Utilizing short-term noise in non-efficient markets by paired assets

-Introducing the Technical AMH trader

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Abstract

In this paper, we present an algorithmic implementation of a pairs trading strategy on the OMXS during the years from 2010 until 2018. In our case, the trading algorithm is based on the Adaptive Market Hypothesis (AMH) theory. Hence, the algorithm scans the market for temporary inefficient behaviour, as defined by AMH. The pairs trading algorithm suggested in the paper revolves around a minimum distance paring method that evaluates different threshold measures. In the paper, we also suggest a new method for the choice of threshold as well as evaluate the efficiency of the strategy by an application on the relatively small Swedish OMXS stock exchange. In this small exchange, other forms of market inefficiency may arise compared with those on a larger international stock exchange. The paper also presents the AMH framework for behaviour in a financial market, a hypothesis that may explain the positive result of the presented application of pairs trading strategy. Hence, this paper connects AMH with the pairs trading strategy. Our result indicates that when we exercise the strategy during a period of trading, in a portfolio consisting of 10 pairs, it generates a positive aggregated return, compared with index, even when we consider a theoretical transaction cost. Furthermore, the strategy outperforms a random naïve trading strategy combined with a low market dependence, measured in correlation. However, even if the strategy is profitable, the return is volatile. This is believed to be an outcome of volatile market reactions to new information in the close chosen substitutes. Such problems with pairing and diversity may be traced back to the small sample of stocks in the example presented in the paper. As such, the algorithm suggested is as a step towards trading based on theoretically motivated algorithmic learning models, in line with trading models developed within the rapidly emerging field of artificial intelligence.

Key words: OMXS, Efficient markets, Adaptive Market Hypothesis, Technical AMH Trader, Pairs Trading

JEL codes: G11, C63 C44

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Adaptive Technical Trading

Technical trading, that is trading based on an analysis of historical asset prices, is a well-known topic in academic finance. Many, and often similar, strategies have been suggested, but due to the combination of complex dynamic nonlinearities and various degrees of efficiency in financial markets, no general best practice trading method based on historical prices have been found.

In this paper, we suggest a technical trading algorithm based on a pairs trading strategy. The Adaptive Market Hypothesis (AMH), as introduced by Lo (2004), give a behavioural motivation for our choice of strategy. Thus, in this paper we suggest the "AMH Trader" as a class of financial agents.

We formulate a possible strategy of the AMH Trader as a trading algorithm. The algorithm is implemented on stocks at Nasdaq OMX Stockholm. OMX Stockholm is a small stock exchange compared with the world market capitalization.

Previous studies of pairs trading have generally focused on large, well-analysed and thus probably more efficient stock markets, such as SP500.

This paper thus add to previous studies by testing pairs trading on a smaller exchange, where other and more significant inefficiencies may be found compared with those on a larger exchange. Moreover, the paper add to previous studies by implementing a new methodology for pairs trading as well as a theoretical framework to explain conditions for profitability of the strategy.

Background

Criticism of technical trading often focus on the fact that strategies only are based on a search for patterns in historical prices. Hence, dependent on the specific analysed period, the result could be a biased forecast, as discussed by the Economist (2009). Furthermore, critics often argues that the technical models does not consider economic market and pricing theories as developed e.g. by the Nobel laureate in economics, Eugene Fama. The Efficient Market Hypothesis (EMH) by Fama (1970), in fact implies that excess profit, in comparison with a relevant index, not may be obtained from an analysis of a set of historical prices.

Later in the paper, the EMH will be explained further but as a preview, we may observe that even in the weakest form of the EMH, there should be impossible to predict short-term prices from pervious prices in a profitable way. According to the EMH, the market almost instantaneous adopts new information. As such, historic patterns are already accounted for in today's price and forecasts of future prices will only reflect so called "random walks".

The French mathematician Bachelier, often considered as the forefather of mathematical finance, is said to have described such a pricing process as a drunks attempt to walk in a straight line, each step is complete random even if the aim is to step on the line. The result of trading based on the information from such a random walk is, Lo (2017), that sometimes you win and sometimes you lose.

Given this, one could ask why technical trading exists? No matter the time spend on analysing series of prices, there is no possibility to beat the market. Nevertheless, we see individuals as well as funds claiming to apply technical analysis successfully. Is it possible that the market actually not always is efficient, not even weakly efficient?

The answer to this question may be found in extensions of the EMH or in deviations from the EMH assumption of "rational investors". Fama shared the Nobel Prize in 2013 with Shiller and Hansen, for their empirical work on asset pricing. This joint award may be seen as strange, since in total contradiction with the EMH, Shiller suggested that investment decisions not are based on rational expectations, but instead emphasized the role of psychology in the market.

Shiller supported his argument by a comparison of fluctuations in a stock price with its dividend, which the price is supposed to reflect. Since the stock price clearly has shown larger fluctuations compared with the fluctuations of the dividend, this implied that at least in the short term, inefficient markets are possible.

Moreover, Hansen concluded that swings in asset prices not fully could be explained by factors of rationality. Instead, he suggested such swings to be explained by differences in risk aversion by investors, Aglionby and Giugliano (2013).

Hence, the findings and suggestions by Shiller and Hansen have given some support to the large existing industry specialised in asset price forecasts. In contrast to the random walk hypothesis, those companies try to gain excess profits from the cornerstone assumption of technical trading, that price patterns may not be complete random.

Ho, Park and Irwin (2004) evaluated the profitability of technical trading models in future, stock and foreign exchange markets. They show that technical trading strategies at least had generated consistent returns in the early 1990s. However, technical stock trading was not found to be profitable in the 1980's. According to their study, problems with the validity of such studies could be traced to data snooping and post rule selection in the trade models. Hence, the result somewhat show that the use of technical trading models is dependent on both the model and the market as well as the timeframe of implementation.

Lo (2004), reaches a similar conclusion when he combines the EMH with behaviour economics in his theory of adaptive markets, the Adaptive Market Hypothesis, AMH. The idea behind AMH is that market efficiency is dependent on the number of "species" that operates in a market. A specie is defined as a group of similar market agents, as for example, hedge funds, pension funds or just a number of agents implementing similar strategies. Given this, a large specie applying the same strategy are as such competing about the same profit. This often results in a more efficient market. In comparison, a specie with fewer member's will results in a surplus of resources, e.g. profit and the specie will flourish for the time being.

Earlier, Black (1986) had introduced the term "noise traders". These traders are simply traders who trades on nonsense information and thus creates a noise in asset pricing with their trades. Lo (2004) further explains that such trade can be seen as human biases based on e.g. irrational probability beliefs. The economic interpretation of such mismatches between human behaviour, choice consistency and maximizing utility may according to Brinbaum (2001) be found in a number of paradoxes e.g. Allias paradox, or the St-Petersburg paradox. Since such irrational trades disturb the equilibrium price, it may be possible to achieve arbitrage profits from trade in that specific market. Market actors would exploit such an opportunity until the arbitrage possibility simply no longer exist, and the price has returned to its equilibrium.

Given this, the role of a "technical AMH trader" is to scan and locate markets where inefficient behaviour are found in historical asset pricing. In these markets a profit could be achieved by implementing models based on the belief that the inefficient behaviour will repeat itself in the upcoming period of time. The profit may be found from the distance between the distorted price and its equilibrium state.

According to Gatev, Goetzmann and Rouwenhorst (2008), pairs trading is one of the best known or perhaps the most known and commonly applied technical model that utilizes such short-term noise in asset prices. The strategy has its root in the early-mid 1980's and could according to Folger (2018) be credited to a group at Morgan Stanley, later lead by Nunzio Tartaglia.

The fundamental idea of pairs trading is to identify relationships between the prices of two (or more) assets. The intuition behind the method is that the price of those assets, in overall, moves in a related pattern, where any difference between the asset prices has the property of mean reversal. Hence, given noise in one of the assets, which create a distance between the price of this asset and the price of the other asset in the group, an agent could make a profit by taking positons, long or short, assuming that the asset will return to the equilibrium given by the group. Hence, the agent gains a profit from the spread, which is defined as the difference in price between the group of assets.

Given that the relationship is mean reversal, this form of trading is classified as a statistical arbitrage strategy. Moreover, pairs trading could be seen as a market neutral and self-sustainable way of trading. For example, if the whole market suddenly would plum down to zero, the losses in the long position could possibly be cancelled out by the short position. Furthermore, if the price of the assets that is sold short, is larger than the price of the long assets, the strategy is self-financed, since the capital gained from short selling the first asset, could be used to finance the investment in the long position.

The explanation given by Tartaglia to the profitability of pairs trading is by Gatev, Goetzmann and Rouwenhorst (2008, pp.4) said to be strict psychological. "Human beings don't like to trade against human nature, which wants to buy stock after they go up not down".

However, according to Celaier (2018), D.E Shaw, who worked in the Tartaglia team and later started his own successful quant fund, had a different explanation. Shaw credits the success of his quant fund to the fact that it was established early, and that the market now more generally has adopted quantitative methods. Hence, an implementation of such a strategy with success now has become slim [Gatev, Goetzmann and Rouwenhorst (2008) pp. 4)].

Most of the academic literature dealing with the subject of pair trading strategies have implemented the strategy on large exchanges, such as stocks on the SP500. Stocks on the SP500 are world famous companies that are under constant surveillance for mispricing by funds and other actors all around the world. Hence, according to the AMH, this large interest from many actors would generally result in markets that are more efficient.

This motivates our focus in this paper on a smaller stock exchange, Nasdaq OMX Stockholm. Nasdaq Stockholm is the largest of the Nordic exchanges. Nevertheless, it did according to Beskopeinvest (2008), only account for one percent of the world market capitalization during 2008.

Moreover, since pairs trading involves taking a short position, it is a bet against the market, which to some extent and for some actors is a legally restricted form of investment. This prevent large actors, such as pension and general funds, from applying the strategy. However, it still leaves hedge funds and independent investors as possible actors in the market. In comparison with the rest of Europe, Sweden has the third largest hedge fund industry, measured as assets under management. Moreover, Prequin (2017) reports that 12 per cent of Swedish hedge funds are users of "relative value trading", a category where pair trading is included.

Given the background above, in this paper *the overall efficiency of the Swedish stock market is evaluated by a pair trading strategy*. While answering this general question, the paper will focus on:

- *Effectiveness of applying a pair trading strategy on a sample of OMXS Stocks?*
- *Efficiency of the Swedish OMXS market.*

In the following, we first discuss earlier attempts to implement pair strategies in financial markets. This will be followed by a further explanation of the economic theories relevant to the strategy. Moreover, the algorithm and assumptions made in the model will be explained, combined with model specifications. Thereafter, our data and some descriptive statics will be reviewed, followed by a presentation of our results. Finally, the results are discussed and related to the economic theory of asset pricing, as well as the efficient and adaptive market hypothesises.

Earlier work

Since the idea of pair trading is relative simple and thus quite well-known, there are a large variety of ways to implement the strategy. The first step of the strategy is to find pairs of assets and evaluate the time consistency of their relationships. In the dissertation by Harlacher (2016), the construction of an algorithm for trading in cointegrated pairs is evaluated.

Generally, cointegration is seen as modelling a long run equilibrium process, which includes the critical mean reversion property. The cointegrated method by Harlecher is a parametric form of pair trading, which assumes a common stochastic trend between a pair of financial assets. The method allows for more than two assets to form a linear combination of a cointegrated pair. The dissertation handles the statistical problems of finding suitable pairs, as well as robustness of estimations. Moreover, the back testing of the strategy is implemented on SP500 stocks from the period 1995-2011 and shows profitable returns, in comparison with the index. Furthermore, the portfolio of the strategy had favourable properties, such as low correlation with the market as well as less volatile during the same period.

The paper by Gatev, Goetzmann and Rouwenhorst (2008) on pair trading is by Harlecher (2016) seen as the pioneer academic paper on the subject. The paper evaluates the performance of a pair trading algorithm for the period 1962-2002. Pairs are chosen from what the author describes to be a simple minimum squared distance criteria. The study uses a fully self-financed portfolio by assuming a possibility to invest one dollar in each pair asset. To prevent data snooping, the study applies a position argument of two standard deviation of the distance criteria as well as out of sample testing. The results is an average yearly profit of 11 per cent for a self-financed portfolio. Finally, the study concludes that the profit from the strategy is made possible from temporary misprices between close substitutes.

Moreover, Perlin (2008) writes in the Journal of Derivate and Hedge funds, about the implementation of a similar methodology as Gatev, Goetzmann and Rouwenhorst (2008), but based on the Brazilian market. Perlin, instead of utilising a parametric position threshold, introduced several fixed thresholds. Moreover Perlin also included tests for different data frequency; daily, weekly and monthly. The paper is a very profitable implementation of the strategy in the interval threshold distance of 1.5-2.0 for daily quotes. It gives excessive returns around 100 percent in thresholds (1.5-1.8) compared with a naïve trading approach after transaction costs. Returns for monthly and weekly quotes both are shown to be less profitable than the use of daily quotes.

Economic theories behind as well as criticism of strict efficient markets

In this section we give a more complete description of the theories earlier mentioned. Three different ways to relate to technical trading and market efficiency may be identified.

Fama and the efficient market theory (EMH)

EMH was presented by Eugene Fama (1970). EMH is a theory which revolves around the price of financial assets. The price of a specific asset is seen as a function of all relevant information regarding the asset. Fama suggests that market efficiency can be described by a three level scale.

In its weakest form, the weak efficient market, it is considered not to be possible to analyse historical data on prices and volumes to create excess return, in comparison with a relevant index. Hence, there is no reason to consider technical analysis for investment decisions. The theory assumes that when such information becomes available, the market will instantaneous incorporate it into the asset price. However, in a weakly efficient market, there is still a possibility to predict further prices by an analysis of public information, such as financial reports, and, if available, insider information.

In the second level of market efficiency, semi strong, the use of public information for prediction future price development is no longer possible. Hence, the market also has incorporated public information in the price. At this stage the only way to create excess market return, is by the use of insider information.

The last and highest level of market efficiency, a strongly efficient market, simply strips the ability of the investor to use insider information. In the strongly efficient market, the market has knowledge of all information, including insider information, and has accounted for the information in today's price. Hence all possibilities to create excess market return, has completely diminish.

Shiller and the price movements by changes in dividends

Shiller's (1981) article in the American economic review, ”*Do stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?”,* questioned the reality in the underlying assumptions of rationality among investors in the EMH. The main augment by Shiller was that if the market really were consistent with an assumption of rational investors, the price of an underlying asset would be reflected by the future discounted value of its dividends. Hence, volatile fluctuations in the stock price would be the result of new information about future dividends. The criticism by Shiller is based on the fact that the stock price indexes seem far too volatile to be traced to new information regarding future dividends. By plotting de-trended index against the discounted actual value of the dividends it hardly seems plausible that the changes in dividends could cause the large fluctuations in the index price. Shiller's results confirm that the stock prices from 1920 had been far too volatile to reflect the changes in information about future dividends. Actually, it was five to thirteen times too volatile compared with what was to be expected. Hence, the conclusion was that the rationality of investments often assumed in financial models not were trustworthy.

Lo and the adaptive market hypothesis (AMH)

Lo (2004) purposes a new framework to analyse financial interactions and markets. The idea by Lo is based on the behavioural fields of finance, which questioned the rationality of investors suggested by EMH. Lo presents several papers that rejects the random walk hypothesis of stock pricing, e.g. Lo and Mackinlay (1988). While behavioural finance often refers the inefficiency to factors such as greed and fear, Lo builds his idea from evolutionary factors such as competition, adaption and the course of natural selection.

Moreover, Lo describes that the AMH should be seen as a revised version of the EMH, but revised in the context of evolutionary factors. Hence, asset pricing should be seen to reflect the environmental conditions and the "species" established on the market. Species are by Lo defined as similar actors fighting over the same resources on a specific market, as for example hedge and pension funds. A large numbers of agents, members of a specific specie, fighting over the same scare resources will indeed make the possibility of profit slim, a fact that results in a more efficient market. Hence, the ability to survive is dependent on the local market as well as competition for specific resources e.g. profit. A too large amount of agents in a local market will result in a decline in the population, since the resources will become too scarce for the whole population to survive. This creates what is described as the *"Survival of the riches"*, since after an amount of losses; poor traders and funds are eliminated from the market. The theory is, just as evolution, based on the fact that the population of a specie change in cycles. Hence, also the efficiency of the markets is cyclic. When the market efficiency is weak, a profit can be made. As long as profit is possible, other participants will start to implement the same strategy. Finally, this will result in an efficient market where the whole population no longer can survive. Moreover, Lo presents first order autocorrelation on the S&P composite index. The graph shows that the index was more efficient in the 1950s than during 1990, which would indicate that the computerisation of trade not has been enough to create consistent and a sustainable market efficiency. Hence, the AMH shows that a Technical AMH trader should focus on smaller and less visible markets with a limited set of actors using similar trading methods as the AMH trader.

The basic idea behind and implementation of the pairs trading algorithm

The algorithm suggested in this paper is based on a relative simple two-step process. More sophisticated econometric models based of statistical arbitrage and mean reversion pairs strategies can always be constructed, as developed by Harlacher (2016). However, more assumptions regarding the process would increase the stochastic properties of the model and the possibility of errors. The infamous Occam's razor, "when choosing between two models use the simpler one", Gibbs and Hirosi (1996), can describe the logic behind our choice of a more restricted model, and a relatively simple structure. Hence, a relative simple, non-parametric, Euclidian distance model is chosen. The simpler model was also motivated by the restrictive supply of data, since only close prices was available for each stock.

As mentioned, the idea behind pairs trading is that if two asset prices have had a similar price development over a specific period of time, the relationship would hopefully continue in the following period as well. However, how long this relationship continues is a stochastic process dependent on both the market and the specific asset factors, which makes it hard to estimate.

There are several ways to find assets who may be classified as a pair. An assumption from logical deduction is often that a pair of assets should reflect the same market or underlying fundamental factors, such as commodities or branch specific factors. However, Gatev, Goetzmann and Rouwenhorst (2008) found a large proportion of mixed sector pairs by use of minimum distance criteria. Hence, a branch specific model could miss other storng relationships between assets. Still, as suggested by Harlacher (2016) considering Ross (1979) arbitrage pricing theory, pairs from the same sector can be assumed to be priced by risk in similar macroeconomic factors, and thus generally (at least in theory) creates a more time consistent pair.

The first step in the construction of the model is to fit asset pairs based on the historical price pattern, over a training period. The training period is an <u>in sample</u> configuration, which means that the model is trained on a known set of data. To prevent “data snooping” and over fitting, the configured model is then applied on, for the model, unknown data. This method is used to test the validity of a forecast of future performance, as called by, Eurostat (2015), <u>out of sample</u> testing. It is important to stress the fact that the model does not know the data in the trade periods and cannot use its information in calibrating future parameters. The process is described in the following Figure 1.

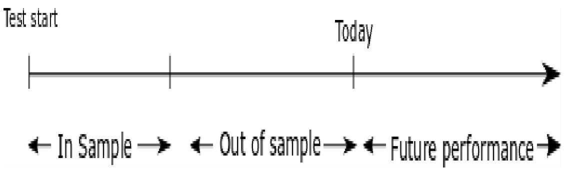

Figure 1. Out of sample back testing.

In this paper, the method of pairing financial assets, as described by Perlin (2008), will be applied. In order to give this process a name, let’s call it for what it is, minimizing the squared Euclidian distance.

First, each assets price is standardized. The price is adjusted to a new notional scale, by equation (1):

$$P_j = \sum_{t=1}^{n} \frac{(P_{t,j}-E[P_j])}{\sigma_j}, for\ j\ in\ 1 \dots 2.k \quad (1)$$

In (1), the time series for each asset is located in a column vector of the matrix **P** (n,k). $E[P_j]$ is the expected value of the price of asset j, here estimated by the arithmetic mean. Moreover, σ_j is the standard deviation of the price of asset j. It is important to note that the price series is a finite time series and hence explains the existence of an expected value and other parameters. Since we take the prices as fixed, there is no reason to use conditional rather than unconditional expectations. Furthermore, the equation is calibrated over a moving monthly window in the trade periods.

If prices were not standardized. as in (1), a minimum distance rule would pair stocks within absolute price ranges rather than similar price patterns. Moreover, different ways of standardizing (or normalising) prices could yield different pairs. In the case of non-standardized price series, correlation or cointegration techniques may be applied, instead of the minimum distance rule.

The pairing itself is performed by (2) below, for asset j.

$$Min\ SSE = \sum_{t=1}^{n} \left(P_{t,j} - P_{t,a}\right)^2, j \neq a,$$
$$for\ a\ in\ 1 \ldots (k)$$
(2)

The purpose of (2) is to find the minimum of the summed squared standardized errors in prices (SSE). This is another way to say that we minimize the sum of the squared Euclidean distances, as the distance as described by Barrett (2005). Hence, the minimum SSE is found by summarize each squared difference in standardized prices between all individual assets. The assets with the least difference are allocated as a pair. Moreover, this implementation allows for several assets to be paired with one and the same asset. In this way, the maximum pairs which may be created for an asset is (*k-1)*. Equation (2) runs over historical, in sample data, and fits pairs from similar price patterns to be used in the out of sample period of trading.

When pairs have been established by (2), there is time to evaluate rules of buy and sell signals. These signals are created by monitoring the absolute difference between two normalized prices of paired assets. Since the pairs are expected to follow similar price patterns, with an equilibrium short distance difference, a noise in one of the assets making the pattern diverge more than an arbitrary threshold distance, *d*, would imply that a position should be created. Hopefully, the difference returns to its equilibrium state and hence a profit could be made by reversion of the spread. The choice of *d* is an important step and will be further discussed below. However, let's assume *d* has been chosen for a specific pair of assets. Then, a position is created when the distance is larger than *d* and again closed when the distance is less than *d.* If data were in continuous time this rule has to be adjusted with an additional threshold. The threshold is implemented to guarantee that the position would not be sold at the same time as it was created, or correct for short term noise which would interfere with the creation of the positions.

At the time a position is created, we must also evaluate which asset that are under respective overvalued, relative to each other. Since the prices are standardized, the asset with higher price has had a larger relative return and therefore simply is assumed to be overvalued compared with its paired asset. Hence, a long position is taken in the asset with lower standardized price at time t and a short position is taken in its pair.

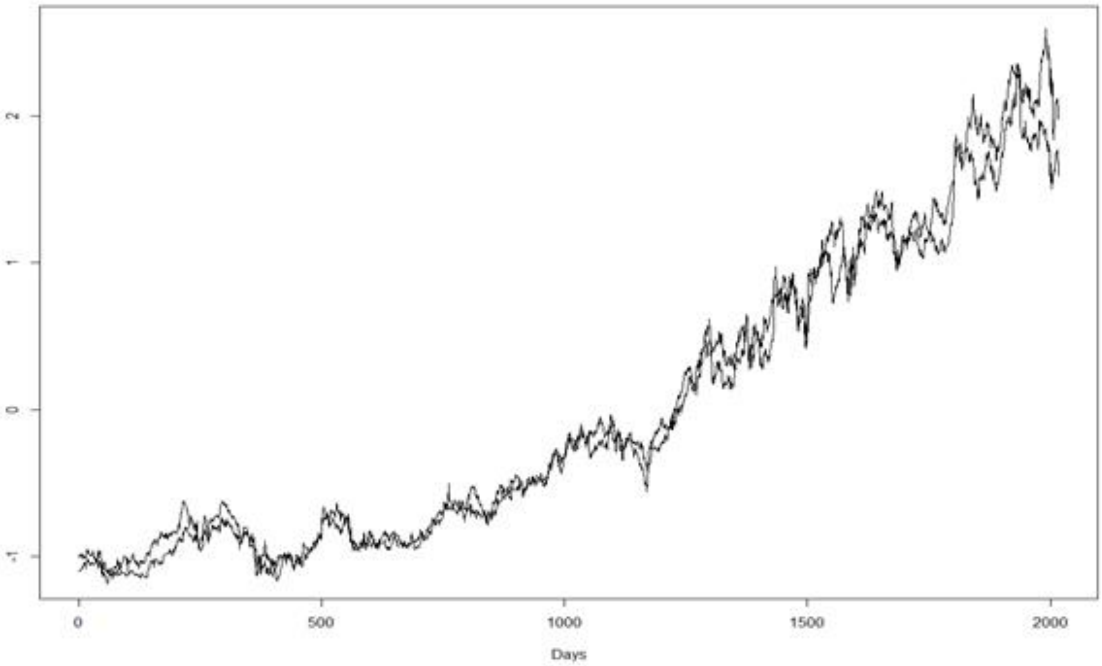

Figure 2. Fitted standardized prices by (2), for a pair consisting of the stocks Industrivärden C and Latour B. Daily data from the period 2010-2018.

As seen in Figure 2, two stocks are fitted as a pair. Since (2) uses the mean value of the price series, which is transformed to the value of zero, the prices are set by their distance from the mean (zero). This also implies that the change in price could have been larger in one of the asset even if the standardized prices seem to move in a similar paired pattern. Both assets represent investment companies, thus the pair may be seen as a sector specific pair. However, if the investment companies are focused on very different underlying sectors they may develop more in common with their portfolio companies. In this case, we consider the two companies to be in related sectors. As seen, the distance between the price series varies in length and which asset that should be considered to be under (over) valued thus shifts frequently.

Model assumptions and choice of specific market

The aim of the paper is to evaluate the efficiency of Nasdaq OMX Stockholm with a non-parametric pair trading strategy. In a theoretical world, one could assume that no matter the cap[1] size and trade volume, an investor may easily take both short and long positions in any stock. However, in practice such an investment would generally require a personal stockbroker and would often be

[1] Cap size is an approximate definition of the company size. Wayman (2018)

associated with large differences in transaction costs between the assets in a pair, factors that makes modelling difficult. Thus, with the aim to create a more general model, this paper only focuses on the stocks on the OMXS that have standardized contracts for both long and short positions. Standardized contracts also generate less problems with market liquidity. The model assumes the following properties to exist on the market:

- *Perfect market liquidity.*
- *Each trade is performed at closing price of each day.*
- *Possibility to continuous take long as well as short positon in all assets.*
- *Constant transaction cost.*
- *Possibility of investing 1 SEK in each asset.*
- *No dividends.*

Let's discuss the effects of such assumptions to simplify our model compared with the reality of the market.

Since the study only looks at OMXS assets with standardized contracts for short and long positions, liquidity should not be considered as a significant problem. However this assumption does not account for market failures such as e.g. technical problems. Moreover, the standardized transaction cost of transaction is still dependent on the amount of invested capital. This fnction has been approximated from earlier studies, such as Perlin (2008).

Furthermore, complications could arise from assumption that assets only are traded at their close prices. It would require additional costs of accessing real time quotes, as well as "considerable" data power not accounted for in this model specification.

Data has also been adjusted for dividends in prices. Problem with dividends may arise, since a short trader has to pay the owner of the stock the dividend amount. Hence, applying a similar model in reality, a rule of excluding assets with dividends during the trading period, has to be implemented.

Further specifications of the model is that each pair is awarded the same principal amount of investment in each trade. This implies that the same principal will be assorted for the next trade regardless of the fact that last trade resulted in a profit or a loss. Hence, no effect of "interest on interest" is accounted for, and provides a suitable way to keep both costs and returns standardized during a trade period.

Finally, it is assumed that a position in each pair is 1 SEK, in respective asset. This assumption is far fetch from reality but have been applied for easier computation and without the need to optimise pair weights, considering marginal changes in asset prices.

Time period of pairs, training and trading

Both the choice of training and trading periods will have an effect on the results of the strategy. Gatev, Goetzmann and Rouwenhorst (2008) choose a 12 month training window followed by a 6 month trade period, chosen arbitrary. In this paper, we will apply shorter moving windows under the assumption that the paired relationships often may change. Hence, an in sample training period of 150 days, i.e. six months, will be applied on arbitrary conditions. The six-month period is supposed to be long enough to differentiate between assets that have had similar price patterns and assets that haphazardly respond in a similar way to short trends.

The training periods will be followed by the out of sample trading periods, tested in two time windows. A longer window consisting of 6 months and a shorter window of only 50 days, before reassessing the pairs. The hypothesis is that the shorter period of 50 days should capture the short-term relationship better, as well as restrict the risk of losses in diverging pairs. However, this could also give as a result that a pair not have an appropriate time to converge, due to the short period of time.

Portfolio structure

In each trading period, a portfolio will be created consisting of 10 pairs Hence, 20 stocks will be traded in each period. The choice of 10 pairs is in line with Gatev, Goetzmann and Rouwenhorst (2008), where the choice to use a multiple pair portfolio resulted in excess returns due to diversification. Moreover, such a diversification also is risk reducing and may limit the effect of losses, in the case of substantial pair price divergence.

Stop loss function

Implementing a pair strategy gives no guarantee of convergence in asset prices. Hence, this may result in a position without loss restriction for the investor, considering the possible unlimited loss of a short position. To adjust the model for divergence in pairs, a stop loss is implemented at the end of each period. This is simply a rule that closes all positions at the last day of a trade period, regardless of when the position was created. Positions are closed by the rule, not only because of relationship divergence, but because the rule is implemented generally with the aim to make it easier to adjust model returns and control for invested capital. Stop losses may also be implemented in order to prevent pairs to diverge drastically, or to keep a position open at a maximum amount of days. However, that has not been implemented in this algorithm.

Assumed threshold distance

The choice of threshold distance is an important measure as shown by Perlin (2008). The choice should be based on market liquidity as well as the transaction cost, both entering fees and possible position upkeep. Hence, a low threshold would generate significantly more trade signals, but likewise more costs. The approach by Gatev, Goetzmann and Rouwenhorst (2008) is to use two standard deviations from the mean distance of the normalised prices as a threshold. Perlin (2008), tested several threshold values without implementing a rule to decide which threshold to be used. This paper will apply a similar approach as Perlin, and test the profitability of thresholds ranging from 0.1-5.0. Moreover, the paper will also test a method that apply the threshold that generated the largest return of each pair in the training period. If no positive return were found in the training period, the pair simply is excluded. Using fixed thresholds will be denoted a *fixed threshold* and when the profit maximizing threshold from the training period is applied it is denoted as a *flexible threshold*.

Calculating asset returns

In asserting the performance of the portfolio over a specific period of time the raw returns of a pair may generally be calculated as:

$$R_e = \sum_{j=1}^{k} \sum_{t=1}^{n} R_{t,j} * I_{t,j} * W_{t,j}$$

Where R_e is the raw return of the portfolio over the implemented timeframe. The matrix R is the real return of pair asset j calculated as $\ln\left(\frac{P_{t,j}}{P_{L,j}}\right)$, where L is a variable taking the value of t when a position is opened. $I_{t,j}$ is a dummy that takes the value 1 if the position in asset j is long and -1 if the position is short at time t. W is a matrix of weights assigned to each asset. The purpose of the weights is to create a proportional absolute return in cash, from a marginal increase in each asset. However, under assumption 5, this paper assumes equal weights, since 1 SEK is invested in both paired assets.

The transaction cost C is calculated for the whole period as a lump sum given in per cent. The cost is at the end of each period subtracted from the raw return. C is calculated as follows:

$$C = T_1 * (c) + T_2 \left(r * \left(\frac{1}{365} \right) \right)$$

C is the total transaction cost over the period. This is the sum of two elements. c is supposed to reflect the fixed transaction cost of the position. Hence, this cost appears each time a position is created, which is accounted for in the summarized dummy T_1.

Moreover, the rent to take a loan to a short positon is accounted for each day the position is open, summarized in the dummy T_2, times the yearly interest rate *r*. The impact of the transaction cost is tested in two levels. First with *c=0.001, r = 0.03* and secondly with *c = 0.002, r = 0.03*.

The rent of capital can be seen as a normal cost for a private investor that especially has an effect on long term investments. The fixed cost, *c*, is relative low in both cases and can only be realistically achieved by investments of 1-2 million SEK in each paired asset, or by separate contracts for active agents. Costs at level one will be denoted *moderate costs* and costs at level two will be denoted as *large costs.*

Evaluating performance

Initially, the strategy will be applied on the real data of the sample stocks. These results is compared with a "Buy and hold" strategy as in Campbell (2011), in a relevant index during the same period of time.

Moreover, in the evaluation of the validity of the strategy, instead of applying the pair process discussed previously, a bootstrap of the pairs is made for 100 runs on the same data. The idea behind this test is that each pair is paired randomly, with replacement, instead of by the use of equation (2) for each trading period. The test is performed to see if there is a significant difference between random pairing and the pair process purposed in this paper.

The strategy is further also tested against a simulated random naïve trader. This trader is assumed to only take long positions in all sample stocks completely random. The method shares a similar structure with the naïve trader as explained in Perlin (2008). Hence, 1000 naïve traders are created by bootstrapping. The trades of a specific naïve trader, are created by bootstrapping random returns responding to the same amount of days in the market as the strategy. Here all daily returns have the same probability of being chosen and is also replaced after each daily pick. The aggregated return of each of the 1000 naïve traders create a distribution which is tested against the return of the pair strategy. Hence, it indicates if the strategy has generated a significant higher aggregated return in comparison with a random trader for the implemented period.

Data of the study

Since the focus of the paper is on the Swedish OMXS stock market and a pair strategy, the choice of assets should reflect both the Swedish market as well as include properties as liquidity and the possibility of short selling. Moreover, the timeframe of the study would preferable be quite long to prevent data snooping in specific market trends.

After examining large stockbroker's standardized short contracts on the Swedish market, 86 stocks were chosen. These assets have been in the market from 2010-03-01 until 2018-03-01, which results in an eight year timeframe. This does however not imply that standardized contracts have existed for these stocks under the whole time period, but it is assumed there has been similar substitutes.

The choice of a relevant index to be compared with the outcome of the strategy fell on OMXS PI, which is a price index reflecting the whole Stockholm exchange. The broad OMXS PI index was chosen since the 86 stocks in the data were from different sectors and cap sizes, making it hard to choose a specific sector index to reflect the different kind of stocks represented in the sample.

All quotes are given in the stock's closing prices and have been collected from Nasdaq OMXS Nordic. A list of the 86 sample stocks may be found in Appendix A. All calculations have been performed in *R-version 3.4.4*.

Descriptive statics

As seen in Figure 3 below, during the tested time period the market has had a strong bull trend. Hence, implementation of strategies on this market could lead to returns caused by the trend, rather than from the strategy itself. Implementation of a "Buy and hold" strategy on the OMXS PI during those eight years would have resulted in a return of 151 per cent. Data consist of 2 017 days, that each represents a daily closing price. The average Swedish trading year is approximately 250 days. Prices are adjusted for company splits and dividends in each specific stock.

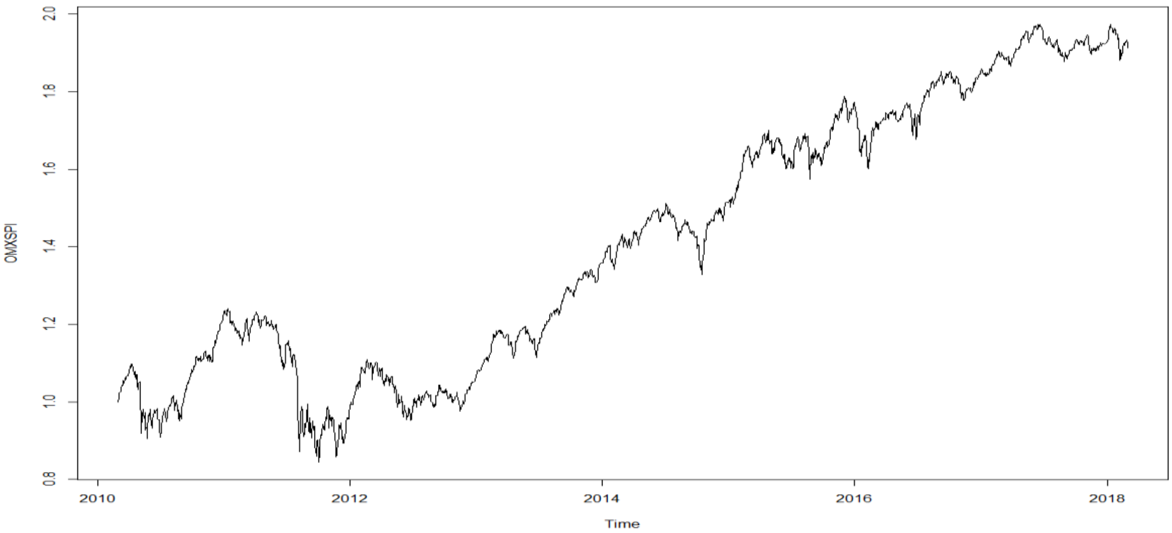

Figure 3. OMXS PI index development from 2010-03-01 until 2018-03-01, continuous compounded. Source: NASDAQ Nordic.

The 86 sample stocks have shown a large variation in development during the period, with returns from a "Buy and hold strategy" in each specific stock ranging from -0.93, in the company *Bong*, up to 11.38 in *Balder*. The mean return of a sample stock, during the timeframe, was a gain of 1.79 with a standard deviation of 2.3. The return distribution of the "Buy and hold" strategy on the sample stocks is shown in the histogram of Figure 4.

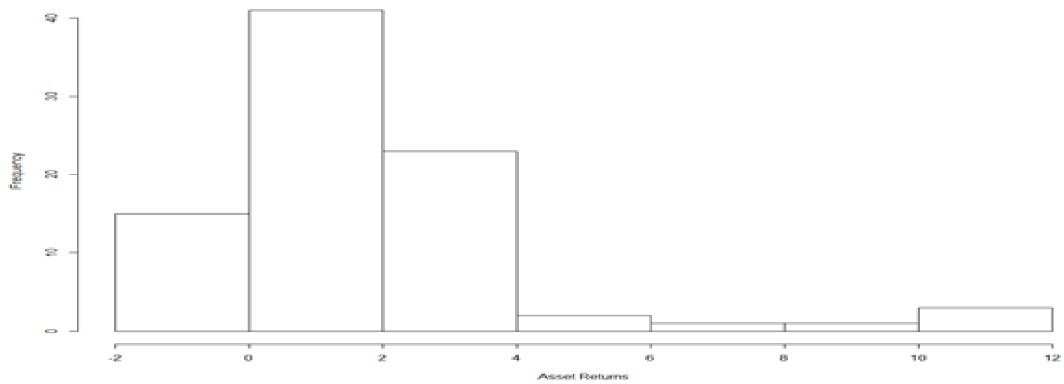

Figure 4. Return distribution of "Buy and hold" strategies in the sample stocks from 2010-03-01 until 2018-03-01.

Results

The results of the simulations made in this paper will be presented separately for each trading window and threshold method. The focus in the presentation of the results will be on the *moderate cost* and *no transaction cost* cases.

Results of simulations with six-months trade periods

Fixed thresholds

Applying the pair strategy on a six-month training period followed by a six-month trade period shows that the most profitable fixed threshold ranges from (0.1-1.8). The results of these thresholds are summarized in Table 1. It is found that the aggregated fixed long positions generate a positive return for all thresholds when *moderate costs* are accounted for, while the returns of the aggregated short positions are strictly negative. Furthermore, *fixed thresholds* generated positive returns until threshold 3.0, when the aggregated returns turned into losses. Increasing the transaction costs to *large costs* generate a similar pattern where again the most profitable aggregated returns may be found in the thresholds (0.1-1.8).

In comparison with a “Buy and hold” strategy of OMXS PI, and a *moderate cost*, the fixed threshold 0.2 gives the largest excess return, 2.79 times the “Buy and hold” strategy. Furthermore, as seen in Table 1, there is a large variation in excess return between the thresholds. The two longest ranges of strict positive excess return are both 0.4, starting at 0.2 and 0.8 each.

Considering *no transaction cost*, all thresholds generate an aggregated positive return. When these returns were tested versus the returns of a sample of 100 bootstrapped pairs, the result varies. Thresholds in the range of (0.1-1.0) give, with 5 % significance, results that generate at least 90 % better results than randomly choosing pairs. However, all thresholds in the range (0.1-1.8) were significant better than 50 % of the runs in the randomized pairs. These tests were performed with binominal tests.

Table 1. Results of fixed threshold combined with a six months trade periods, 2010-2018.

Thresholds	*Long*	*Short*	*Aggregated Return Moderate Costs*	*Excessive returns Buy and hold OMXPI*	*Days in market, %*	*Large transaction*	*No Transaction Costs*	*P value random pairs, no costs*
0.1	7.0	-5.6	1.40	-0.11	0.85	0.78	4.39	0.02
0.2	8.3	-3.9	4.30	2.79	0.83	3.10	9.84	0.00
0.3	6.8	-4.1	2.70	1.19	0.80	2.00	7.95	0.00
0.4	6.4	-4.4	2.00	0.49	0.77	1.29	6.59	0.02
0.5	6.5	-4.3	2.10	0.50	0.75	1.41	6.96	0.00
0.6	5.6	-4.2	1.40	-0.11	0.72	0.39	4.89	0.03
0.7	5.1	-4.2	0.90	-0.61	0.70	0.41	4.94	0.02
0.8	5.4	-2.9	2.50	0.99	0.67	1.48	7.05	0.00
0.9	5.7	-3.6	2.10	0.59	0.65	0.98	5.99	0.00
1.0	5.4	-3.6	1.70	0.19	0.63	0.71	5.37	0.00
1.1	5.2	-3.7	1.54	0.03	0.61	0.46	4.47	0.20
1.2	4.8	-3.4	1.34	-0.17	0.58	0.23	4.17	1.00
1.3	4.8	-3.2	1.59	0.08	0.56	0.23	4.06	1.00
1.4	4.1	-2.8	1.31	-0.20	0.54	0.05	3.50	1.00
1.5	4.2	-2.35	1.90	0.39	0.52	0.78	4.92	1.00
1.6	3.9	-2,35	1.58	0.07	0.49	0.84	4.92	1.00
1.7	4.6	-2.7	1.90	0.39	0.46	0.86	4.80	1.00
1.8	4.6	-3.1	1.40	-0.11	0.44	0.53	4.00	1.00

Moreover, when the results of *no transaction cost* are tested against a distribution of a naïve, long only, traders, the results of t-tests show that all thresholds in the range (0.1-1.8) had significant larger aggregated return, in comparison with the mean of 1000 naïve traders, at 5 % significance level.

Flexible threshold

Applying the method *Flexible threshold,* where the choice of thresholds are decided by optimizing the profits in the training period, also resulted in profitable results. For *moderate cost* the *flexible thresholds* aggregated return was 4.15, making it the second highest aggregated return, only to be beaten by the *fixed threshold* 0.2. Moreover, *flexible threshold* created an excess return of 2.54 compared with the "Buy and hold" strategy on OMXS PI. The distribution of returns for each period is shown in Figure 5. The distribution median is 0.14. However, the periodic returns form a volatile distribution with a largest period loss of 0.61 and a highest return of 2.23. The distribution is characterised by right skewness with large tails created by periods with large profit.

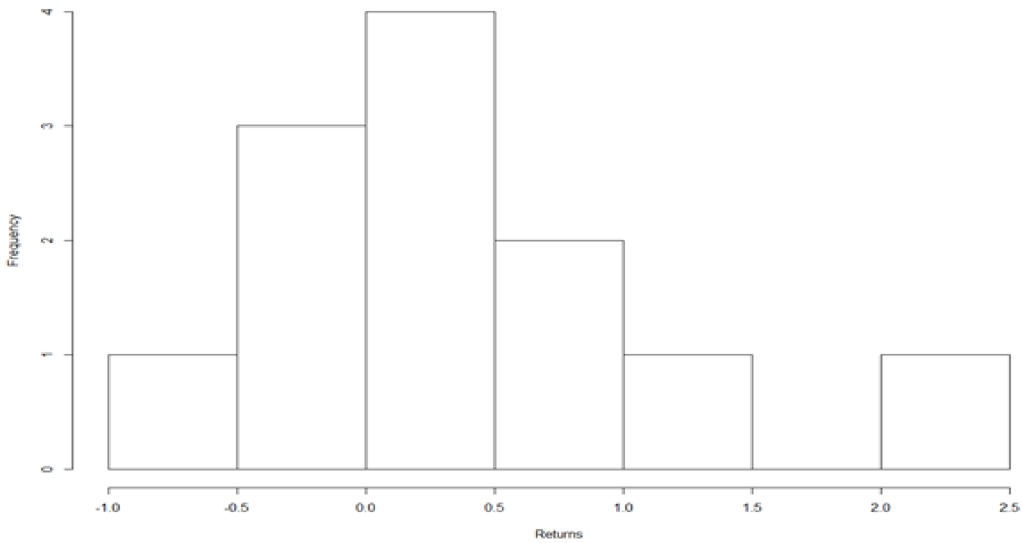

Figure 5. Histogram showing the return distribution of flexible threshold, six months trade periods, moderate costs.

Figure 6, shows the *flexible threshold,* six months periods, return distribution with *no transaction costs*. The median is 0.48, with a maximum period return of 4.63 and a minimum of -1.014. Therefore, this distribution has a larger maximum period loss, compared with the *flexible threshold, moderate cost,* distribution. This is possible since the algorithm chooses different thresholds depending on the cost structure. Hence, the relationship could still diverge drastically and end up in large losses as shown. Moreover, the distribution is right skewed with outliers in the profit tail. The aggregated return of *no transaction cost* with *flexible threshold* is 10.47.

The returns of *flexible thresholds*, *moderate* and *no transaction cost* are not found to be significantly correlated with the returns of OMXS PI. A regression of the portfolio returns against the index over six-month periods results in non-significant coefficients close to zero, making the portfolio market neutral. Moreover, when tested against the periodic returns of the most profitable *fixed thresholds*, the results indicates signs of high correlation, ranging from 0.91 to 0.17.

The cumulative return of six-month trade period over the 8 years and *flexible thresholds,* are shown in Figure 7, indexed from 1.

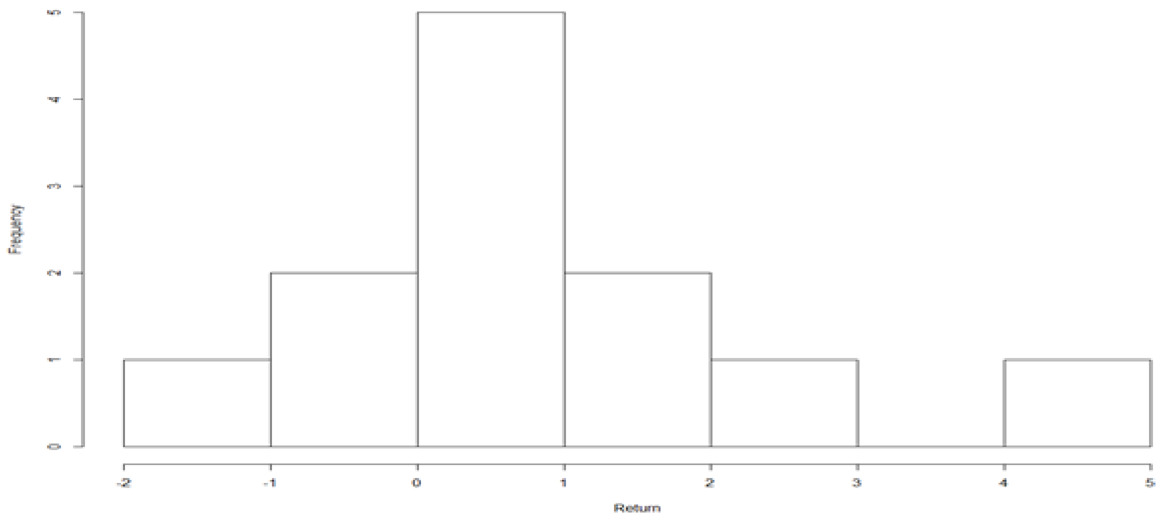

Figure 6. Histogram of the return distribution, six month flexible threshold, no transaction co sts.

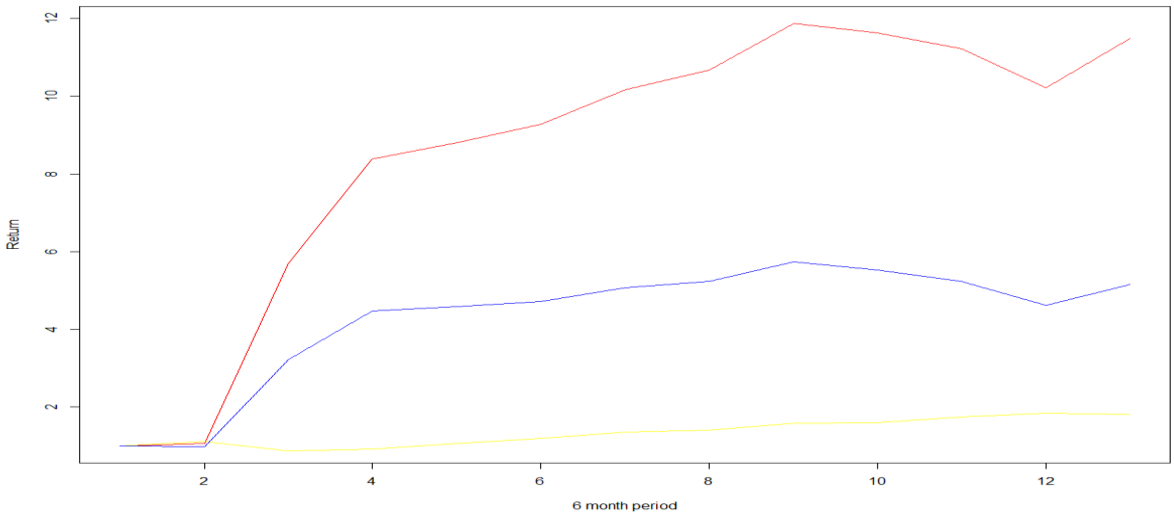

Figure 7. Indexed cumulative return of flexible thresholds. Each index on the x-axis represents a six months trading period. Red line indicates a portfolio with no transaction costs, blue is a portfolio with moderate transaction cost and yellow indicates OMXS PI.

Results of a 50 days trading period

Fixed thresholds

When the algorithm was applied on six months of training data followed by a 50 day trade period, the result show thresholds (1.3-2.2) as the most profitable for *moderate costs*. In Table 2 the aggregated returns of long positions are strictly positive, while the short positions are strictly negative. Furthermore, all thresholds in range (1.3-2.2) show positive aggregated returns, while the rest of the tested thresholds have mixed results, often negative. In comparison with a "Buy and hold" strategy of OMXS PI, the aggregated returns indicate strictly negative excess returns. When tested for larger transaction costs, the aggregated returns were negative until threshold 1.8. Results from *large transaction costs* show a considerable reduction of the losses when larger thresholds are applied, which restricts the total number of trades.

Table 2. Results of 50 days trade periods, fixed thresholds, 2010-2018.

Threshold	*Long*	*Short*	*Aggregated return Moderate cost*	*Excessive return OMXSIPI Buy and hold*	*Days in market, %*	*Large costs*	*No Transaction costs*	*P-value no cost > 90 %*	*P-value No cost >50%*
1.3	3.70	-2.64	1.02	-0.50	0.50	-0.44	5.0	1	<0.05
1.4	3.10	-2.33	0.77	-0.74	0.47	-0.41	4.2	1	<0.06
1.5	3.10	-2.03	1.07	-0.44	0.45	-0.37	4.8	1	<0.05
1.6	3.00	-2.30	0.77	-0.74	0.43	-0.20	4.3	1	<0.06
1.7	3.30	-2.39	0.90	-0.61	0.41	-0.18	4.3	1	<0.05
1.8	3.40	-2.70	0.72	-0.79	0.39	0.20	4.2	1	<0.05
1.9	3.10	-2.79	0.39	-1.12	0.37	0.25	3.6	1	1.00
2.0	3.20	-2.71	0.52	-0.99	0.34	0.21	4.3	1	<0.01
2.1	3.10	-2.52	0.61	-0.90	0.31	0.16	4.0	1	<0.01
2.2	3.10	-2.81	0.31	-1.20	0.31	0.11	3.2	1	1.00

A binominal test on the aggregated returns against random paired assets, applying the same thresholds and no costs, does not give significant results indicating that our pair process generates better returns than random pairs, in 90 % of the runs. However, when tested for outperformance of 50 % of the randomised pairs runs, several thresholds gave significant results.

Aggregated return of *no transaction cost* were also tested against 1000 bootstrapped random long only trading patterns of a naïve investor. T-tests show that the strategy created larger aggregated return compared with the mean return of the 1000 naïve traders at 5 % significance level for all thresholds in the range (1.3-2.2).

Flexible thresholds

Applying *flexible thresholds* with *moderate transaction costs* give an aggregated return of 1.002. The return distribution, displayed in Figure 8, has a median of -0.029 with range from 0.86 until -0.88, which indicates a large periodic volatility. The ratio between positive returns and negative returns, is 0.98. Thus, the results indicate that positive periods generally give larger returns then loss periods, but we are expected to experience a loss in a given period at approximately 50 % of the times.

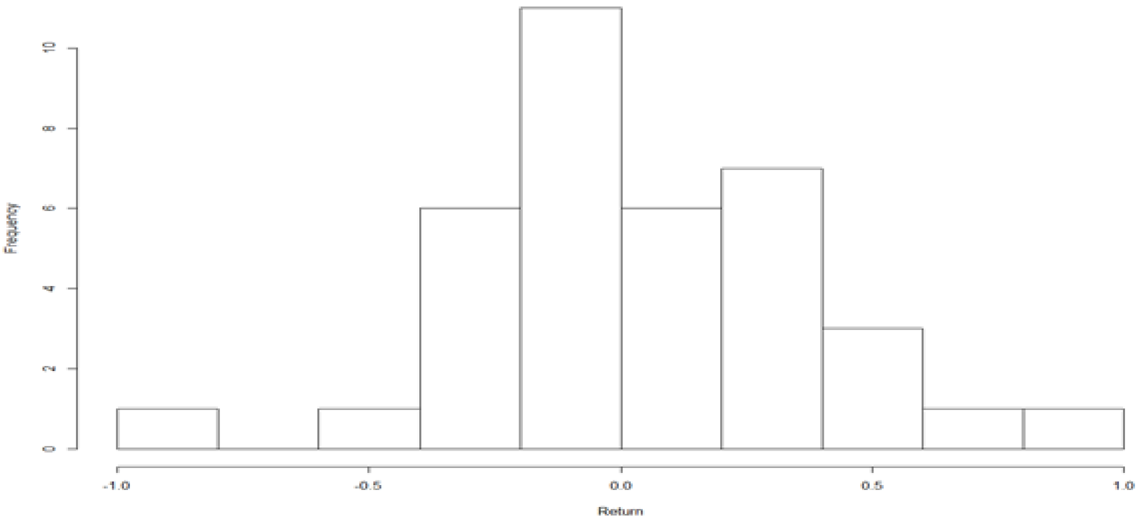

Figure 8. Histogram of flexible threshold aggregated returns; 50 days trade periods, moderate costs.

Applying the *flexible threshold* with *no transaction cost*, results in an aggregated return of 7.53 over the eight years. Figure 9 shows the distribution of periodic returns that have a median of 0.21 and a range from 1.88 until -1.56. Again, it indicates a larger maximum period loss than the return distribution with *moderate transaction costs* shown in Figure 8 above.

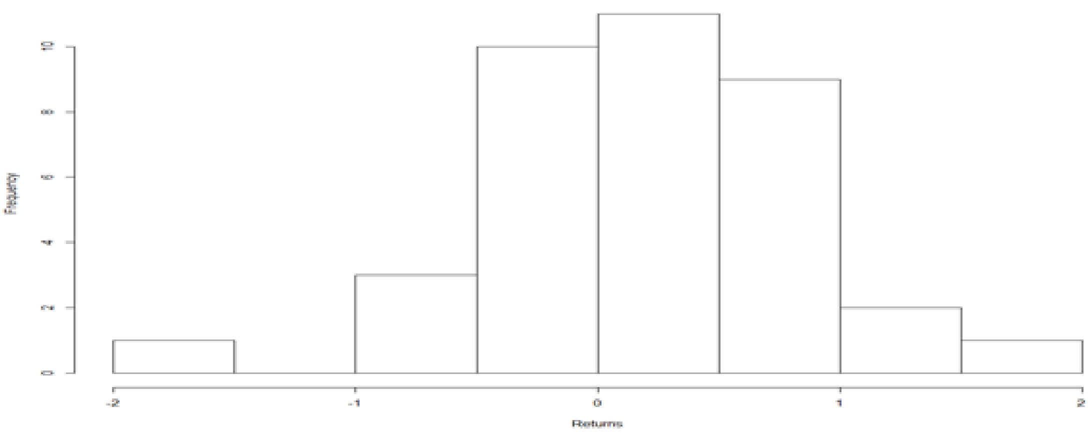

Figure 9. Histogram over return distribution of 50 days trade periods, flexible threshold, no transaction costs.

The correlation between the *flexible thresholds* periodic returns and the most profitable *fixed threshold,* gave correlation coefficients ranging from 0.7-0.4, indicating a relationship between the methods. A regression on the returns of *flexible threshold* against the index gave non-significant coefficients close to zero that indicates a low dependency between the strategy and the market.

Diversification

In this paper no clear evidence of excess return by diversification was found. For *flexible thresholds* with *moderate transaction costs,* the use of 10 pairs instead of only 1 pair, gave no significant improvement in providing a larger number of positive period returns in the 50 days nor the six-month trade periods. Using only the best fitted pair, resulted in an excess aggregated return of 59 % (50 days), and 39 % (six-month), compared with the aggregated mean return of each period in the 10 pairs portfolio.

Discussion of the results

In this paper, we have evaluated the results of applying a pairs trading strategy on stocks at the Nasdaq OMX Stockholm market. We have also tested different methods of strategy implementation, considering both timeframe, trading periods, as well as threshold distances. This section will start with a discussion of the algorithm and its implementation, which is followed by an analysis of the results, considering the theories we discussed initially.

Overall, the implementation of a pair strategy on the Swedish stock market during the timeframe 2010-2018 was shown to be profitable. Applying the strategy with a longer time of trade, six months, generated the highest aggregated return. This approach often resulted in an excess return compared with index. Both the tested trading periods significantly generated larger aggregated returns than a naïve, long only, trader. As seen in the results, the profit is largely dependent on the implemented transaction costs. However, since transaction costs in turn are dependent on invested capital, these costs could further be minimized by the use of structural derivates, e.g. debt financing instruments. As such, the main finding is that the results were profitable when *no transaction costs* were considered.

Furthermore, we found that the aggregated returns of the long positions are positive in all thresholds, as well as that the short positions were found to be strictly negative. It should although be clarified that not all trades gave negative results in the short positions. However, since the market has had a strong bull trend during the implemented period, the aggregated negative return in the short positions were expected.

The new use, suggested in this paper, of a *flexible threshold* indicated profitable results. For both periods, the aggregated *flexible threshold* return placed itself among the top of the *fixed thresholds,* as well as outperformed the aggregated return of *fixed thresholds,* considering *no transaction costs*. However, the *flexible thresholds* had high correlation with some of the *fixed thresholds* and the result seem to be dependent on the period chosen rather than the method applied. Moreover, the result may be caused by the fact that *flexible thresholds* were able to reject the use of pairs that were found to be non-profitable in the training period. Hence, we have shown that use of flexible thresholds provides a way to reject poorly fitted pairs.

Moreover, even if the aggregated returns are profitable, there still is a fact that the periodic returns of the strategy still are highly volatile. As for example, in the six-month *flexible threshold* with *no costs* case, the aggregated return is positive, but one period still shows a loss of 101%. The reason for those extreme losses is somewhat mysterious since the returns gave no indications of market dependency, considering regressed beta values. These periods of negative return are simply believed to be caused by shocks to the standardized distance in equation (1), making the algorithm believe that a pairs has converged. Mismatched pairs could also cause the extreme losses. Such pairs generate divergence among the prices of paired assets, such that they never converge.

Pairs may thus be supervised for specific shocks in each asset, which could disturb the price pattern observed in the training period. Alternatively, a periodic stop loss, that restricts the total loss in a specific period, may be implemented. However, such measures would require an active trading approach, which generates more costs in comparison with this completely computerised algorithm.

The effect of using a diversified portfolio of 10 pairs instead of only the best fitted pair proved, against our expectations and earlier research, to be less profitable. Tests to evaluate if a diversified portfolio generally had less periods of negative returns, or generated an aggregated larger return, than the use of only one pair, gave no significant result.

This result thus is opposite to the findings in Gatev, Goetzmann and Rouwenhorst (2008). A plausible explanation may be that the sample of 86 stocks were too small to find 10 good enough matched pairs. As such, it forced less likely pairs to be included in the portfolio. Anyhow, our result restricts that generality of the result in Gatev, Goetzmann and Rouwenhorst (2008).

We have considered two different lengths of the trading period. The hypothesis was that the shorter timeframe would create better results, since it faster would capture diverging pairs. The results however shows that the longer period of six-month outperformed the shorter, 50 days period, in all tested thresholds, considering *moderate costs*. This may be caused by different factors. First of all, we want to highlight the fact that even if the paper rejects the use of a shorter timeframe, the result could simply be explained by the implemented stop loss, closing all pairs at the end of a trading period. Thus punishing the shorter time period when diverting price paths are longer. However, the results show that the disturbance of the equilibrium pair distance, often results in longer divergence than a daily reversion. This may be strengthen by the fact that the more profitable six-month period, has strictly more days in the market than the 50 days periods have.

In future research along the lines of this paper, we suggest improving the algorithm by allowing opened pairs to stay open, for a number of days after the trading period is closed. Then the effect of using a shorter time to evaluate profitability of pairs may be evaluated further.

The pairs were fitted by (2), which provides a way of matching price movements. Equation 2 is a quite simple way of fitting pairs, and there are several other ways such as correlation or distance measures which could be applied with a similar purpose. The choice of (2) in this paper, were governed by its previous use in academic papers, such as Perlin (2008). Furthermore, when the results of the pair strategy was tested against 100 runs of bootstrapped pairs, and hence complete random, the results were not as clear as expected. The hypothesis was that the fitted pairs would significantly outperform the randomized pairs in at least 90% of the runs. As seen in the results, only a few thresholds at the six-months trading period significantly supported this hypothesis. However, most of the thresholds, including 50 trading days, outperformed random pairs at 50% of the runs, by a 5% significance level.

These results are not in favour of the fitting process, but should still be interpreted cautiously. There are a small amount of sample stocks to be randomized from, and all stocks are located in the same market, OMXS. Hence, all stocks have some dependence with the market and thus with each other. Future studies of evaluations of the pair fitting process may be performed on a larger sample, where clear differences between some of the assets are present. Hence, this would create a more robust environment to test the goodness of fit of the pairs.

Theoretical conclusions

The main goal of this paper was to evaluate the efficiency of a pairs trading strategy on the Nasdaq OMX Stockholm stock market, and as a result of this, also the efficiency of the market. Fama's EMH states that there are no possibility to create excess returns by analysing historical prices in any state of market efficiency, something that is the sole purpose of this algorithm. The results indicates, against EMH, that there actually is a possibility to outperform an index, by use of our suggested pair model. However, this paper revolves around a model, not reality. In our theoretical model, one could argue that there are signs of inefficient behaviour in the Swedish market. This inefficiency is what has allowed the strategy to be profitable. To be able to question the results of random walk models, such as EMH, this model has to be implemented in a more realistic scenario. The model would then have to take account of factors which may change the results of the study, such as more realistic transaction costs, while dividends as well as asset capital weighting, is assumed to be non-existent here.

However, in inefficient markets such as this theoretical environment, what is it that makes pairs trading profitable? Since a pair may be seen as two close substitutes, because of the similarity in price pattern, changes in the prices of the assets may be suspected to be caused by changes in similar underlying factors. As such, it would be logical to assume that news concerning these factors is what causes the prices to behave in a similar rational manner. Moreover, returning to Shiller (1981), who's concern was that non-rational investors makes the price far too volatile to reflect the underlying value, the profitability of the strategy in our model may be the result of an utilising of such non-rational volatile behaviours in prices. The strategy realises that the volatile outburst is either temporary or that a similar behaviour is expected to be observed in its paired substitute. Longer periods of divergence may furthermore be explained by Black's (1986) noise traders, which believe that the outburst are signs of e.g. new trends, reinforcing the duration of non-equilibrium prices by their trades. This may explain the large amount of days in market of the six months trading strategy.

Hence, in this theoretical model where inefficiency is found, there are possibilities for the Technical AMH trader to exist and achieve a profit. Hence, according to the evolutionary view of AMH, this is a market where the population of the pairs trading specie probably would increase. Still, since the OMXS is considered to be a small market, in terms of percipients and trading volume, it's possible that the explanation of the profit may lie in the fact that the species agents yet has not fully integrated trading in this market. Moreover, since the rapid increase of structural financial derivates, allows agents both to take long and short positions in instruments without actually affecting the price of the underlying asset, it is possible to create consistent inefficient markets, where noise is utilized in sub-markets, that not directly affect the price of the underlying asset. This may create a longer timeframe to gain profits from equilibrium price disturbances, since the resource, the profit, is harvested without a direct impact on its supply, which is the prices of the assets.

Summary and future research

In this study we have applied a pairs trading strategy on the OMXS exchange and found both a profitability in the strategy as well as a new method of implement thresholds. Further, by combining earlier studies, results from simulations and economic theories, disputing strictly efficient market, we have introduced the new financial agent "Technical AMH trader" as well as suggested a link between volatile reactions to new information in close substitutes, with the profitability of the pairs trading strategy.

More research has to be made in order to further explain both the outcome of the strategy as such, as well as the links between the pair trading strategy and a certain theory of inefficient behaviour. A possible way of doing this would be to follow a distinct pair for a long period of time and evaluate the specific causes behind each trade. This research would contribute to the theory of relative value investments, as well as further add to the understanding of financial asset price theory.

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Appendix A - Sample stocks

Table 1.A. Sample stocks used in the paper.

AAK AB	NIBE INDUSTRIER B
ABB LTD	DIÖS FASTIGHETER
ALFA LAVAL	DUNI
ASSA ABLOY AB	ELEKTROLUX
AZTRA ZENICA	ELKTA
AUTOLIV	ERICSSON
ASHELL AB	FABERGAGE
AVANZA	BALDER
AXFOOD	GETINGE
AUTOLIV INC SDB	GUNNEBO
BETSSON	HENNES & MARUTIZ B
BILIA A	HEXAGON
BILERUD	HEXPOL
BIOTAGE	HMS NETWORK
BIOVITRUM	HOLMEN
BONAVA	HUFVUDSTADEN
BOLIDEN	NOBIA
BURE EQUITY	NORDEA
BGGMAX	NOLATO B
BONG	PEAB B
CASTELLUM	RATOS B
CELLAVISION	REZIDOR HOTEL GROUP
CLAES OHLSON	SAAB
CLOETTA	SANDVIK
CONSILIUM	SAS
HUSQUARNA	SEB A
ICA	SKANSKA B
INDUSTRIVÄRLDEN C	SKF B
INDUTRADE	SKISTAR B
INVESTOR	SSAB B
JM	STORA ENSO R
KAPAHL	SVENSKA HANDELSBANKEN
KINNEVIK B	SWECO B
KUNGSLEDEN	SWEDBANK A
LATOR	SWEDISH MATCH
LINDAB INTERNATIONAL AB	TELE 2 B
LOOMIS	THETYS OIL
LUNDBERG B	TIETO OYJ
LUNDINS PETROLIUM	TRELEBORG
MEKONOMEN	VOLVO B
MILICOM INTERNATIONAL CELLULAR SA	WALLENSTAM BYGGNADS B
MODERN TIME GROUP B	WIHLEBORGS FASTIGHETER
NCC	ÅNGPANNEFÖRENINGEN B
NETENT B	ÖRESUNDS