strategy: The investor invests in the benchmark index portfolio and is currently standing in time period t. The GARCH(2,1) model is used to forecast returns of the benchmark index one period ahead, $t + 1$. If the forecasted return is negative, the investment is taken out of the stock market, and if the forecasted return is greater than one, the investment is kept in the stock market. As one period passes, an index return is realized in period $t + 1$. The realized return is incorporated in the model and is used when forecasting the return in period $t + 2$, at the same time the first observation in the model is dropped to keep the sample size constant. If the model specification is a good fit to the index data, a strategy such as this one will remove many of the negative returns that the index realizes, thereby creating high average returns and growth in value. A good fit in this case does not mean that the model can forecast the exact returns, but rather that it can foresee the general direction of the index, determining whether one should expect positive or negative returns. In short, the fictive investor is using a roll-over forecast technique to estimate future returns of the index and letting the forecasted returns guide investment decisions. The final comparison in the analysis is made between the returns forecasted by the fictive investor's strategy, for a period stretching from April 2014 to March 2017, i.e. 36 months, and the returns achieved by the three best funds during the same period. The results of this comparison are presented table 10.

Before the results of the analysis are presented, arguments are presented for the choice of investment strategy used by the fictive investor. The strategy is purely empirical in the sense that no corporate information, e.g. ratios such as book to market or similar, is used. It is also clear that the strategy is not a ready-made one which is just applied. An example of such a ready-made strategy could be using Fama's and French's three factor model to determine whether or not an asset should be acquired. The intuitive reason behind the purely empirical strategy is that if the investor utilizes various financial measurements of asset quality and a strategy that requires extensive knowledge of finance, he/she is arguably emulating a financial professional rather than an investor without much experience of financial economics. Since the purpose of this step of the analysis is to determine if the financial professionals are in fact outperforming an investor without extensive financial knowledge, it is critical that the investment strategy is not too similar to one which can be used by a financial professional. The degree to which financial professionals are outperforming the index is determined by earlier stages of the analysis, so the focus of this comparison is to settle the second of the two parts of the research purpose: Is it worth the required fees to let a financial professional manage one's investment? If the managers of the three best funds are not outperforming the fictive investor, who has no real knowledge of finance, it is clearly not worth the cost of fees to have the investment managed by a fund company.

A comparison between the returns achieved with the fictive investor's strategy and just passively owning the benchmark index is found in table 8 and table 9 below.

Table 8: Descriptive Statistics, Fictive Investor’s Returns

Descriptive Statistics, Fictive Investor’s Returns (in %)	
Mean	0.789
Median	0.000
Standard Error	0.395
Skewness	1.417
0,9 CI, Lower Bound	0.138
0,9 CI, Upper Bound	1.439

Note: The confidence interval in the table is the 90% confidence level interval.

Table 9: Descriptive Statistics, Benchmark Index Returns

Descriptive Statistics, Benchmark Index Returns (in %)	
Mean	0.789
Median	1.368
Standard Error	0.562
Skewness	0.057
0,9 CI, Lower Bound	-0.135
0,9 CI, Upper Bound	1.715

Note: The confidence interval in the table is the 90% confidence level interval.

From the tables above one can draw the conclusion that the average returns of the fictive investor’s strategy and passively investing in the index are the same, but the strategy based on the GARCH(2,1) model produces returns that are more stable above zero. This is also confirmed in the data. For the 36 month period during which returns are forecasted, only 16.2% of the fictive investor’s returns are negative. The corresponding fraction for the benchmark index is 37.8%. Looking at the confidence intervals in the tables above, one can see that returns of the fictive investor’s strategy are greater than zero at the 90% confidence level, which from the point of statistical arbitrage implies that this strategy is preferred.

The fictive investor’s strategy will now be compared to the three best funds in order to determine how well fund managers are performing at exploiting the statistical arbitrage opportunities that can be found in the Swedish equity market. The excess returns of the funds are now calculated as $r_{et} = r_{ft} - r_{FIt}$, where r_{ft} is the net return achieved by the fund in period *t*, and r_{FIt} is the return achieved by the fictive investor in period *t*. The results of this comparison are presented in table 10 below.

Table 10: Descriptive Statistics, Best Three Funds' Excess Returns

Descriptive Statistics, Excess Returns, Best Three Funds (in %)						
	Mean	**Median**	**Standard Error**	**Skewness**	**CI, Lower Bound**	**CI, Upper Bound**
Didner & Gerge Aktiefond	0.236	0.343	0.409	-0.197	-0.594	1.066
Cliens Sverige B	0.237	0.166	0.404	-0.375	-0.582	1.057
Cliens Sverige A	0.137	-0.026	0.414	-0.198	-0.703	0.977

Note: The confidence interval in the table is the 95% confidence level interval

The numbers in the table above are clearly suggesting that all the three best funds are outperforming the fictive investor on average. Interestingly though, none of the confidence intervals are strictly above zero. The probabilities of the funds' excess returns being positive are roughly 58% for Didner & Gerge Aktiefond, 56% for Cliens Sverige B, and 50% for Cliens Sverige A, which, together with the fact that the average excess returns of all the funds are positive, implies that when fund managers beat the fictive investor's strategy they beat it with a larger margin than they lose to it. This suggests that the knowledge possessed by financial professionals actually contributes to generating real value.

The results section of this essay will now be summarized. Firstly, descriptive statistics regarding fund returns are produced. These statistics and the graphs in 4.1 motivate that the analysis is restricted to only considering the best three funds. If an investor is rational in the sense that she/he is evaluating funds based on their returns, there is no reason why that investor should invest in a poorly performing fund. The best three funds in the data are, in order, Didner & Gerge Aktiefond, Cliens Sverige B, and Cliens Sverige A. The descriptive statistics regarding these funds' returns are found in Table 4: Descriptive Statistics, Net Fund Returns of Best and Worst Funds. These funds' net returns are initially compared to the returns realized by the underlying benchmark index in table 5, and it is concluded that one can be certain that these funds generate positive excess returns at an 80% confidence level. This implies that fund managers are very likely able to exploit statistical arbitrage opportunities. Following this result, the strategy implemented by the fictive investor is outlined and compared to the alternative of passively owning an index portfolio in table 8 and table 9. The coefficient estimates of the GARCH(2,1) model underpinning the fictive investor's strategy are found in table 7. It is concluded that the fictive investor's strategy generates returns that are more consistently positive than the returns generated by the index. From a statistical arbitrage point of view this strategy is preferred to passively owning the benchmark index. Finally, a comparison between the fictive investment strategy and the best three funds is made in table 10. On average, the three best funds generate returns that are higher than those achieved by the fictive investor. The probabilities of these funds' net returns being greater than the fictive investor's returns are 58%, 56%, and 50% respectively. This implies that when the fund managers beat the fictive investor, they do it by such a margin that the excess returns generated are offsetting the occasions on which they lose to the fictive investor. This analysis shows that not only can fund managers exploit statistical arbitrage opportunities, they can also use their financial knowledge to create substantial excess returns, even when the funds are measured against something more sophisticated than a passive index portfolio.

4.3 Practical Illustration of the Results

It is concluded above that investing in an actively managed fund is a good idea, in general, but in order to illustrate how good of an idea it is, a numerical example will now be presented. Assume that an initial amount of 10,000 SEK is invested in one of the three best funds and kept in the chosen fund for five years, i.e. 60 months. Using the average monthly net returns in Table 4: Descriptive Statistics, Net Fund Returns of Best and Worst Funds, the investment will be worth the following at the end of the five year period:

Didner & Gerge Aktiefond: Approximately. 18,340.25 SEK

Cliens Sverige B: Approx. 17,984.41 SEK

Cliens Sverige A: Approx. 17,846.02 SEK

Discounting these values using the Swedish inflation target of 2%, the investment will have the following net present values:

Didner & Gerge Aktiefond: Approx. 16,611.33 SEK

Cliens Sverige B: Approx. 16,289.03 SEK

Cliens Sverige A: Approx. 16,163.69 SEK

Clearly, investing in the funds generates substantial growth in value, even when future values of the investment are discounted. Being passively invested in the index for 60 months yields the following the results, using the average return of the index:

Index: Approx. 16,024.64 SEK

Net present value of the index: Approx. 14,514.01 SEK

Since the average return of the fictive investor's strategy is the same as the index's average return, one would expect the same net present value from an investment that was invested according to the fictive investor's strategy. As mentioned earlier though, the volatility of the fictive investor's strategy is lower than the volatility of the index, implying that the investor's strategy is preferred.

5. Conclusion

The analysis is divided into two parts in order to adequately answer the research purpose, namely to investigate if an investor can earn money, in real terms rather than nominal, by simply investing in a fund and waiting for the money to grow in value. If that is really the case, it is assessed whether or not it is worth paying the required fees to have fund companies manage the investment. The analysis presents descriptive statistics that describe relevant aspects of the funds' returns and compare these to the benchmark index. Investing in poorly performing funds is, under reasonable assumptions, not an option for the investor, why the analysis is restricted to the three best funds. From table 4 and table 5 it is concluded that fund managers are able to exploit statistical arbitrage opportunities. Average excess net returns of the funds are greater than zero with a confidence level of at least 80%, depending on which of the three best funds one is considering. The analysis can so far conclude that fund managers are able to exploit statistical arbitrage opportunities well enough to create a growth in value that, in the long run, beats the benchmark index. The second part of the analysis, which concerns whether or not it is worth paying the fees that fund management is associated with, compares the returns achieved by fund managers to those achieved by a fictive investor following the strategy explained in section 4.2. The strategy is based on a GARCH(2,1) time series model that is used to roll-over forecast the returns of the benchmark index. When the forecasted return is negative, the investment is taken out of the market, generating a return of 0, and when the forecasted return is positive the investment is re-invested in the benchmark index portfolio. In table 8 one can see that the returns generated by this strategy are greater than zero at a 90% confidence level. This investment strategy, which is free and does not require financial sophistication, is compared to the three best funds in table 10, and the comparison shows that all of the three best funds are on average beating the fictive investor. This implies that not only can fund managers exploit statistical arbitrage opportunities, they can also use their financial knowledge to create substantial excess returns, even when the funds are measured against something more sophisticated than a passive index.

In other words, fund managers are able to exploit statistical arbitrage opportunities to create excess growth in value, and the excess returns that they create are substantial enough to beat an active, but free, investment strategy that a private investor can implement him-/herself. The conclusion implies that investing in funds is worth the fees, given that a good fund is chosen. This result is concretely exemplified in 4.3 Practical Illustration of the Results.

For a discussion on the scope and limit of the analysis, see the Discussion section below.

6. Discussion

A number of questions arose during the course of working with the analysis. In this discussion we will address the most interesting ones. The first and perhaps most obvious question is: Why are we using the specific investment strategy described in 4.2? What is it based on? The idea behind the investment strategy is that the investor should not need financial sophistication. If the strategy is supposed to emulate what an investor without financial expertise should be able to achieve, without constantly checking on the investment, a number of relevant explanatory variables should not be included. Such a strategy is arguably not describing a behavior that a financially non-skilled investor would exhibit. The model is of course not optimal in any sense, but trying to create an optimal investment strategy is roughly what the professionals within the finance field are trying to do, why it is not really possible to claim that an financially non-skilled investor should do the same thing.

Another issue that was considered was that of commission. When a private person trades equities, commission is paid to the broker. This type of trading fee is not included in our analysis. It is reasonable to suspect that the exclusion of commission affects our results. After all, the fictive investor would in reality need to pay commission every time the investment is moved into or out of the market. The fees are however very small. At Nordnet, for instance, there are options of 0.25%, 0.15%, and 0.069% commission, each class having different minimum commissions. Which class is used is based on the amount invested. One could invest 50,000 SEK and only pay a minimum amount of 69 SEK in commission. Virtually nothing. Since the amounts are so miniscule, we chose to exclude them from our calculations in order to improve readability of the results. Different brokers have different commissions and there is no way of determining which of these commission rates that should be used. It is also the case, as see just above, that a single broker can have many different commission rates as well.

Another question one could raise regards the performance of the fictive investor's strategy. Why was it not performing better? The tedious but obvious answer is that data was lacking. Observations are spread with too long time intervals. The magnitude of the correlation left between returns after an entire month is not great. If more frequent data would have been used it is very likely that the GARCH-based investment strategy would perform better. Since the investor in our analysis is only updating his/her position once a month, the investment is perhaps left in/out of the market for too long a period to counter the movement of the index very well. This is perhaps a reason why the BIC values are quite small, but given that the data is spread with so long time intervals we are not sure that one can easily improve on the model specification we use. The fact that the ARCH LM tests give non-significant results makes model specification quite difficult. None of the other versions that are examined give better BIC scores though, why the GARCH(2,1) in table 7 is used. And as mentioned in the body of the essay, the model does not need to able to pinpoint future returns, it is enough that it predicts the movement of future returns. Given that the probability of receiving a negative return with the model is less than half of that probability for the ‘untouched’ index indicates that the model is in fact successful at doing this.

Another data related question is the following: Why are we not forecasting a longer period? A sample of historical data is needed for model estimation, and the larger the sample is, the more accurate the estimates will be in general. A fairly large sample was kept because we wanted enough observations for the parameter estimates to be somewhat accurate. If the model includes parameters that are related to each other in reality, it is preferable if the parameter estimates of this relationship are significant. Another reason is that we wanted the sample period to cover the volatility clustering that one can observe in figure 2.

When we were studying previous literature on the topic of statistical arbitrage we were of course trying to assess the literature objectively. After all it is not yet completely determined that such opportunities exist. Some classic theories are not leaving much room for it. The joke described in section 2 is a testament to this. We did however conclude that statistical arbitrage opportunities do exist. This is mainly based on the fact that it seems extremely unlikely that financial markets are efficient. We do not believe that all relevant information for correct pricing of an asset is possessed by or available to the public. The inner workings of companies and their plans for the future are not likely made public until they are actually set in motion. A company can lose some of its competitive edge by e.g. revealing plans of mergers or major organizational transformations too soon. Such information would definitely affect the value of a company’s stock, but since the company has incentives not to reveal it, it is very unlikely that the price of the stock reflects that information. Hence we find it reasonable to assume that statistical arbitrage exists.

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Appendix 1

List of Funds Included in the Analysis

- Aktie-Ansvar Sverige A
- AMF Aktiefond Sverige
- AstraZeneca Allemansfond
- Carnegie Sverigefond
- Catella Reavinstfond
- Cliens Sverige A
- Cliens Sverige B
- Danske Invest Sverige
- Didner & Gerge Aktiefond
- Enter Sverige
- Gustavia Sverige SEK
- Handelsbanken Sverige Selektiv
- Handelsbanken Sverigefond
- Handelsbanken Sverigefond Index
- Länsförsäkringar Sverige Aktiv A
- Monyx Svenska Aktier
- Nordea Alfa
- Nordea Swedish Stars icke-utdelning
- Skandia Sverige
- Spiltan Aktiefond Stabil
- Swedbank Humanfond
- Swedbank Robur Ethica Sverige
- Swedbank Robur Sverigefond
- Öhman Sverige Smart Beta

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