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IMPLEMENTING A MARKET NEUTRAL TRADING STRATEGY TO NORWEGIAN SALMON STOCKS

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Abstract

In this paper, we will analyze two salmon farming stocks, Lerøy Seafood Group (LSG) and Marine Harvest (MHG), listed on Oslo Stock Exchange (OSEBX). The basis for the analysis is the statistical arbitrage, market-neutral trading strategy, known as Pairs Trading.

The main goal of the analysis is to determine whether a pairs trading strategy is applicable, and profitable on OSBEX. We will examine data from 2005 to the end of 2012 to develop a model, and then apply our optimized trading model on empirical data from 2013 to the end of 2015 to see how well it performs under realistic circumstances.

This paper consists of an introduction to the strategy, how the strategy is unaffected by market movement and important risk factors. Furthermore, we will discuss the assumptions we have made to simplify the model, and the limitations of our paper.

Theory

The Market Neutral Pairs Trading Strategy

Pairs trading is a market-neutral equity trading strategy. This strategy is a relative value investment strategy designed to be unaffected by overall market movements (Harris, 2003). If there exists an equilibrium between two stocks and anomaly is observed in this relationship, a profit possibility arises. The comparative mispricing is exploited by selling (going short) in the relatively overvalued stock, and at the same time buying (going long) the undervalued asset. When the equilibrium is reached, the two positions are closed and profits are achieved. This profit can be a result from the short leg, the long one, or from both (Hoel, 2013).

The pairs trading strategy was pioneered by Gerry Bamberger, a Morgan Stanley analyst. The arbitrage strategy quickly got renowned and its popularity grew into the 1990's. David Shaw, head of one of the most successful modern quant shops suggests that the profit possibilities have declined due to the popularity of the strategy, but we still believe, and hope, that there are possibilities for profits in a small market like the Norwegian. (Gatev et al, 2006).

Market Neutrality and CAPM

Strategies that are market neutral are strategies that are neutral to movements in the market, therefore returns made from pairs trading are uncorrelated with returns in the market. The main aspect of these kinds of strategies is to avoid market risk. Market neutrality can be elucidated by the Capital Asset Pricing Model (CAPM). This model explains how we can determine the expected market returns based on correlation to the market, expressed by the following relationship:

$$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big) + \alpha_i$$

In this model, $E(R_i)$ represents the return on the market, explaining how much more we can expect by entering the market compared to a risk free investment (R_f).

The β_i represents the volatility of the stock relative to the market, with β values typically between –3 and 3. A stock with a beta value β <1, has price movements less than the market and therefore represents a low volatility stock. A stock with a beta value β >1 has price movements more than the market and therefore represents a high volatility stock. Beta values equal to 1 represents a perfect correlation between the stock and the market. Beta values below zero will move in the opposite direction of the market, showing negative correlation.

In order for this strategy to be market neutral the beta value of the portfolio needs to be equal to zero, eliminating the systematic risk. To achieve that we need to create a portfolio of two stocks with exactly opposite beta values, or go long and short with two highly correlated stocks, with equal beta values. By

combining two stocks with equal beta values we can theoretically create a portfolio with a beta-value of zero, implying zero market risk according to CAPM.

The alpha value (α_i) in this model represents the stock's over- and underperformance on the market. It is possible to interpret this as the deviation from the security market line from CAPM. This value is expected to be zero in the long run (Vidyamurthy, 2004). Because we disregard market returns, the alpha value represents the entire return of the pairs trading strategy. Because the expected value over time is zero, it is possible to predict a strong mean reverting behavior where α_i varies around its historical mean. This mean reverting behavior is what we use to predict future returns.

Risk Factors

Harris (2003) mentions several types of risks that makes it challenging to implement arbitrage strategies profitably. In order to trade successfully we have to take the risk into consideration. We will focus on four main types of risks.

Basis risk is the risk that the pair of stocks will continue to move in the opposite directions, deviating further from the mean, resulting in a decreased value of the hedged portfolio. These movements can be very expensive and in some cases they may force the trader to close the position with big losses. This is one of the primary concerns of investors when being briefed about pairs trading, for good reason. Previously the prices of fish and soy oil were closely correlated, a relation that stopped abruptly, shown in Figure 1. Obviously great losses may incur and investors are correct in addressing the issue. The phenomenon is referred to as a squeeze and a large capital buffer is required in order to avoid having to close the position, when it is at its most attractive for the arbitrageurs. (Harris, 2003).



Figure 1 Soy oil and Fish oil correlation

Implementation risk is the risk that the transaction costs might be greater than expected. This is a risk that needs to be taken into consideration regardless of whether the trader uses market orders or limit orders.

With market orders the risk is due to execution price uncertainty, where the price might be less favourable than expected. Regarding the limit order, there is an execution uncertainty, which is means that the trade might not be executed because the price moves away from the placed limit order. However, this can sometimes cause favourable prices, and transactions to be executed. There is a chance for less favourable prices, and therefore it is an important risk factor to while using a pairs-trading strategy. (Harris, 2003).

Model risk, often known as *analytic risk,* is that the arbitrage traders fail to properly understand the fundamental value relations among the traded instruments. The use of simplified models can cause the trader to make mistakes due to assumptions and limitations in the models that should have been taken into consideration. (Harris, 2003).

Carrying cost risk is the risk that the hedging position will be costlier than initially estimated. The increased costs can be a result of unexpected increase in the nominal size of the hedge portfolio or the need to hold the position over a longer period of time than expected. Movements in interest rates can also cause the traders to experience increased costs. (Harris, 2003).

Other important aspects

There are other issues alongside the risk factors regarding pairs trading. In addition to carrying cost risk the traders incur literal transaction costs in order to take on the long and short positions of the stocks. Commissions and fees often make arbitrage trades less favorable and harder to execute profitably in the real market. Pairs trading is especially disadvantageous due to the doubled transactions costs, since the trader has to take on both long and short positions.

Arbitrage trades like pairs trading are harder to execute today than several years ago when the strategies were relatively new in the market. Increased competition makes it harder for investors to trade profitably on the strategy. Several hedge funds even specialize in these kinds of arbitrage strategies. As a result, the prices seem to converge faster, making it harder to profit pairs trading. This is confirmed by an ongoing master thesis by Trygstad and Sandøy (2016), which shows that the excess profits from pairs trading used to be positive, but that it has been slightly negative in the Norwegian markets after 1999. This suggests that the markets have become more efficient, but this is neither something we will elaborate on nor assume in our paper.

These two effects are opposing. The increased competition will cause the transaction costs to decrease, positively effecting our strategy. Despite of the lower transaction costs, the faster price convergence probably outweighs the positive effect in terms of return on our pairs trading strategy.

Methodology and testing

Data set and method

The data we have span across eleven years from the 3rd of January 2005 to the 30th of December 2015. Our approach is to pretend that the present date is 1.1.2013, and then back-test on the data from January 2005 to find an optimized pairs trading model. We will subsequently apply that model on the data from 2013-2015 to see if the strategy is successful without us snooping in the data, to artificially affect the result. Hopefully this will create a reliable result and show the outcome of our strategy when applied in reality.

Identifying target asset pairs

The key aspect of pairs trading is to identify a suitable pair of assets for the strategy. We did this by searching for stocks with a high degree of correlation. An assumption made in the search is that historical correlation implies a future correlation between the two.

To narrow down possible pairing fits, the search was limited to stocks within the same industry where fundamental similarities are more likely to be found than cross industry pairing. By looking at stocks within the same sector, the securities depend to a larger extent on some industry specific variable, making the search for correlated stocks easier. (Reverre, 2001).

Due to Norway's worldwide importance in the salmon farming industry, we decided to look for potential pairing fits within this sector, which is known to be highly impacted by the price of salmon. In addition to this we found it interesting to further research the industry because of the growing visibility of salmon farming stocks on OSEBX.

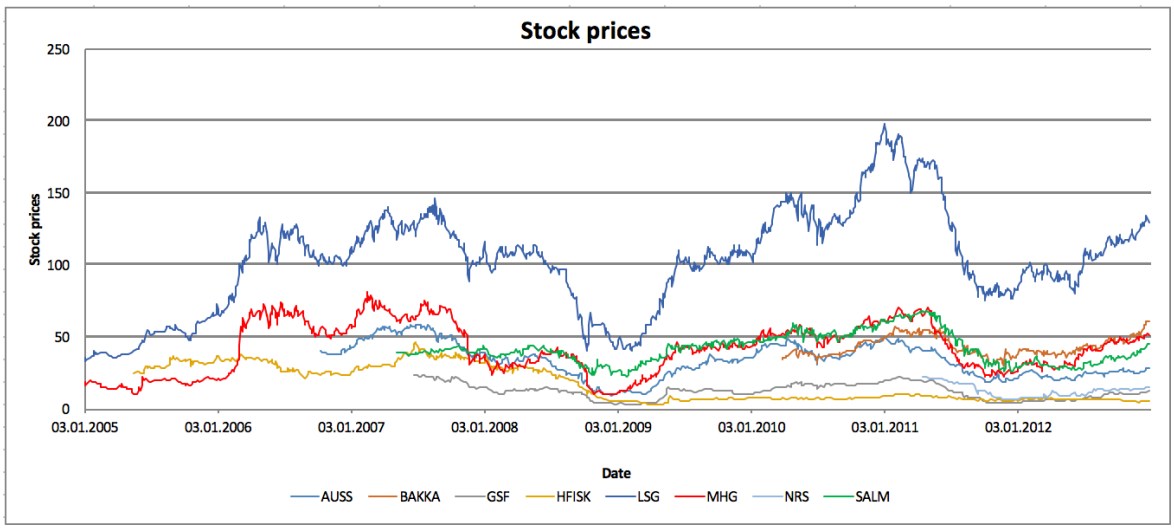


Figure 2 Stock prices of salmon farming companies

When we had decided on this, we found the correlation between the different stocks shown in the matrix below. We chose to proceed with Marine Harvest (MHG) and Lerøy Seafood group (LSG) because we have data going back all the way to January of 2005, visible in figure 2. They are also the two companies with the highest market cap, making them interesting to examine and it implies a lower risk of bankruptcy.

	AUSS	BAKKA	GSF	HFISK	LSG	MHG	NRS	SALM
AUSS	1,0000							
BAKKA	0,4372	1,0000						
GSF	0,7754	0,5436	1,0000					
HFISK	0,6065	0,4619	0,4865	1,0000				
LSG	0,7754	0,6800	0,8159	-0,0953	1,0000			
MHG	0,8939	0,6984	0,8831	0,1936	**0,8516**	1,0000		
NRS	0,8179	0,6480	0,8859	0,4631	0,7955	0,6784	1,0000	
SALM	0,6695	0,5403	0,7796	-0,0500	0,8638	0,7276	0,8809	1,0000

Table 1 Correlation matrix salmon stocks

To make the pair more comparable, we normalized the stock prices (P_t) to 1, using the following formula

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

We also retrieved the beta values by using two methods. We calculated the beta using its covariance with the returns of OSEBX before 2012. This was not a yearly beta, we simply used as much data as we had for each individual stock. As a control we also found the past 1 year (2015-2016) beta from the financial news site E24.no, as earlier values were not available we could not use our pretended present date of 01.01.2013. These values are shown in table 2 below.

Beta values		
	Calculated	**E24**
AUSS	0,57	0,41
BAKKA	0,61	0,34
GSF	0,42	0,87
HFISK	0,02	N/A
LSG	0,49	0,50
MHG	0,88	0,39
NRS	0,06	0,60
SALM	0,36	0,34

Table 2 - Beta Values of Companies

The beta values of our chosen companies are not identical, and therefore we are exposed to movements in the general market. This means that our strategy is not perfectly market neutral, as that can only be achieved by having the exact same beta values for both stocks. Nonetheless we chose to prioritize the high correlation of the companies, as well as the similar financial structure and size instead of solely focusing on the beta values.

Salmon Farming

Salmon farming, known as Salmon Aquaculture in generic terms, is the fastest growing industry within the animal-based food producing sector. It accounts for 70 % of the world's salmon production, while most of the farming production takes place in Norway, Scotland and Chile (Marine Harvest, 2016). In Norway, Salmon farming is a NOK 46.7 billion industry as of 2015, making Norway the biggest supplier. The industry in Norway has a workforce of 6730 people as of 2016 (SSB, 2016).

Marine Harvest (MHG)

Marine Harvest is the world's largest producer of farmed salmon and had a revenue of approximately NOK 28 bn in 2015. (Marine Harvest, 2015). The company is headquartered in Bergen, Norway, and is responsible for the whole production chain of farmed salmon. Marine Harvest has operations in 24 countries, employing more than 1600 people worldwide (Marine Harvest, 2016)

Lerøy Seafood Group (LSG)

LSG had a revenue of approximately NOK 13.5 bn in 2015 making it the world's second largest salmon producer. Its core activities are distribution, sales and marketing, and Lerøy employs 2300 people. The wholly integrated company is based in Bergen, Norway. (Lerøy, 2015).

Pairs trading match

By choosing Lerøy Seafood Group and Marine Harvest, we have two companies which are fundamentally similar. The two companies have fairly similar net asset values, size, location, capital structure, operational activities and therefore exposure to risk. This is somewhat confirmed by the historical data showing a high historical correlation between the two.

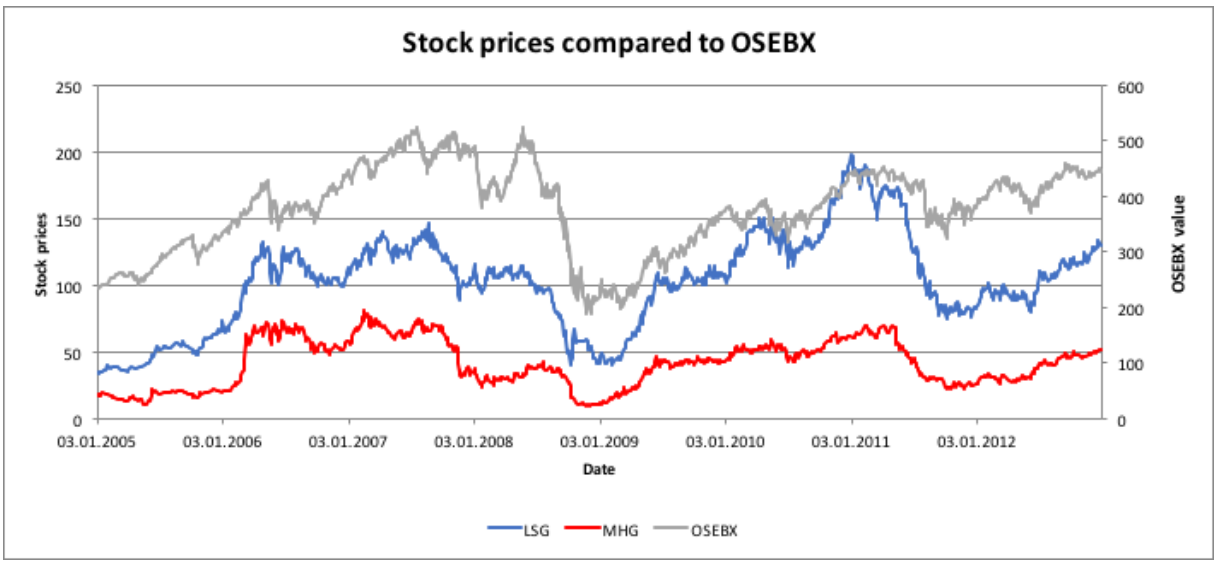


Figure 3 Stock prices compared to OSEBX index

By Looking at figure 2 we can see that the prices of the stocks seem quite correlated with the index. This does not imply that our strategy will be less effective. Our goal to eliminate the systematic risk, would still be possible by simultaneously going long and short with two stocks with beta values of 1.

Designing our trading model

As pairs trading is a known statistical arbitrage strategy, we had many existing models to extract knowledge from. First we investigated the strategy of Gatev et al (2006) and Do and Faff (2010, 2012), which in summary trades on the price difference between two stocks. This entails opening a position when the difference exceeds a given strike value. We tried this, and the optimal strike value was varying excessively in different periods. Later we discovered a strategy developed by Stephane Reverre (2001), who criticises the previously mentioned method because "an absolute value of $1 does not have any particular meaning for the stocks we are considering. It is smarter to introduce one more step, in which we normalise the value of the difference" (Reverre, 2001). This takes into consideration, that you should interpret the spread differently in times of high volatility compared to times of low volatility. With this thought in mind we explored an approach in which we compute the normalised spread, where Δ is the spread between the stocks, in this manner:

$$\Delta_{norm} = \frac{\Delta - \mathrm{MA}_t(\Delta)}{\sigma_t(\Delta)}$$

Δ_{norm} represents the "mispricing" of the spread in terms of standard deviations, where $\sigma_t(\Delta)$ is the t-day standard deviation of the spread. $\mathrm{MA}_t(\Delta)$ represents the t-day moving average, which is the average stock price the last t days. By introducing this to the model, we are enabling it to cancel out noise, but at the same time reflect market movements. This model relies on the assumption that the Δ_{norm} is normally distributed with an expected mean of 0 and a standard deviation of 1. We tested this assumption on our data, and even though it is not perfectly distributed, it shows signs of being a normal distribution. This test is shown in Figure 4 below.

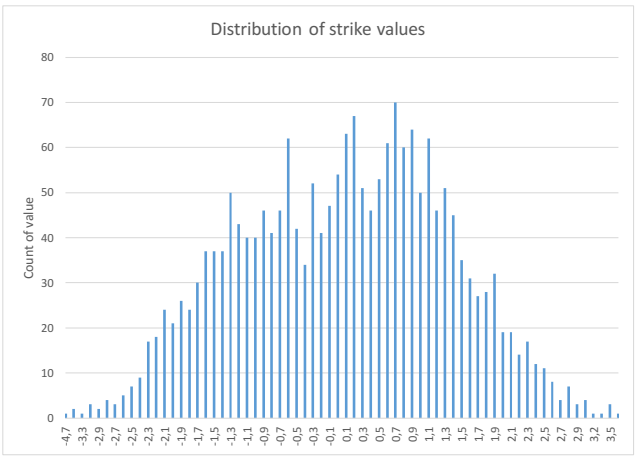


Figure 4 Distribution of Δnorm

The instant advantage of this model compared to the other, is that we know the distribution of Δ_{norm}, making the strike value of our choosing much more meaningful. If we choose a value of ± 2, we would know that there is roughly a 2.3 percent chance that the normalised spread will exceed this value, assuming a normal distribution. (Reverre, 2001).

Choosing the optimal moving average

The optimal moving average is when the fundamental market changes are reflected, but the unnecessary noise is cancelled out. An optimal value here is difficult to find, as the amount of days should reflect how long a period of a given volatility is expected to be. Set the value too high and a period high volatility in the past would distort present values. Set the value too low and it would be sensitive in both directions to short periods of low or high volatility. (Reverre, 2001)

We tried to optimize this value as well, and with some sample testing we noticed that a longer moving averages favoured lower strike prices. This is presumably because variations would to a larger degree get evened out as the time span increased. As an example, shown in table 3 below, the same amount of trades would occur at lower strike prices when you use longer periods.

Duration in days	Strike	# Trades
30	1,5	40
100	0,5	40

Table 3 Different moving averages and strike values

After more sample tests we concluded that increasing the optimization problem by another dimension would increase the scope of the paper considerably. And acknowledging that different durations would affect the optimal strike value, it did not seem to have a large impact on the profits gained by the optimal value. This assertion definitely needs further research, but we decided to simplify our problem by selecting a set duration.

Reverre (2001) suggests using 30 days, his argumentation is that "Thirty days is short enough to be reactive to the market and long enough to appear reasonably efficient in stripping noise out." He argues that this is a point that needs further inspection, but we assume his estimate to be better than ours.

We apply t = 30 to our previous formula.

$$\Delta_{norm} = \frac{\Delta - MA_{30}(\Delta)}{\sigma_{30}(\Delta)}$$

Calculation of profits and transaction costs.

Our model calculates profits on a daily basis, and they are accumulated throughout the time series by summing daily returns.

As with any trading strategy we are subject to transaction costs. We examined prices offered by an online broker (Nordnet, 2016), and used their public VIP price point with a brokerage fee of 0,035%. This is applied four times, as we are selling one stock and buying the other when we close and open our positions. When shorting a stock, we would also be subject to a shorting interest rate at 4,5% p.a. and a fixed sum fee of 250NOK. The interest costs are calculated with a continuous interest every day the asset is held (also accounting for weekends). We did not consider the fixed expense, as it is a disproportionately large sum compared to our simulated buying sum of 1000 NOK. Although this cost should be a genuine concern for somebody wanting to implement this strategy, an institutional investor would probably be able to negotiate a better deal and would surely use a larger amount of capital when implementing this strategy, making the fixed sum relatively less of an issue.

Our daily percentage returns are calculated as $\frac{return}{1000}$. This method is debatable, as one could say the return should be calculated as a percentage of 2000, that being the total amount of capital set into positions. One could also say that because this is a self-financing strategy the net outstanding capital amount is zero, and a percentage return could therefore be considered irrelevant.

We used a socioeconomic approach, where we assume the percentage return should give us a profit comparable to an opportunity cost. On the amount shorted this is represented by the 4,5% interest paid. This leaves us with 1000 NOK, which we could have invested in some other way, expecting a return. Using this, our calculated percentage return should therefore be comparable to alternative projects when deciding how to invest.

Because we wanted a risk adjusted measurement of return, we calculated the annualized Sharpe ratio:

$$S_p = \frac{\left(\left(1 + \overline{r_p}\right)^{250} - 1\right) - r_f}{\sigma_p * \sqrt{250}}$$

$$\overline{r_p} = \ Average\ of\ daily\ percentage\ returns$$

$$r_f = Risk\ free\ rate$$

This equation requires some assumptions:

That the year has 250 business days,

A constant risk free rate of 1,57%, given by 10-year Norwegian gvt. Bond.

Additionally, for this Sharpe ratio to be comparable with other strategies, you must assume that the returns of both are normally distributed.

Choosing the optimal strike value

When determining the optimal strike value there is an evident trade-off between accumulated profit and the success rate. The higher the strike, the higher the success rate, but this comes at the expense of accumulated profit (Reverre, 2001). The same logic holds in the opposite direction. The optimal value is, as mentioned earlier, highly dependent on the duration of our moving average and standard deviation, as well as our implementation of transaction costs. There are also several other limitations affecting our model, which we will go through at the end of the paper.

Having decided that the Sharpe ratio was the value we wanted to optimize, we had to look into how we would use our dataset.

At first we optimized the strike price in the whole period from 2005 to 2012, which gave us a value of 2,3483, and a Sharpe ratio of 1,3. To make sure that our findings were robust we split the eight-year period into two parts. The first part from 2005-2008 gave us an optimal strike value of 2,3203, with a Sharpe ratio of 0,775. The last part from 2009-2012 resulted in a strike value of 0,4365, and a Sharpe ratio of 3,507. Now, this result is very positive, and one could argue that 0,4365 would be the best value to choose because of the potential profits. On the other hand, this value applied in the period from 2005-2008 yields a negative return, while the value of 2,3203 is profitable regardless of the time span. These findings led to discussions within the team, and we had to come to an agreement regarding this trading strategy's preferences.

We concluded with the strike value optimized from 2005-2012 because of the implied lower risk, because it never resulted in a loss over a longer period. This value also fits into a longer timeframe. This might not be a durable argument; as newer but shorter datasets could be more accurate for the present day implementation than longer. However, we concluded that the higher strike value were best suited to our preferences.

After this we reran the optimization with some different sample values to secure that the strike value we had found was a global maximum and not a local maximum. This is necessary when using excel's solving algorithm, as it depends on trial and error. Charting the Sharpe ratio further confirmed that our value truly was the global maximum, shown in figure 5.



Figure 5 Sharpe ratio and different strike values

Our optimized model

$$\Delta_{norm} = \frac{\Delta - MA_{30}(\Delta)}{\sigma_{30}(\Delta)}$$

Open positon when $\Delta_{norm} > |2{,}3483|$

Close position when $\Delta_{norm} = 0$

Short LSG, Long MHG when $\Delta_{norm} > 2{,}3483$

Short MHG, Long LSG when $\Delta_{norm} < -2{,}3483$

Application of our model

When applying the model, with a strike value of 2,3483, in the timespan between 1.1.2013 to 31.12.2015 we opened 14 positions and closed 13. From figure 5, it is easy to see when we are opening and closing our position, and the high correlation between the stocks is striking.

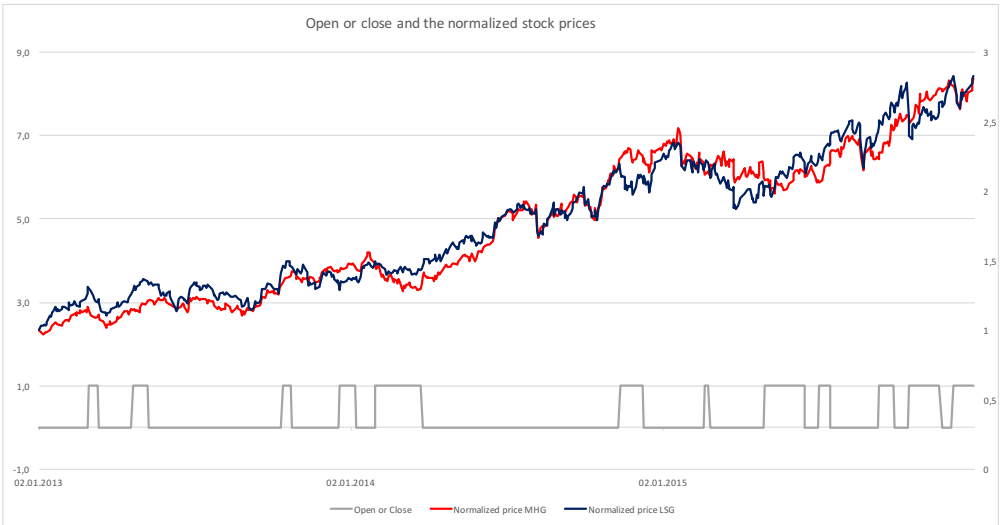


Figure 6 Opening and closing of our position

In this period of three years we achieve a positive return of 266,88NOK including the transaction costs. We have a success rate of 64,3% and a Sharpe ratio of 0,847. We are overall satisfied with the fact that the strategy proves profitable, despite of the claims by Hoel (2013), stating that the fundamental factors governing the stocks generally make the strategy less profitable.

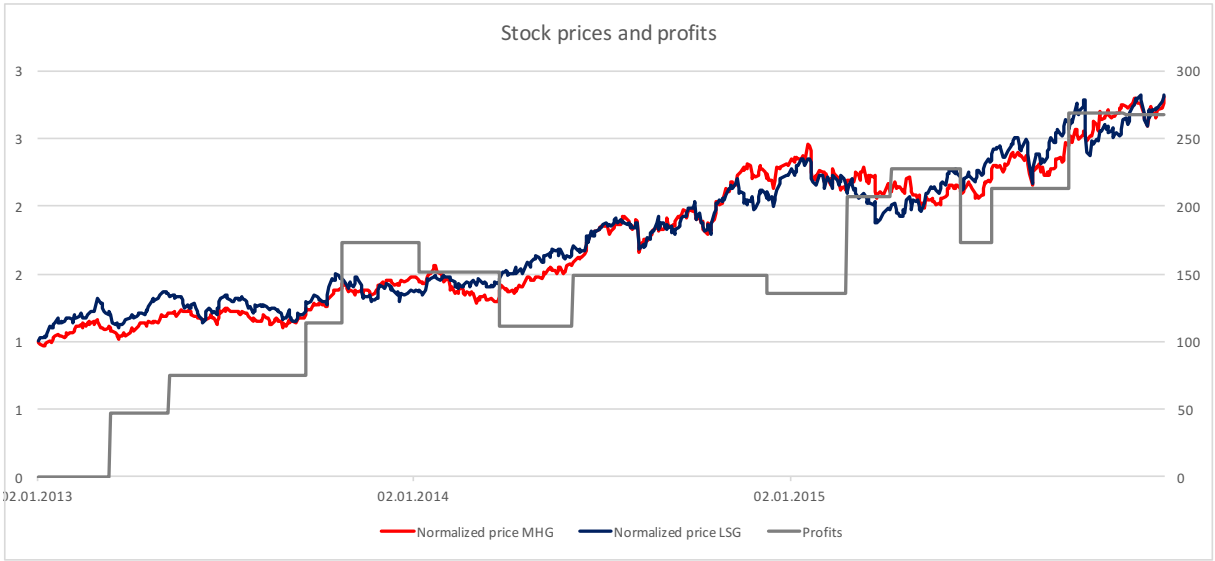


Figure 7 Stock prices and accumulated profits

From the normalized spread and strike values you can see which of the stocks we go long in, and which of the stocks we short. Our first trade occurs after around three months and contains a short leg in LSG, and a long leg in MHG. This position was held for two weeks and resulted in a profit of 47NOK. Going short in LSG and long in MHG is the most common position we undertake during this period, although we also take on the opposite position. One example is in 02.06.2014, a position we only keep for three days. This quite brief position leads to a profit of 38NOK, and illustrates the profit possibilities the strategy has, even in a short time span. Our biggest loss incurs 16.06.2015, after a position held for one and a half month. This results in a loss of 55NOK. This shows a drawdown of the accumulated portfolio value of 4,8%, as the portfolio value goes from 1227 to 1172.

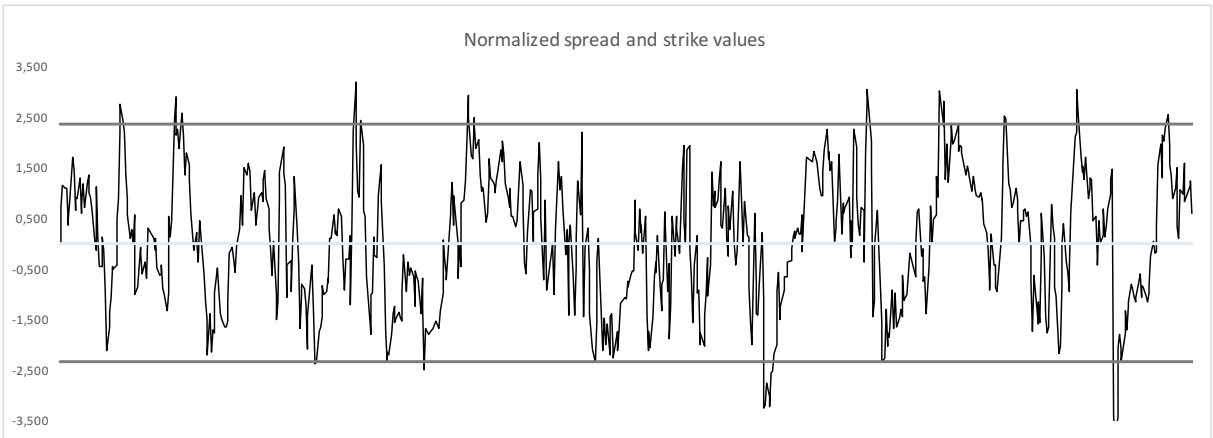


Figure 8 Normalized spread and strike values

Year	P&L Including Transaction Costs	%Return	Sharpe
2013	173,56	17,36 %	1,951
2014	-38,53	-3,85 %	-0,870
2015	131,85	13,18 %	1,087
Total:	**266,88**	**26,69 %**	**0,847**

Table 4 Yearly Profit and Loss

By implementing the strategy and pairing of MHG and LSG, we ended up with different P&L for each year, shown in Table 4.

Table 4 shows that not all the three years of implementing the strategy were profitable. Year two in the strategy had a small loss of approximately NOK40, mostly due to losses on two of the trades executed this year in addition to the transaction costs. One of these trades was mentioned in above resulting in a 55NOK loss. However, the strategy resulted in a net positive P&L, with a net return of 26,69 per cent.

Despite mostly experiencing profits, and thinking that we found a decent strike value, we understand that we could have done better. While performing a sensitivity analysis regarding the strike value, we unveil that the strike value indeed could have been improved. This is an exciting find, and might be due to the much higher correlation during this period, compared to the one we made the model from. Looking at figure 8, it is easy to see that the number of trades decrease as the trigger value increases. Because the success rate is quite steady, it leads us to the realization that a lower strike value would have been better. It still shows from figure 9 that the optimal value regarding the Sharpe ratio is at 1,4, and not lower than this. The reasons for this value to be lower than the one we used, can be a lot of things. Still, we find the increased correlation between the two stocks to be the most apparent among them. The insight to derive from this is that almost every trade will be successful, because the stock prices will immediately revert to its mean. With a lower correlation this would not be the case, and to take on positions more frequently could induce more risk, and more durable, unfavorable holding periods. The result definitely aligns with our preferences from developing the model, where we decided to limit the risk on behalf of the profit possibilities.

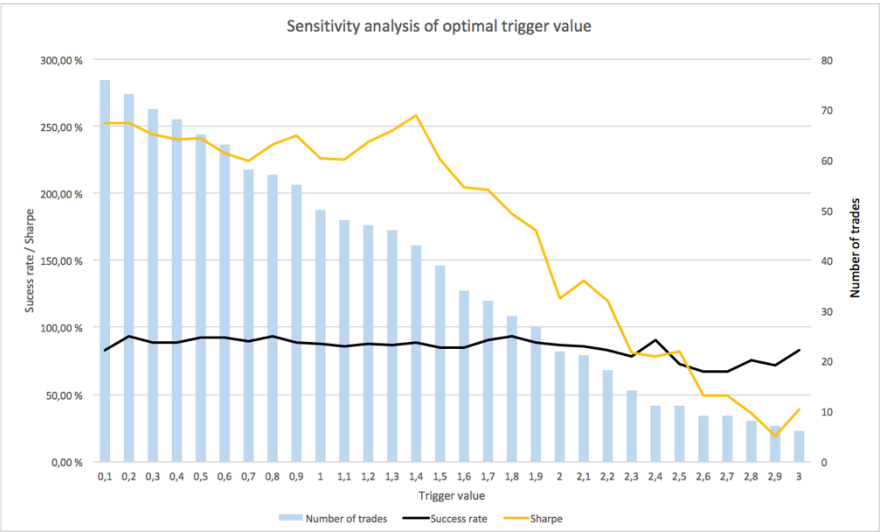


Figure 9 Sensitivity analysis of strike value

Limitations of our paper

To restrict the scope and extent of our paper, our model is subject to several limitations.

Model risk

Model risk is the risk associated of having the stock price affected by fundamental factors. As our model is purely based on calculations from the stock prices, this risk applies to our model to large extent. A change in the fundamental factors that only affects one of the companies, such as; change in management, work-related accidents (thereby incurring costs) or a market changing innovation, would not be taken into consideration in our model.

This risk is mitigated over time by correcting for the moving average, because after 30 days the change in the fundamental factors will no longer affect the strike values. However, it will not lessen the risk of opening an unfortunate position because of sudden changes in fundamental factors.

An additional exposure of model risk is our choice of the relative fair value. We normalize the stock prices to get a relative fair value of 1:1 at the first date of our dataset. If you assume an efficient market, this would always give the correct relative value between the companies. However, in perfect market efficiency, there would be no room for arbitrage strategies like ours. We could do a fundamental analysis and determine if the companies are mispriced relative to each other at that time, but this would be an entirely different paper, which would be subjected to further limitations. As contradictory as it is, we assume that the relative fair value is given by the efficiency of the market, to thereafter exploit the inefficiencies of the market to gain profits.

Basis risk

Our model does not take into consideration the possible event of a large change in fundamental factors that ends the mean reversion, thereby incurring basis risk. As a result, the trader could incur massive losses. This could be implemented by having an exit strategy, but we have not included this because of the scope of our paper. The typical application of an exit strategy, would be the use of a "stop-loss". A value at which the position is closed regardless of strike values, as a way of cutting your losses.

This risk is reduced by optimizing for Sharpe ratio instead of absolute profits. This is because the model will avoid "cherry picking" single trades with excessive profits that would increase variance greatly. We observed this in the early stages of development of the model, and optimizing for Sharpe ratio reduced this considerably.

Implementation risk

In our model, we assume that it is possible to buy and short stocks at continuous quantities. This means that we can buy 3,5 shares of a company. In reality we would have to buy whole shares, and not parts of a share, making this a limitation in how realistic our model is.

This is an implementation risk, because being forced to use whole numbers would imbalance the weighting of the portfolio, resulting in market risk and involuntary speculation in a stock. This would be less of an issue with an excessive buying sum, because one extra stock would have less of a relative impact, due to decimal rounding. Another way of decreasing this risk would be to choose a sum divisible by both stock prices.

Excess returns

In our model, we always use 1000NOK as our buying and shorting sum. Despite generating returns, positive or negative, we do not take past returns into consideration when taking on a new position. Therefore, we will not gain excess returns on our profits. We leave the assessment on how to invest these values up to the trader.

Number of pairs

We are limiting our strategy to just one pair. If you are pursuing a portfolio based on pairs trading, one way of reducing risks could be to use more than one pair to diversify and thereby reduce risks. Our methodology could easily be reapplied to find another pair in another sector, or market, but we limit our paper to only one because of the desired scope.

Adjustment of the strike price

Our model uses the same strike price for the full length of the time series. It could be split up, to make adjustments underway. Our assumption is that a larger dataset leads to better data. This might be inaccurate, as large fundamental changes inside our timeframe could make our optimized strike price less optimal for future use.

Conclusion

We have found that, even without data snooping, it is possible to generate positive returns from a pairs trading strategy. By back-testing on an eight-year period, we observed different periods, where different strike values were optimal. This made us reflect around what strike value is the best, and using the theory, we were able to make an educated decision to fit the model to our preferences. On the three-year period we actually tested the model we experienced both profits and losses, but ended with an absolute profit of 266,88NOK.

The result also reflect that the strategy works in spite of the bullish salmon market. Both of the stocks increase at least two-fold in value, and most people would roll their eyes to the proposition of shorting any of them at that time. Still, the pairs trading strategy yields a positive profit, which is convincing. The results are quite contradictory to recent research on the matter, where at least two master theses have dismissed the possibility of realistic profitability using the strategy. We do not dismiss the fact that this might be the case. During our discussion of limitations of this paper we suggest several factors, which might artificially contribute to a more positive result for our paper, than what would be the case if applied in the real market.

Summarized, we have found evidence that pairs trading might be profitable for some investors, however it is certainly not profitable for all, and there are several factors to take into consideration when applying such a strategy.

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