An Empirical Assessment of Statistical Arbitrage:

A Cointegrated Pairs Trading Approach

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Abstract

This paper assesses the aspect of market neutrality for a pairs trading strategy built on cointegration. This was conducted by evaluating the strategy’s performance during a negative market environment, 2007-06-01 to 2008-12-30, and a positive market environment, 2013-05-31 to 2014-12-30, for the stocks listed in the OMXS30 index. The results indicate market neutrality and that profitability of pairs trading is higher in prolonged periods of turbulence.

Keywords: Market neutrality, cointegration, pairs trading, mean-reversion
1 Introduction

Within the field of econometrics, a time series that oscillates around a long run equilibrium is said to exhibit mean reversion. This is a property that, in recent years, has received a lot of attention in the financial literature (e.g. Do and Faff 2010; Do and Faff 2012; Gatev, Goetzmann, and Rouwenhorst 2006). The reason behind the attention is its applications in the financial market and statistical arbitrage. The idea is that when a security, or a combination of securities, is mean reverting and these securities depart from their mean, positions can be taken to profit from the reversion. Research has proposed numerous strategies of how this can be done: one that is commonly used among institutional investors is pairs trading (Vidyamurthy 2004). Pairs trading can be described as a nondirectional relative-value investment strategy that seeks to identify two securities with similar trading characteristics whose prices are trading outside their relative range of historical movement. The deviation in range entails taking a long position in the undervalued security and a short position in the overvalued security, to then close the positions when the range reverts to its mean (Ehrman 2006).

The strategy is thus a bet on the relative pricing and not on the market. This means that the strategy in theory is hedging out the market risk, an aspect that is appealing in a financial climate of constant market shocks. Another aspect of pairs trading is that the technique is driven by utilizing short term mispricing’s in a pair of securities, a phenomena which is rather straight forward to find. This unlike many other market neutral strategies, like alpha transport, where success while being market neutral is derived from ambiguous security selection skills, leverage, and mathematical optimization (Do and Faff 2010).

Critique of the technique has for this reason been whether pairs trading simply is relying on spurious relations without any underlying financial theory, and that pairs trading with underlying financial theory should be more profitable (Vidyamurthy 2004). This issue has been investigated by introducing the concept of cointegration (Engle and Granger 1987) and arbitrage pricing theory (Ross 1976) to pairs trading. With these factors, the procedure of pair selection becomes a method where one searches alike securities that are cointegrated, with common risk factors, and, has a stationary price spread. Any deviations from the equilibrium level of the spread are hence derived from security specific shocks and the mean reverting process ensured by the cointegration between the
Whilst the strategy in essence appears simple, there are still, due to the proprietary of trading, grey areas in the literature on the subject (Ehrman 2006). Earlier research has had results pointing in different directions and has mainly been focused on techniques for picking pairs and on which distance measures to use (Vidyamurthy 2004). Recent years has however given some consensus in the field. Gatev, Goetzmann and Rouwenhorst’s article “Pairs Trading: Performance of a Relative-Value Arbitrage Rule”, published in 2006, gave empirical evidence of positive returns over a large sample and Do and Faff’s article “Does Simple Pairs Trading Still Work?”, published in 2010, showed that the techniques profitability continues even if its downward trending. Empirical assessments have also found evidence that cointegration in pairs trading yields higher returns than the spurious equivalent (Huck and Afawubo 2015). One undebated area is however the aspect of market neutrality, no recent assessments exist and no explicit empirical studies has provided consensus to the field.

This paper hence aims to farther the theory of pairs trading by empirically assessing the property of market neutrality in a real trading environment. The methodology for doing so constitute of trading during two different time periods. One where the cohort market movement yields a negative return and one where the cohort market movement yields a positive return: this to examine the differences in performance for the pairs trading strategy under the two financial climates.

The remainder of the paper is organized as follows: The theoretical background of the underlying statistical and financial theory is presented in section two. The used methodology and measurements for evaluation are described in section three. The result from the assessment is presented in section four, and section five discusses and concludes the paper.
2 Theoretical Background

2.1 Statistical Theory

2.1.1 Stationarity and Non-Stationarity

Covariance-stationarity is, within the field of time series, an assumption of the probabilistic structure on a stochastic process. It assumes that neither the mean, \( \mu \), or the autocovariances, \( \gamma_j \), depend on the time, \( t \), i.e. are constant. Following the outline by Hamilton (1994), the mathematical representation is

\[
E(Y_t) = \mu \quad \forall t
\]

\[
E(Y_t - \mu)(Y_{t-j} - \mu) = \gamma_j \quad \forall t \text{ any } j
\]

where the first condition states that the mean of the stochastic process is independent of time and constant. The second condition states that the covariance structure of the time series only depend on the lag length, \( j \), and not on the time, i.e. the stochastic process has a constant variance. The statistical representation of a covariance-stationary process is

\[
Y_t = \phi Y_{t-1} + \varepsilon_t
\]

where \(|\phi| < 1\) and \( \varepsilon_t \) is a random variable with mean \( \mu \) and variance \( \sigma^2 \). An extension to this is assuming unitary coefficients, i.e. \( \phi = 1 \), which means that the process is a unit root process. This changes the probabilistic structure of the stochastic process and allow previous time periods to affect the current time periods stance. The previous process is then

\[
Y_t = Y_{t-1} + \varepsilon_t
\]

where \( Y_{t-1} \) can be replaced with \( Y_{t-2} + \varepsilon_{t-1} \). Doing so leads to

\[
Y_t = Y_{t-2} + \varepsilon_{t-1} + \varepsilon_t
\]

Further substitution leads to

\[
Y_t = \varepsilon_{t-k} + \cdots + \varepsilon_t
\]
where the stochastic process now contains $t \varepsilon$’s. This means that the variance of the process is scaled by $t$, and hence dependent on time. To see this, remember that the variance of $\varepsilon$ was constant and equal to $\sigma^2$. The variance of a unit root process is then

$$Var(Y_t) = t\sigma^2$$ (7)

A process with these characteristics are often called a random walk and can be used as a proxy for how the equity price of a company moves on the stock market. This also indicates that the future price of the equity of a company is impossible to estimate, due to its underlying process having an infinite variance (Malkiel 2011). It is from this also clear what happens when the first difference is taken on a unit root process

$$Y_t - Y_{t-1} = Y_{t-1} + \varepsilon_t - Y_{t-1}$$ (8)

which is equal to

$$\Delta Y_t = \varepsilon_t$$ (9)

i.e. the first difference of a unit root process is a covariance-stationary process.

### 2.1.2 Augmented Dickey-Fuller’s test

The Augmented Dickey-Fuller (ADF) test aims to investigate whether a time series contains a unit root. The procedure starts by estimating the following model

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 t + \sum_{i=1}^{n} \delta_i \Delta Y_{t-i} + \nu_t$$ (10)

where $\alpha_0$ is the intercept, $\sum_{i=1}^{n} \delta_i \Delta Y_{t-i}$ is the sum of all the differentiated lagged $Y$ variables with their respective coefficients, $\alpha_2 t$ is the trend component, and $\nu_t$ is the error term. The ADF then test the null hypothesis $H_0 : \alpha_1 = 0$ against the alternative hypothesis $H_1 : \alpha_1 < 0$, where a non-significant result indicates that $Y_t$ is non-stationary, i.e has a unit root. (Asteriou and Hall 2011) This is conducted by comparing critical values for the Dickey-Fuller test with the following test statistic

$$ADF_{obs} = \frac{\hat{\alpha}_1}{\hat{\sigma}_{\alpha_1}}$$ (11)
2.1.3 Cointegration

A combination of time series, \( Y_t \) and \( X_t \), is cointegrated if the series are integrated of order \( d \) and a linear combination of the two are integrated of order \( d - b \), where \( d \geq b \geq 0 \) (Engle and Granger 1987). To see this, take the two stochastic processes, \( Y_t \) and \( X_t \), that are integrated of order, \( d \), a linear combination of the two can then be written as

\[
\theta_1 Y_t + \theta_2 X_t = u_t \sim I(0)
\]

(12)

where \( \theta_1 \) and \( \theta_2 \) represents the cointegrating vector for the variables \( Y_t \) and \( X_t \). Rearranging the terms for \( Y_t \), results in the following expression

\[
Y_t = -\frac{\theta_2}{\theta_1} X_t + \epsilon_t
\]

(13)

i.e. the long run equilibrium of \( Y_t \) given the values of \( X_t \). Therefore, if two variables are cointegrated they have a long-term equilibrium relationship. This means that a error correction mechanism is present, which implies that even though the variables may be exposed to temporary short-term shocks they will revert back to their long-term equilibrium. Formally, the representation of this mechanism and the Error Correction Model (ECM) is as follows (Asteriou and Hall 2011).

\[
\Delta Y_t = \gamma_0 \Delta X_t - (1 - a) [Y_{t-1} - \beta_0 - \beta_1 X_{t-1}] + u_t
\]

(14)

where \((1 - a)\) measures the error correction rate, i.e. the speed of the correction of the time series to the long-run equilibrium, and \(Y_{t-1} - \beta_0 - \beta_1 X_{t-1}\) represents this long-run equilibrium. Thus, the ECM incorporates both the short- and long-run effects. To derive the ECM mathematically, consider a general linear autoregressive distributed lag (ARDL) model with one lagged term of \( X \) and \( Y \)

\[
Y_t = a_0 + a_1 Y_{t-1} + \gamma_0 X_t + \gamma_1 X_{t-1} + u_t
\]

(15)

For simplicity we assume

\[
X_t^* = X_t = X_{t-1}
\]

(16)

\[
Y_t^* = Y_t = Y_{t-1}
\]

(17)
Rearranging the terms in the ARDL model leads to

\[
Y_t^* = a_0 + a_1 Y_t^* + \gamma_0 X_t^* + \gamma_1 X_t^* + u_t
\]

\[
Y_t^*(1 - a_1) = a_0 + (\gamma_0 + \gamma_1) X_t^* + u_t
\]

\[
Y_t^* = \frac{a_0}{1 - a_1} + \frac{\gamma_0 + \gamma_1}{1 - a_1} X_t^* + u_t
\]

\[
Y_t^* = \beta_0 + \beta_1 X_t^* + u_t
\]

i.e. the ECM is just a reparametrization of the original ARDL model

\[
\Delta Y_t = \gamma_0 \Delta X_t - (1 - a) [Y_{t-1} - \beta_0 - \beta_1 X_{t-1}] + u_t
\]

### 2.1.4 Engle-Granger’s test

The Engle-Granger test for cointegration is a test used to assess the cointegration between two variables. The first step of the method is to test the variables order of integration. This have to be determined, since two variables only can be cointegrated if they are integrated of the same order. (Asteriou and Hall 2011) The Engle-Granger approach use the ADF test presented in section 2.1.1 to test this.

If the variables are integrated of the same order (and not order 0, since this implies that they already are stationary and that it is not necessary to proceed) the next step is to regress one variable on the other to estimate the long run relationship between the variables

\[
Y_t = \beta_1 + \beta_2 X_t + u_t
\]

which leads to

\[
u_t = Y_t - (\beta_1 + \beta_2 X_t)
\]

If the residuals of the regression, \(u_t\), are stationary then the variables \(Y_t\) and \(X_t\) are cointegrated. Therefore, a ADF test will be conducted to find the order of integration of the residuals. If they are integrated by order 0, the null hypothesis of the variables not being cointegrated can be rejected. Moreover, if the variables are cointegrated, then the residuals can be used to estimate a ECM. The output from this model may be interpreted to determine short- and long-run effects of the variables.
2.1.5 Vector Autoregression

A vector autoregression (VAR) is a representation of several regressions in matrix form, where each variable in a system is regressed on a constant and \( p \) number of its own lags and \( p \) number of lags of the other variables in the system (Hamilton 1994).

\[
Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_p Y_{t-p} + \varepsilon_t \tag{22}
\]

where \( Y_t \) is a vector and \( \Phi_j \) represents a \((n \times n)\) matrix of the autoregressive coefficients for \( j = 1, 2, ..., p \). The \( c \) and \( \varepsilon_t \) both represent a \((n \times 1)\) vector for the constants and error terms in the system.

2.1.6 Johansen’s test

A technique to test for potential cointegration in a multivariate situation is the Johansen’s test. The test is superior to the Engle-Granger approach due to the property of being able to detect more than one cointegrated relation. The underlying idea of the Johansen approach is to test multiple equations simultaneously for cointegration by making use of a VAR system and extending the ECM to a vector representation. Following the framework by Asteriou and Hall (2011), the procedure for a vector of two variables, such that \( Z_t = [Y_t, X_t] \), is as follows

\[
Y_t = \zeta_{10} - \zeta_{12}X_t + \gamma_{11} Y_{t-1} + \gamma_{12} X_{t-1} + \ldots + \gamma_{1k-1} Y_{t-k} + \gamma_{1k} X_{t-k} + e_{Y,t} \tag{23}
\]

\[
X_t = \zeta_{20} - \zeta_{21} Y_t + \gamma_{21} Y_{t-1} + \gamma_{22} X_{t-1} + \ldots + \gamma_{2k-1} Y_{t-k} + \gamma_{2k} X_{t-k} + e_{X,t} \tag{24}
\]

where we assume that both \( Y_t \) and \( X_t \) are non-stationary, and the error terms are uncorrelated white-noise terms. Rewriting the system, to get the reduced form equations, we get

\[
\begin{pmatrix}
1 & \zeta_{12} \\
\zeta_{21} & 1
\end{pmatrix}
\begin{pmatrix}
Y_t \\
X_t
\end{pmatrix} =
\begin{pmatrix}
\zeta_{10} \\
\zeta_{20}
\end{pmatrix} +
\begin{pmatrix}
\gamma_{11} & \gamma_{12} \\
\gamma_{21} & \gamma_{22}
\end{pmatrix}
\begin{pmatrix}
Y_{t-1} \\
X_{t-1}
\end{pmatrix} +
\ldots +
\begin{pmatrix}
\gamma_{1,k-1} & \gamma_{1,k} \\
\gamma_{2,k-1} & \gamma_{2,k}
\end{pmatrix}
\begin{pmatrix}
Y_{t-k} \\
X_{t-k}
\end{pmatrix} +
\begin{pmatrix}
\varepsilon_{Y,t} \\
\varepsilon_{X,t}
\end{pmatrix} \tag{25}
\]
which, with substitution, is equal to

\[ BZ_t = \Gamma_0 + \Gamma_1 Z_{t-1} + \cdots + \Gamma_k Z_{t-k} + e_t \]  

(26)

and

\[ B = \begin{pmatrix} 1 & \zeta_{12} \\ \zeta_{21} & 1 \end{pmatrix}, \quad Z_t = \begin{pmatrix} Y_t \\ X_t \end{pmatrix}, \quad \Gamma_0 = \begin{pmatrix} \zeta_{10} \\ \zeta_{20} \end{pmatrix}, \quad \Gamma_1 = \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix}, \quad \Gamma_k = \begin{pmatrix} \gamma_{1,k-1} & \gamma_{1,k} \\ \gamma_{2,k-1} & \gamma_{2,k} \end{pmatrix}, \]

\[ Z_{t-k} = \begin{pmatrix} Y_{t-k} \\ X_{t-k} \end{pmatrix}, \text{ and } e_t = \begin{pmatrix} e_{Y,t} \\ e_{X,t} \end{pmatrix}. \]  

By now multiplying both sides of the system by \( B^{-1} \), we obtain

\[ Z_t = A_0 + A_1 Z_{t-1} + \cdots + A_k Z_{t-k} + u_t \]  

(27)

with \( A_0 = \Gamma_0 B^{-1}, A_1 = \Gamma_1 B^{-1}, A_k = \Gamma_k B^{-1} \), and \( u_t = e_t B^{-1} \). Which has the vector error-correction model of

\[ \Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \Gamma_2 \Delta Z_{t-2} + \cdots + \Gamma_k \Delta Z_{t-k-1} + \Pi Z_{t-1} + u_t \]  

(28)

where \( \Gamma_i = (1-A_1-A_2-\cdots-A_k) \) for \( i = 1, 2, \ldots, k-1 \), and \( \Pi = -(1-A_1-A_2-\cdots-A_k) \). Decomposing \( \Pi \) to \( \alpha / \beta' \), where \( \alpha \) is the speed of adjustment to equilibrium and \( \beta' \) is the long run matrix of coefficients, and assume \( k = 2 \) we obtain

\[ \begin{pmatrix} \Delta Y_t \\ \Delta X_t \end{pmatrix} = \Gamma_1 \begin{pmatrix} \Delta Y_{t-1} \\ \Delta X_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_{1,1} & \alpha_{1,2} \\ \alpha_{2,1} & \alpha_{2,2} \end{pmatrix} \begin{pmatrix} \beta_{1,1} & \beta_{1,2} \\ \beta_{2,1} & \beta_{2,2} \end{pmatrix} \begin{pmatrix} Y_{t-1} \\ X_{t-1} \end{pmatrix} + e_t \]  

(29)

where two methods for determining the number of cointegrated relations is common in practice, both involve reduced rank regression to estimate the matrix \( \Pi \). The first method tests the null hypothesis of \( \Pi \)'s rank being equal to \( r \) against the alternative hypothesis of the rank being \( r+1 \). The null hypothesis is hence that there are cointegrated vectors and up to \( r \) cointegrated relationships. The test statistics for the procedure is based on the eigenvalues, i.e. the characteristic roots, obtained from the estimation of \( \Pi \)'s. To test the number of characteristic roots that are significantly different from zero, the method uses the following test statistic

\[ \lambda_{\text{max}}(r, r+1) = -T \ln \left( 1 - \hat{\lambda}_{r+1} \right) \]  

(30)

The second method is built on a likelihood ratio test for the trace of \( \Pi \). The test assesses whether adding more eigenvalues past the \( r \):th increases the trace. The null hypothesis is that number of cointegrated vectors is equal to or less than \( r \). The test statistic is
calculated as
\[
\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^{n} \ln \left(1 - \lambda_{r+1}\right)
\]  
(31)

2.2 Financial Theory

2.2.1 Model of the Financial Market

To assess the theory of statistical arbitrage and pairs trading, we follow the outline of Ross (1976). The mathematical representation of the underlying financial market is then as follows:

The return of an asset \(j\), is defined as the percentage change in its value, \(P_j\)

\[
r_j = \frac{P_{j,\text{final}} - P_{j,\text{initial}}}{P_{j,\text{initial}}} \approx \log \left(\frac{P_{j,\text{final}}}{P_{j,\text{initial}}}\right)
\]  
(32)

where \(r_j\), according to arbitrage pricing theory, is composed by three components: a constant asset specific component, \(r^e_j\), which is a numerical representation of the asset fundamentals, a linear combination of factors \(f_i, i = 1,2,\ldots,n\), which are indicators of the state of the market, and a random variable, \(\epsilon_j\), that is uncorrelated with \(f_i\) and has a zero mean. That is

\[
r_j = r^e_j + \sum_{i=1}^{n} \beta_{j,i} f_i + \epsilon_j \tag{33}
\]

where the coefficient \(\beta_{j,i}\) is a measure of impact from factor \(i\) of asset \(j\). When the linear combination of factors \(f_i\) are uncorrelated, \(\beta_{j,i}\) is given by

\[
\beta_{j,i} = \frac{\text{cov}(r_j, f_i)}{\text{var}(f_i)} \tag{34}
\]

The expectation of \(r_j\) is

\[
E[r_j] = r^e_j + \sum_{i=1}^{n} \beta_{j,i} E[f_i] \tag{35}
\]

To further the framework to include more than one time period, some additional comments and assumptions on the specific components must be made. The asset specific component, \(r^e_j\), will not change without a reconstruction within the asset; \(r^e_j\) is therefore

\(^{1}\)The only form of assets this paper handles are stocks, but the formula applies to a broader range of assets.

\(^{2}\)It is common to also include the risk free rate, as monthly treasury bills, doing so would however not affect the derivations nor the theory. We have hence decided to disregard this fact for simplicity.
assumed to be constant in the time periods we consider. Any asset specific deviation from $E[r_j]$ is due to this captured in $\epsilon_j$. The coefficient $\beta_{j,t}$ is represented in the structure of the asset and will hence be constant in the short run. The market indicators $f_i$ are assumed to vary over time and to be exogenous, the process of $(f_{i,1}, f_{i,2}, \ldots, f_{i,n})$ is hence observable but cannot be affected. Lastly, the model allows non-perfect relationships between the market indicators. Mathematically, a perfect relation between two indicators would mean that a reduced form of the model would contain the same information and be preferable.

### 2.2.2 Pairs Trading

Pairs trading is an investment strategy that is built on utilizing relative mispricing’s between two securities whose historical prices have a pattern of co-movement. The argument is that if two security prices co-move, then they might be driven by the same underlying factors and, according to the law of one price, hence be priced in the same way. Changes in the relative price between the two will therefore only be temporary. (Elliott, Van Der Hoek, and Malcolm 2005)

Another perspective is that the price spread between the two, defined as $p_X - p_Y$, will oscillate around a long run equilibrium, where the deviations are derived from relative mispricing’s. Oscillations will therefore entail taking positions in the two, to then close these when the spread reverts to its equilibrium and thus profit from the reversion. I.e. if two securities $X$ and $Y$ have the individual return series of

$$r_{X,t} = r_X^e + \sum_{i=1}^{n} \beta_{X,i} f_{i,t} + \epsilon_{X,t}$$

$$r_{Y,t} = r_Y^e + \sum_{i=1}^{n} \beta_{Y,i} f_{i,t} + \epsilon_{Y,t}$$

where perfect co-movement in prices means that the company specific components $r_X^e$ and $r_Y^e$, are equal, and that the two securities react equally to the market factors, i.e. $\beta_{X,i} = \beta_{Y,i}$, which means that a deviation is derived from a change in the error terms. For example, that $\epsilon_{X,t}$ is positive while $\epsilon_{Y,t}$ is zero, which would mean that the relative price of security $X$ has increased. A trade in this setting would motivate creating a portfolio of a short position in security $X$ and a long position in security $Y$, with the knowledge
that a future $\epsilon_X$ must be negative to correct for the shock. If this happens in $t+1$ while $\epsilon_{Y,t+1}$ is zero and the positions are liquidated, the following portfolio return is achieved

$$r_{XY,t+1} = - \left( r_X^c + \sum_{i=1}^{n} \beta_{X,i} f_{i,t+1} + (-\epsilon_{X,t+1}) \right) + \left( r_Y^c + \sum_{i=1}^{n} \beta_{Y,i} f_{i,t+1} + \epsilon_{Y,t+1} \right)$$

(38)

which can be rewritten as

$$r_{XY,t+1} = (-r_X^c + r_Y^c) + \left( \sum_{i=1}^{n} (-\beta_{X,i} + \beta_{Y,i}) f_{i,t+1} \right) + (\epsilon_{X,t+1} + \epsilon_{Y,t+1})$$

(39)

and due to $r_X^c = r_Y^c$ and $\epsilon_{Y,t+1} = 0$ is equal to

$$r_{XY,t+1} = \sum_{i=1}^{n} (-\beta_{X,i} + \beta_{Y,i}) f_{i,t+1} + \epsilon_{X,t+1}$$

(40)

where $\beta_{X,i} = \beta_{Y,i}$ and the first term is zero, which means that the return for the trade is independent from the market movements, $f_{i,t+1}$, i.e. the strategy is market neutral.

The aspect of market neutrality can also be seen from the expected value of holding the same portfolio

$$E[r_{XY}] = E \left[ (-r_X^c + r_Y^c) + \sum_{i=1}^{n} (-\beta_{X,i} + \beta_{Y,i}) f_{i} + (-\epsilon_X + \epsilon_Y) \right]$$

(41)

where we the first two terms are equal to zero and $E[\epsilon_X] = 0$ and $E[\epsilon_Y] = 0$, which leads to

$$E[r_{XY}] = 0$$

(42)

i.e. the expected return of a buy and hold strategy for the portfolio is zero and not dependent on the market. This also indicates the importance of taking positions when the spread diverge from its long run equilibrium. This is a result that also point on what happens when the condition of $\beta_{X,i} = \beta_{Y,i}$ does not hold. The expected return then becomes

$$E[r_{XY}] = E \left[ \sum_{i=1}^{n} (-\beta_{X,i} + \beta_{Y,i}) f_{i} \right]$$

(43)

which means that it is dependent on how the market moves and on how the two specific securities react to these movements. Any pair trade is therefore also dependent on the probability of the historical relation of $\beta_{X,i} = \beta_{Y,i}$ to hold for all time periods of which a trade is in progress. This means that true expected return of the portfolio, and the
extended form of the expression above is

$$E[ r_{XY} ] = E \left[ \sum_{i=1}^{n} \left[ (-\beta_{X,i} + \beta_{Y,i}) f_i \times P (\beta_{X,i} = \beta_{Y,i}) \right] \right]$$  \hspace{1cm} (44)

which means that failure to reject false co-movement before a trade and structural breaks under a trade are threats to the validity of market neutrality. This also opens up for the possibility of skewed returns in small samples.

### 2.2.3 Iterating Confidence Intervals

Iterating confidence intervals\(^3\) is a tool in finance used to measure the relative range of movement for a security’s value in a non static behaviour. Iterating confidence intervals hence allows creating a channel whom is supposed to give information of the current level of the value. The intervals are constructed by an iterating process which calculates the mean, \(\mu\) and the standard deviation, \(\sigma\), of the security’s value as

\[
\mu_t = \frac{1}{w} \sum_{i \in A_t} \text{value}_i
\]

\[
\sigma_t = \sqrt{\frac{\sum_{i \in A_t} \left( \text{value}_i - \text{value}_{A_t} \right)^2}{w - 1}}
\]

where \(t\) is the day and \(w\) is the size of the iterating window and \(A_t\) a vector such that \(A_t = \{t - w, ..., t\}\). One then adds and subtracts a scaled value of the standard deviation from the mean in period \(t\)

\[
\text{Upper band}_t = \mu_t + M \times \sigma_t
\]

\[
\text{Lower band}_t = \mu_t - M \times \sigma_t
\]

where \(M\) is the scale of the channel. Depending on the statistical properties of the security’s value and the scaling of the interval, one can hence assume that movements outside the channel are short run deviations due to temporary shocks, and that the security’s value will revert back into the iterating range of historical movement.

\(^3\)Within finance often called Bollinger bands and named by John Bollinger.
2.2.4 Sharpe Ratio

A way of measuring the return of an investment relative to the risk taken is the Sharpe ratio. This is conducted by subtracting the risk-free rate, $r_f$, from the average return of the portfolio, $\bar{r}_p$, and dividing the result by the standard deviation of the portfolio, $\sigma_p$. (Sharpe 1994) Thus, the Sharpe ratio calculates the risk adjusted return of an investment

$$SR = \frac{\bar{r}_p - r_f}{\sigma_p}$$

(49)

A value of the Sharpe ratio above one indicates that the return of the investment is high relative to the portfolio risk, and that the excess return of the investment is positive after adjusting for the risk. Hence, a Sharpe ratio below one implies that the risk adjusted excess return for the investment is negative.
3 Methodology

3.1 Determine Pair Candidates

As mentioned in the introduction, this paper uses the technique of cointegration to find pairs for pair trading. We are hence trying to identify two assets whom returns are cointegrated. This put in the framework outlined in the previous section is as follows; the return of assets $X$ and $Y$ is

$$r_{X,t} = r_X^e + \sum_{i=1}^{n} \beta_{X,i} f_{i,t} + \epsilon_{X,t}$$

$$r_{Y,t} = r_Y^e + \sum_{i=1}^{n} \beta_{Y,i} f_{i,t} + \epsilon_{Y,t}$$

where cointegration is present when some linear combination between the series is stationary. This means that for some $\gamma$

$$E(r_{X,t} - \gamma r_{Y,t}) = E(r_X^e - \gamma r_Y^e) + \sum_{i=1}^{n} (\beta_{X,i} - \gamma \beta_{Y,i}) E[f_{i,t}] + E(\epsilon_{X,t} - \epsilon_{Y,t})$$

has to be stationary. This expression, by the properties stated in previous section, is equal to

$$E(r_{X,t} - \gamma r_{Y,t}) = r_X^e - \gamma r_Y^e + \sum_{i=1}^{n} (\beta_{X,i} - \gamma \beta_{Y,i}) E[f_{i,t}]$$

so as $E[f_{i,t}]$ can be modelled by a non-stationary process, the only way the expression of $E(r_{X,t} - \gamma r_{Y,t})$ can be stationary is if

$$\beta_{X,i} = \gamma \beta_{Y,i}, \quad \forall i$$

which leads to

$$E(r_{X,t} - \gamma r_{Y,t}) = r_X^e - \gamma r_Y^e$$

To test this relation we use the Engle-Granger approach outlined in the previous section. The first step in the procedure is an augmented Dicky-Fuller test, that is testing the following series for unit roots

$$r_{X,t} = \vartheta r_{X,t-1} + \epsilon_t$$

$$r_{Y,t} = \vartheta r_{Y,t-1} + \epsilon_t$$
Due to the properties of our data, the functional form of the ADF performed is

$$\Delta r_{X,t} = \alpha_0 + \alpha_1 r_{X,t-1} + \alpha_2 t + \sum_{i=1}^{n} \delta_i \Delta r_{X,t-i} + v_t \quad (58)$$

i.e. having a trend and an intercept. If both series exhibit unit root characteristics, we then proceed by estimating the long run relationship between our series

$$r_{X,t} = \theta_1 + \theta_2 r_{Y,t} + e_t \quad (59)$$

this to get the residual series of

$$\hat{e}_t = r_{X,t} - (\theta_1 + \theta_2 r_{Y,t}) \quad (60)$$

which is modelled and tested by the ADF as

$$\Delta \hat{e}_t = \alpha_0 + \alpha_1 \hat{e}_{t-1} + \sum_{i=1}^{n} \delta_i \Delta \alpha_1 \hat{e}_{t-i} + v_t \quad (61)$$

If the ADF-test rejects the null of a unit root, we conclude that the residual series from the two specific securities are stationary and, the pair, hence a candidate for trading. However, due to specification sensitivity\(^4\) of the Engle-Granger approach we also perform Johansen’s test of cointegration. We hence set up the bivariate system of

$$r_{X,t} = \zeta_{20} - \zeta_{21} r_{Y,t} + \gamma_{21} r_{X,t-1} + \gamma_{22} r_{Y,t-1} + \cdots + \gamma_{2k} r_{X,t-k} + \gamma_{2k} r_{Y,t-k} + e_{X,t} \quad (62)$$

$$r_{Y,t} = \zeta_{10} - \zeta_{12} r_{X,t} + \gamma_{11} r_{Y,t-1} + \gamma_{12} r_{X,t-1} + \cdots + \gamma_{1k} r_{Y,t-k} + \gamma_{1k} r_{X,t-k} + e_{Y,t} \quad (63)$$

where \(r_{X,t} = r_X + \sum_{i=1}^{n} \beta_{X,i} f_{i,t} + \epsilon_{X,t}\) and \(r_{Y,t} = r_Y + \sum_{i=1}^{n} \beta_{Y,i} f_{i,t} + \epsilon_{Y,t}\). Which, by the outline in section 2.1.6, has the following general vector error-correction model representation

$$\Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \Gamma_2 \Delta Z_{t-2} + \cdots + \Gamma_{k-1} \Delta Z_{t-k-1} + \Pi Z_{t-1} + u_t \quad (64)$$

where \(\Gamma_i = (1 - A_1 - A_2 - \cdots - A_k)\) for \(i = 1, 2, \ldots, k-1\), and \(\Pi = -(1 - A_1 - A_2 - \cdots - A_k)\).

Decomposing \(\Pi\) to \(\alpha \beta'\), and assuming \(k = 2^5\) we obtain

\(^4\)This problem arises by the difference in residual series between regressing on \(r_{X,t}\) or \(r_{Y,t}\), which is due to our limited samples. Asymptotic theory shows that as \(n\) goes to infinity the residual series are equivalent.

\(^5\)The lag length is chosen ad hoc due to simplicity in derivation. This might not represent the length appropriate for the test.
\[
\begin{pmatrix}
\Delta r_{X,t} \\
\Delta r_{Y,t}
\end{pmatrix}
= \Gamma_1 \begin{pmatrix}
\Delta r_{X,t-1} \\
\Delta r_{Y,t-1}
\end{pmatrix}
+ \begin{pmatrix}
\alpha_{1,1} & \alpha_{1,2} \\
\alpha_{2,1} & \alpha_{2,2}
\end{pmatrix}
\begin{pmatrix}
\beta_{1,1} & \beta_{1,2} \\
\beta_{2,1} & \beta_{2,2}
\end{pmatrix}
\begin{pmatrix}
r_{X,t-1} \\
r_{Y,t-1}
\end{pmatrix}
+ e_t
\] (65)

where Johansen’s reduced rank regression is applied to estimate \( \alpha \) and \( \beta \), which leads to the rank of \( \Pi \) and the number of cointegrated relationships in our system. If the reduced rank regressions show that we have at least one cointegrated relation, combined with a positive result from the Engle Granger test, we conclude that the pair should be traded when the opportunity is given.

### 3.2 Trading

As explained in the theoretical part of this paper, the aim is to take positions when the prices of two securities deviate from their range of historical movement to then liquidate these when the deviation has been corrected. In this paper, this is defined as when the spread between the prices of the two securities, \( P_X - P_Y \), diverge by more than 1.5 standard deviations from its mean. Moreover, to maximize the possible return, positions are not taken until indication that the mean reverting process has started, i.e. when \( \text{spread}_i - \text{spread}_{i-1} \) changes sign. Practically, if the spread diverge by a positive value, one takes a short position in security \( X \) and a long position in security \( Y \), and vice versa if the spread deviation is negative. Lastly, if positions are taken and the spread once again starts to diverge, a stop loss for the positions exists. This stop loss is built by a scaled lagged standard deviation of two days. The reasoning behind it being lagged is so the day \( i \)'s trade is bounded by yesterdays information, and the bounds hence disregards the impact of unexpected changes in the underlying securities. The function of the stop loss is to limit the possible losses of a trade.

Moreover, to avoid static trading and to take macroeconomic and security-specific structural breaks into account, we have chosen to use iterating confidence intervals (Bollinger bands) for these trading rules. This means that any reference to the mean or to the standard deviation is a reference to the specific in an iterating window process of 20 days, i.e.

\[
\mu_t = \frac{1}{w} \sum_{i \in A_t} \text{spread}_i
\] (66)
\[ \sigma_t = \sqrt{\frac{\sum_{i \in A_t} (\text{spread}_{i} - \text{spread}_{A_t})^2}{w - 1}} \]  

where \( t \) is the day and \( w \) is the size of the iterating window and \( A_t \) a vector such that \( A_t = \{ t - n, ..., t \} \). By these definitions our trading rules are

\[
\begin{align*}
\text{buy}_{1,t} &= \mu_t + 1.5 \times \sigma_t \\
\text{buy}_{2,t} &= \mu_t - 1.5 \times \sigma_t \\
\text{stop}_{1,t} &= \mu_t + 3 \times \sigma_t \\
\text{stop}_{2,t} &= \mu_t - 3 \times \sigma_t
\end{align*}
\]

The scalars on these rules, and the size of the iterating window, have been chosen after in sample calibrations with maximizing the return as the aim. An illustration of these trading rules are as follows: consider the first figure below (Figure 1): here the rules indicate taking a long position in security \( X \) and a short position in security \( Y \) on day 16, to then liquidate these positions on day 19 for a positive return. Another example is figure 2: during this period, the trading rules indicate taking a long position in security \( X \) and a short position in security \( Y \) on day 13, to then liquidate the positions on day 18, due to re-divergence of the spread, for a negative return.

**Figure 1**: Example of the trading rules for the spread between security \( X \) and \( Y \), defined as \( P_X - P_Y \). During this period, the rules indicated taking a long position in security \( X \) and a short position in security \( Y \) on day 16, to then liquidate these positions on day 19 for a positive return.
Figure 2: Example of the trading rules for the spread between security X and Y, defined as $P_X - P_Y$. During this period, the rules indicate taking a long position in security X and a short position in security Y on day 13, this to then liquidate the positions on day 18, due to re-divergence of the spread, for a negative return.

3.3 Data and Evaluation

The data used to assess the aspect of market neutrality constitutes of the stock prices for two periods of time for all stocks included in the OMX Stockholm 30 index (OMXS30). The first period of time stretches between 2007-06-01 and 2008-12-30 and the second period stretches between 2013-05-31 and 2014-12-30. This gives us 435 candidates to trade during a total of 826 trading days. The cohort market movement for the first period is negative (a bear period) and the cohort market movement in our counterfactual (a bull period), i.e. the second period, is positive. The first window is hence the window where we test whether pairs trading successfully manages to hedge out the market risk in a negative environment and the second window for the corresponding reason in a positive environment. The OMSX30 index is used to hinder the live trading problem of non-liquidity and being stuck in a position.

To assess the effectiveness of the strategy, we use a cumulative return and a corresponding Sharpe ratio. For a specific portfolio in one of the time windows, the Sharpe ratio is calculated by firstly calculating the average return

$$\bar{r}_p = \frac{1}{n} \sum_{i=1}^{n} \frac{price_{i,\text{final}} - price_{i,\text{initial}}}{price_{i,\text{initial}}}$$

(72)
where \( p \) is the portfolio and \( i \) represent the specific stock number in the specific portfolio, which ranges from 1 to 30 for the buy and hold strategy and from 1 to the number of cointegrated pairs for the pairs trading strategy. This average return is then divided by the standard deviation of the series of the final returns from the stocks in the specific portfolio

\[
\sigma_p = \sqrt{\frac{\sum_{t=1}^{n}(return_t - \overline{return}_p)^2}{n-1}}
\]  

which gives the Sharpe ratio of

\[
SR_p = \frac{\overline{r}_p}{\sigma_p}
\]

i.e. we have assumed the risk-free-rate to be zero. Moreover, to fully represent a real trading environment we use the 200 first days of these windows as our sample in which we test for cointegration and calibrate our algorithm: this to then trade the following 213 days. Any trades are therefore conducted out of sample and relying on tests, estimations, and calibrations done in sample. This is hence a comparable situation to how institutional investors work and a good test of theory.
4 Results

The following section aims to evaluate how our methodology performed during the two time windows of 2007-06-01 to 2008-12-30 and 2013-05-31 to 2014-12-30. This is done by first assessing the time window where the aggregated market environment (measured as the cumulative movement of the OMXS30-index) was negative, this to then move onto the window of a positive aggregated market. The measurements used to evaluate the performance of pairs trading are a cumulative return for the strategy and the respective Sharpe ratio. For comparison, we also present the corresponding measurements for a non-weighted buy and hold strategy of the OMXS30 index.7

4.1 2007-06-01 to 2008-12-30 - Bear Period

For the first period a total of twelve cointegrated relationships between the stocks was indicated by the in sample calculations. The total number of trades for these pairs was 72, which gives an average of six trades per pair and 0.34 trades per day for the 213 days. The cumulative return for portfolio was 11.87 % and the Sharpe ratio 1.45. This while the buy and hold strategy had a cumulative return of -33.26 % with a Sharpe ratio of -1.43. The total difference between the strategies for the window is 45.13 percentage points.

<table>
<thead>
<tr>
<th>Performance</th>
<th>Pairs Trading</th>
<th>Buy and Hold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative return</td>
<td>11.87 %</td>
<td>-33.26 %</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>8.17 %</td>
<td>23.30 %</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>1.45</td>
<td>-1.43</td>
</tr>
</tbody>
</table>

Table 1: Performance statistics for a pairs trading strategy versus a buy and hold strategy for the out of sample period under the time window 2007-06-01 to 2008-12-30.

7For the same comparison in all of the pairs, see Appendix A.
Figure 3: The cumulative return for a pairs trading strategy versus a non-weighted buy and hold strategy for the out of sample period under the time window 2007-06-01 to 2008-12-30.

4.2 2013-05-31 to 2014-12-30 - Bull Period

The second time window, our counterfactual and positive market, indicated a total of four cointegrated relations. The total number of trades for these pairs was 23, which gives an average of 5.75 trades per pair and 0.11 trades per day for the window. The cumulative return for the portfolio was 2.73 % with a Sharpe ratio of 1.05. The buy and hold strategy for the corresponding period had a cumulative return of 8.52 % with a Sharpe ratio of 0.43. The difference between the strategies is 5.79 percentage points.

<table>
<thead>
<tr>
<th>Performance</th>
<th>Pairs Trading</th>
<th>Buy and Hold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative return</td>
<td>2.73 %</td>
<td>8.52 %</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>2.59 %</td>
<td>18.28 %</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>1.05</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Table 2: Performance statistics for a pairs trading strategy versus a non-weighted buy and hold strategy for the out of sample period under the time window 2013-05-31 to 2014-12-30.
Figure 4: The cumulative return for a pairs trading strategy versus a buy and hold strategy for the out of sample period under the time window 2013-05-31 to 2014-12-30.
5 Discussion

The aim of this paper was to assess the aspect of market neutrality for a pairs trading strategy built on cointegration. This was conducted by evaluating the strategy’s performance during a negative market environment, 2007-06-01 to 2008-12-30, and a positive market environment, 2013-05-31 to 2014-12-30, for the stocks listed in the OMXS30 index.

The results of the assessment indicate that the theoretical aspect of market neutrality holds. Trading in the first window, our bear period, achieved a cumulative return of 11.87% with a Sharpe ratio of 1.45, while the return and Sharpe ratio for the second window were 2.73% and 1.05. The cumulative returns do differ, but the patterns for the periods are the same. Nonetheless, the differences we do have can partially be explained by the variance in the number of cointegrated pairs and the underlying theory.

The first period trades 12 pairs with a total of 72 trades: this while the second period only trades 4 pairs with a total of 23 trades. This is of importance since section 2.2 showed that the expected return of a trade is dependent on the probability that the estimated historical pattern between the underlying securities holds throughout a trade. The average return in a sample of trades might therefore be skewed, it will however, asymptotically move towards its expected value when the number of trades increases.

Moreover, previous research has stated that pairs trading perform better in prolonged periods of turbulence. The theoretical part of this paper showed that the technique is purely driven on utilizing short term mispricing’s between two cointegrated securities. Arbitrage pricing theory derives this from security specific shocks. One could argue that such security specific shocks are more common in a volatile economical climate, which spells onto the financial market. The difference in return does therefore not mean that the aspect of market neutrality is compromised. Market neutrality simply means that one successfully manages to hedge out the market risk.

Lastly, we also found that the technique of pairs trading continues to be profitable in today’s financial climate. The return was positive in both periods with a Sharpe ratio exceeding the respective for the buy and hold strategy. Therefore, one could also use our results as empirical evidence of the continuing profitability of pairs trading. A conclusion that is consistent with previous research (see Do and Faff 2010; Do and Faff 2012; Gatev,
Goetzmann, and Rouwenhorst 2006; Huck and Afawubo 2015).

5.1 Conclusion

After empirically evaluating a pairs trading strategy built on cointegration during one time window where the cohort market movements were negative and one time window where the cohort market movements were positive, we can conclude that our results indicate that the aspect of market neutrality holds. The strategy had a positive cumulative return for both periods, and a higher Sharpe ratio than an un-weighted buy and hold strategy of the index. Our results also imply that pairs trading is more successful in a climate of prolonged turbulence, a conclusion that coincide with previous research.

5.2 Suggestions for Further Research

It would be interesting to study how our results and the indication of market neutrality compare to a study stretching beyond two windows and including more than the OMXS30 index. A more comprehensive study may support our conclusions and provide consistency to the literature.
References


Appendix A

2007-06-01 to 2008-12-30

Figure 5: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Atlas Copco A and Atlas Copco B, for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was -0.02 %. The corresponding numbers for the two buy and hold strategies was -33.58 % and -35.68 % respectively. The pairs trading strategy performed a total of three trades.

Figure 6: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Atlas Copco A and Skanska B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 18.51 %. The corresponding numbers for the two buy and hold strategies was -33.58 % and -32.90 % respectively. The pairs trading strategy performed a total of four trades.
Figure 7: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Atlas Copco A and SKF B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 17.78%. The corresponding numbers for the two buy and hold strategies was -33.58% and -30.41% respectively. The pairs trading strategy performed a total of seven trades.

Figure 8: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Atlas Copco B and Skanska B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 12.84%. The corresponding numbers for the two buy and hold strategies was -35.68% and -32.90% respectively. The pairs trading strategy performed a total of seven trades.
Figure 9: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Atlas Copco B and SKF B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 10.93 %. The corresponding numbers for the two buy and hold strategies was -35.68 % and -30.41 % respectively. The pairs trading strategy performed a total of six trades.

Figure 10: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Getinge B and Swedish Match B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 23.45 %. The corresponding numbers for the two buy and hold strategies was -39.87 % and -20.74 % respectively. The pairs trading strategy performed a total of seven trades.
Figure 11: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Investor B and Skanska B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 10.59%. The corresponding numbers for the two buy and hold strategies was -11.70% and -32.90% respectively. The pairs trading strategy performed a total of seven trades.

Figure 12: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case MTG B and Skanska B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 2.26%. The corresponding numbers for the two buy and hold strategies was -48.26% and -32.90% respectively. The pairs trading strategy performed a total of seven trades.
Figure 13: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Sandvik B and Skanska B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 6.80%. The corresponding numbers for the two buy and hold strategies was -52.66% and -32.90% respectively. The pairs trading strategy performed a total of eight trades.

Figure 14: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case SEB B and Skanska B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 15.07%. The corresponding numbers for the two buy and hold strategies was -61.55% and -32.90% respectively. The pairs trading strategy performed a total of six trades.
Figure 15: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Skanska B and Handelsbanken A for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 23.25 %. The corresponding numbers for the two buy and hold strategies was -32.90 % and -72.59 % respectively. The pairs trading strategy performed a total of eight trades.

Figure 16: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Handelsbanken A and Swedish Match B for the time period of 2007-06-01 to 2008-12-30. The return for the pairs trading strategy was 0.99 %. The corresponding numbers for the two buy and hold strategies was -24.32 % and -20.74 % respectively. The pairs trading strategy performed a total of four trades.
2013-05-31 to 2014-12-30

Figure 17: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Atlas Copco A and Securitas B for the time period of 2013-05-31 to 2014-12-30. The return for the pairs trading strategy was 5.66%. The corresponding numbers for the two buy and hold strategies was 31.20% and 17.64% respectively. The pairs trading strategy performed a total of six trades.

Figure 18: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Atlas Copco B and Securitas B for the time period of 2013-05-31 to 2014-12-30. The return for the pairs trading strategy was 0.61%. The corresponding numbers for the two buy and hold strategies was 13.17% and -1.70% respectively. The pairs trading strategy performed a total of four trades.
Figure 19: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case Lundin Petroleum B and Tele 2 B for the time period of 2013-05-31 to 2014-12-30. The return for the pairs trading strategy was 4.16 %. The corresponding numbers for the two buy and hold strategies was -11.22 % and 21.11 % respectively. The pairs trading strategy performed a total of five trades.

Figure 20: Returns for our pairs trading strategy and a buy and hold strategy of the underlying securities, in this case SCA B and Handelsbanken A for the time period of 2013-05-31 to 2014-12-30. The return for the pairs trading strategy was 0.49 %. The corresponding numbers for the two buy and hold strategies was -11.89 % and 7.77 % respectively. The pairs trading strategy performed a total of eight trades.