Long-Short Investment*

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*Other theoretical parts of this study have been ommited in this version to provide clarity of analysis

5 DATA and METHODOLOGY

5.1 Data

The initial dataset used in this study is comprised of the 600 independent stocks that make up STOXX Europe 600 index and the historical series is obtained based on the membership of the index as of 9th May 2014. The STOXX Europe 600 Index is representative of all size of companies ranging from large, mid and small capitalization companies across 18 countries of the European region. These countries include Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

The distribution of currencies in the StoxxEurope 600 is as shown in **Table 1**. The Euro (E) is the dominant currency being the operating currency for 294 firms but these firms are spread across different countries in the economic zone. The United Kingdom Pound (£) however has 185 firms giving an indication of major influence of the UK based firms on the index performance. Other currencies include Danish Krone (DK), Swiss Franc (SF), Norwegian krone (NK), Swedish krona (SK), and the Czech koruna (CK).

Table 1: Distribution of currencies in the dataset

Currency	**Firm Count**
CK	2
DK	18
E	294
NK	15
SF	46
SK	40
£	185

This study is focused on stocks that use the Pound (£) as the operational currency; these firms are geographically located in the United Kingdom and therefore exposed to similar market conditions and macro-economic shocks. The sample size therefore consists of 185 firms that use the pound as their operating currency. Other stock price series (denominated in other currencies) are not included in the study since it would require convertion of the price series to a common currency. Such an approach is not desirable in the context of this study for purposes of restricting price changes only to stock price movements and thereby avoiding distortions that may be induced by major fluctuations in exchange rates brought about by events such as devaluations that tend to introduce jumps and structural breaks in the data (Syllignakis and Kouretas 2011). Additionally, modeling the strategy by forming pairs of stocks listed in different markets would only be practical for stocks that are cross listed. In the absence of such information, following such an approach reduces the practical appeal of the trading results obtained.

From the 185 Pound based stock price series, stocks with a significant number of missing data points are eliminated, these are stocks with more than 2 trading months (44 days) of continuously missing observations. This ensures that the data sample contains only liquid stocks. Following this elimination, 134 stock prices are left in the sample that forms the basis of this study. The dataset spans from 01 January 200 to 08 May 2014.

Following the Industry Classification Benchmark (ICB), the stocks in the dataset are classified in to the respective ICB Level 2 names. In this classification, there are 10 possible groups. **Table 2** shows this classification and the number of firms in the dataset that are grouped with a given sector name. Industrials, Financials and Consumer Services constitute the largest group with 34, 29 and 23 firms classified respectively. The classification model applied follows ICB's system as indicated in the Stoxx Europe 600 guidelines (ICB Home 2015).

Table 2: Industry classification and number of firms

Industry	No of Firms
Basic Materials	10
Consumer Goods	14
Consumer Services	23
Financials	29
Healthcare	5
Industrials	34
Oil & Gas	7
Technology	3
Telecommunications	3
Utilities	6

5.2 Methodology

The studies reviewed in the literature review section largely utilized sum of squared deviations (SSD) mechanism to determine trading pairs by using a low SSD value to indicate closeness in price movement. Gatev, Goetzmann, and Rouwenhorst (2006) further argue that using comparing SSD for stocks in the same industry increases the chance of finding a properly matching SSD pair. This study follows a similar approach to determine trading pairs. Further, it is assumed that there are no trading costs incurred during the trading activity and the market is constantly liquid therefore facilitating frictionless construction of portfolios on demand.

5.2.1 Pairs Formation

Trading pairs are determined during the formation period before being traded in the subsequent trading period. In this study the formation period is 260 days or one trading year during which trading pairs are identified. The process begins by converting the price series to a cumulative total returns index for each stock series as shown in **Equation 1** where r_τ^i is the return series of a stock i.

$$P_t^i = \prod_{\tau=1}^{t} \left(1 + r_\tau^i\right) \tag{1}$$

A matching stock pair is determined based on finding the stock that minimizes the sum of squared deviations between two normalized price series over the formation period. Various combinations of pairs are tested for their distance based in **Equation 2** where P_t^i is the normalized price for a stock i and P_t^j is the normalized price for stock j.

A combination consisting of a pair i, j includes testing for one-way combination such that the distance of the pair formed from j, i is not calculated since the order of selection is not critical due to the fact that a square of the resulting value is obtained. For example there are 34 stocks price series classified as industrial, within this group, there are 561 possible trading pairs.

$$Distance^{i,j} = \sum_{t=1}^{260} \left(P_t^i - P_t^j\right)^2 \tag{2}$$

5.2.2 Trading Rules

The trading period consists of 130 days or half a trading year immediately following a formation period and returns are calculated for each trading period. The formation period is rolled such that a continuous series of non-overlapping returns data are obtained. **Figure 1** shows an illustration of the formation and trading periods. The first 260 days of the sample due to the first formation period.

After pairs of stocks are identified, they are traded forming a portfolio of pairs. Trading begins the next day following the end of the formation period based on a trading rule. Following a similar approach as (Gatev, Goetzmann, and Rouwenhorst 2006) a position is opened and closed based on a standard deviation metric. Prices in the trading period are also normalized and a trading market signal (long, short or exit) is generated based on the historical two standard deviations of the spread obtained in the formation period as shown in **Equation 3**.

$$Signal^{i,j} = \pm 2\sigma_{i,j} \tag{3}$$

$$\sigma_{i,j} = StandardDeviation\left(P_t^i - P_t^j\right) \tag{4}$$

A long signal is generated when the spread at time t negatively exceeds the historical two standard deviations. When a long (short) position is taken on stock i, a short (long) position is simultaneously taken on the trading pair j and a signal to exit the market is generated when the prices next cross each other. To this effect a positions vector is formed.

$$Position_t^{i,j} \equiv \begin{array}{cc} 0 & \textit{Exit Market} \\ +1 & \textit{Short A,; Long B} \\ -1 & \textit{Long A; Short B} \end{array}$$

The trading positions are held until the next crossing of the prices. If convergence of prices does not take place during the trading period, gains or losses are calculated at the end of the last trading day of that particular trading interval.

5.2.3 Excess return compution

Returns to a traded pair are obtained as a result of the product of the positions vector with the spread of the returns as shown in **Equation 5** where r_t^j and r_t^i are the raw returns of the stocks i and j at time t respectively and $R_t^{i,j}$ is the return obtained from trading pair i and j.

$$R_t^{i,j} = Positions_t^{i,j} \left(r_t^j - r_t^i \right) \tag{5}$$

In any traded pairs, returns (positive or negative) are generated if the spread of the normalized prices diverges by more than two standard deviations. The pairs may also produce zero returns as a result of no divergence during a given trading period. In a similar approach to Gatev, Goetzmann, and Rouwenhorst (2006) the long and short positions are marked to market on a daily basis.

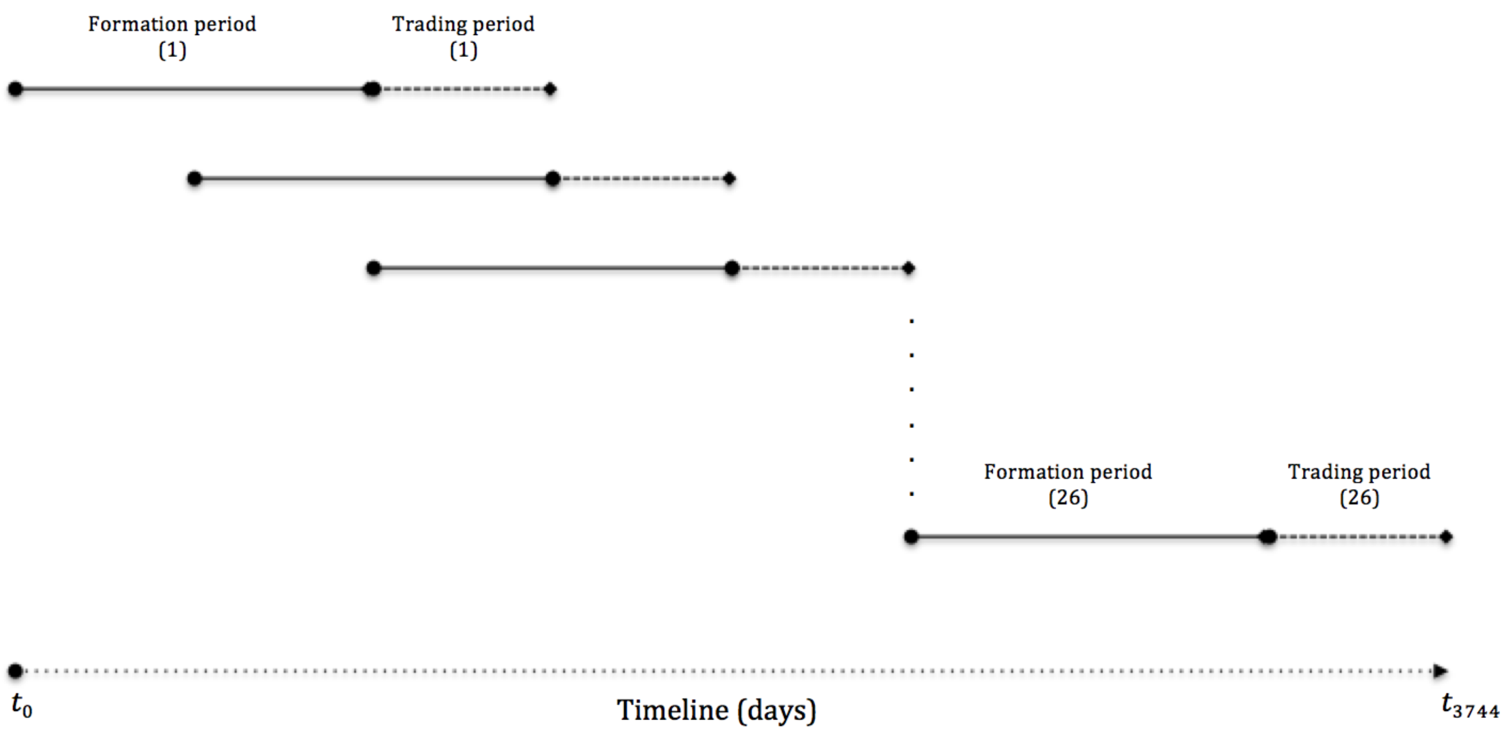
Returns on a portfolio of pairs are calculated over a trading period as

$$R_t^{Portfolio} = \frac{1}{No.of Pairs} \sum_{pair=1}^{No.of Pairs} r_t^{ij,pair} \tag{6}$$

This approach scales the portfolio payoffs by the number of pairs that are selected for trading irrespective of whether the pairs diverged enough to be traded or not. Gatev, Goetzmann, and Rouwenhorst (2006) refer to this approach as obtaining the returns on committed capital.

Figure 1: Illustration of formation and trading periods

The formation period is one trading year (260 days) and the trading period is half a trading year (130 days). The first formation period leads to the loss of 260 observations and the last 104 days are also lost since they do not fill a trading period.



5.2.4 Portfolio re-balancing effect

To test the effect of portfolio rebalancing in pairs trading, two different trading approaches are tested. The first approach tests a buy and hold investment strategy with a portfolio that is never changed over the entire sample period. The second approach tests a portfolio that is continuously rebalanced prior to every new trading period.

The buy and hold strategy trades the same pairs over the entire trading period but the trading formation and trading are still on a rolling basis. The main point is that the portfolio formed in the beginning is not changed save for the trading parameters that are updated based on the most recent formation period.

Also, the buy and hold strategy is implemented to trade all possible combinations of pairs within a given industry group. The column Pair Combinations in **Table 3** shows all the pair combinations that are formed from a given industrial group. For example following this approach, the Industrials group constitutes the largest portfolio with 561 pairs while the Technology and the Telecommunications groups have the smallest portfolios comprised of three pairs. There is no size bias in the portfolios returns since they are scaled to the number of pairs in the portfolio.

Table 3: Industry classification and number of pairs per industry

Industry	No of Firms	Pair Combinations
Basic Materials	10	45
Consumer Goods	14	91
Consumer Services	23	253
Financials	29	406
Healthcare	5	10
Industrials	34	561
Oil & Gas	7	21
Technology	3	3
Telecommunications	3	3
Utilities	6	15

Portfolio rebalancing is implemented by sorting the formed trading pairs based on their minimum sum of squared distance (SSD) as measured at every new formation period. Once the pairs are sorted, 20 pairs with the lowest minimum distance are selected to form a new trading portfolio. In each new pairs formation period, the entire industry set is the universe of stock that is tested for minimum distance, followed by picking 20 pairs with the lowest distance for trading in the upcoming trading period. The decision to use 20 pairs as the cut-off point (i.e. why only 20 pairs to be traded and not 30 for example) has been arbitrarily selected. However, using this number of stock pairs will facilitate comparison of the results obtained in this study with previous results obtained by in studies by Gatev, Goetzmann, and Rouwenhorst (2006); Do and Faff (2010) where also the top most twenty pairs are used for trading.

6 EMPIRICAL RESULTS

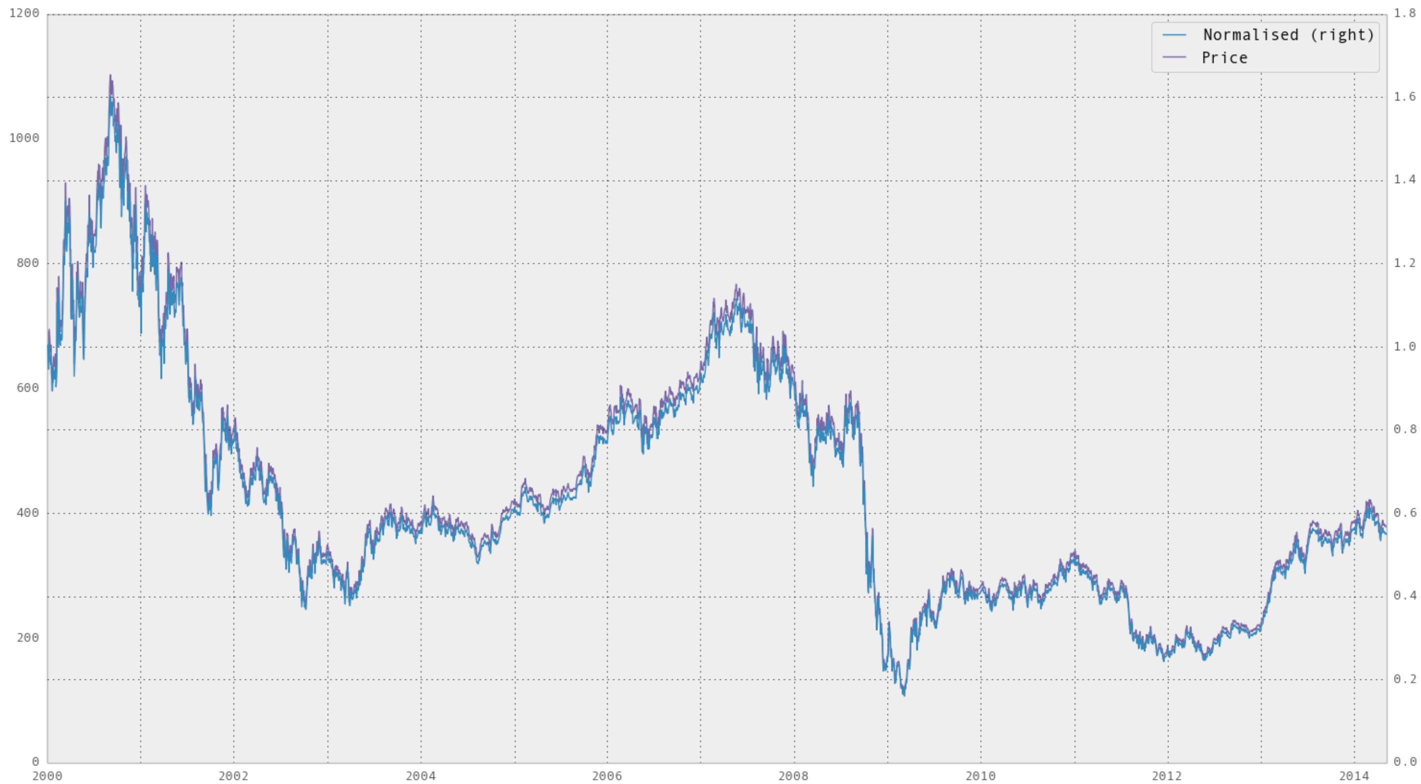
A summary of the trading data is shown in **Table 4**. There are 260 observations lost in the beginning due to the first formation window and there are 104 days at the end of the sample that are not traded since they do not meet the criteria of a full trading block of 130 days. The sample has a total of 26 trading periods with an equal number of accompanying formation periods. Each trading period has a length of 130 days thereby resulting in 3380 trading days in the sample.

Table 4: A descriptive summary of trading setup

(i)	**Total sample (days)**	3744
(i)	**Formation period (days)**	260
(iii)	**Trading period (days)**	130
(iv)	**Number of trading periods in sample**	26
(v)	**Total trading days in sample(26 * 130)**	3380
(vi)	**Days lost due to initial formation period**	260
(vii)	**Days lost at end of sample**	104
(viii)	**Check of total days(vi + v + vii)**	3744

During the formation period, stock prices are normalized following the process outlined in **Equation 1**. This process does not remove the dependency structures of the time series; the moments of the series are preserved. **Figure 2** shows the normalized price of a sample stock and the level price of the same stock, by visual inspection, the series are seen to have the same structure. The normalized price begins at 1 and changes according to the stocks gross return compounded on a daily basis. The right hand y-axis represents the normalized price and the left hand y-axis represents the price levels of the same stock. The plot is generated for the entire sample period.

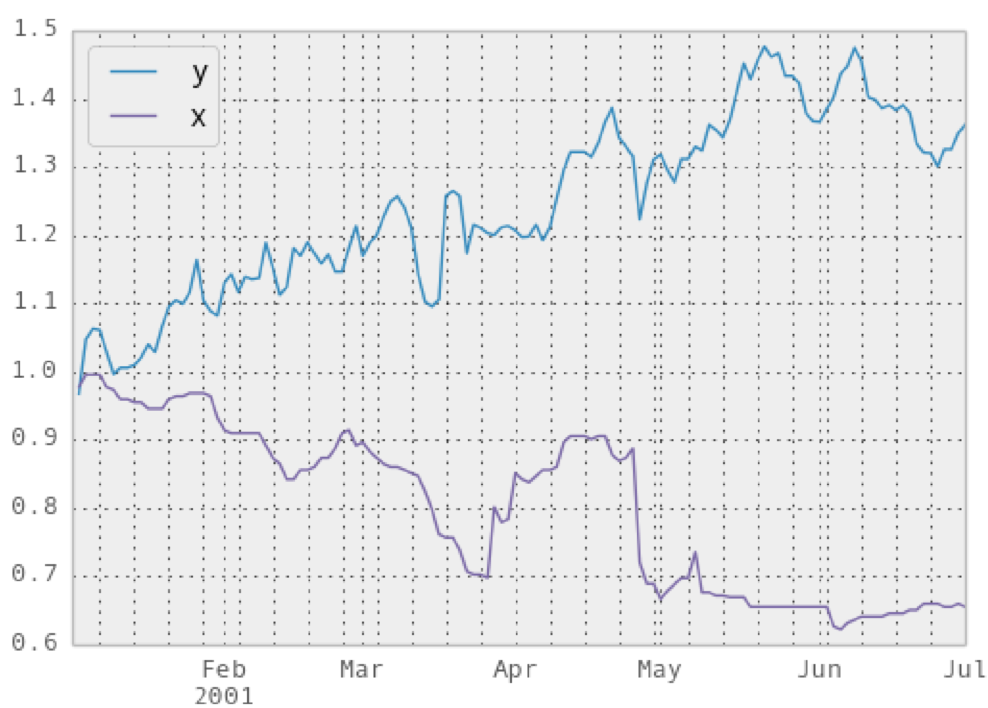
Figure 2: An example of a stocks level price and its normalized price series over the sample period.



During the trading period, positions are held until the next crossing of the prices. If convergence of prices does not take place during the trading period, gains or losses are calculated at the end of the last trading day of that particular trading interval.

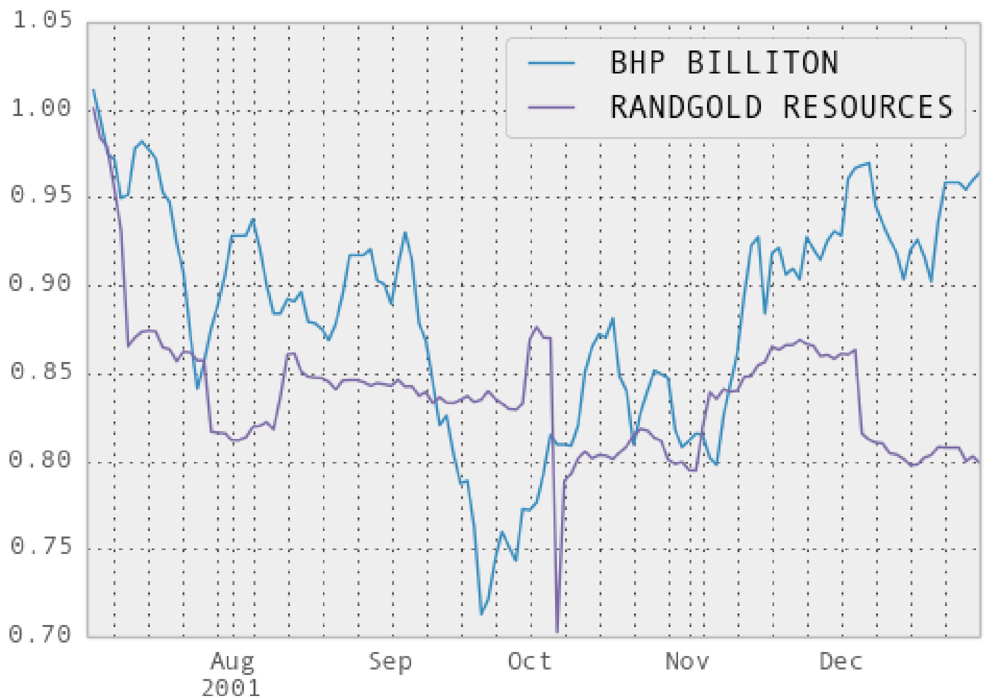
Pairs that continue to diverge after a position has been taken can lead to significant losses. **Figure 3** shows an example of a traded pair that continues to diverge during a trading period. The positions from this scenario would include taking a short position on stock y while taking a long position on stock x. Both of these positions would lead to losses as y continues to appreciate in value as the trader holds a short position and x continues to depreciate in price while the trader holds a long position on the stock. To mitigate such risk, the positions are closed after the trading period and the accumulated losses added to the portfolio.

Figure 3: An example of a traded pair whose prices do not converge over the trading period



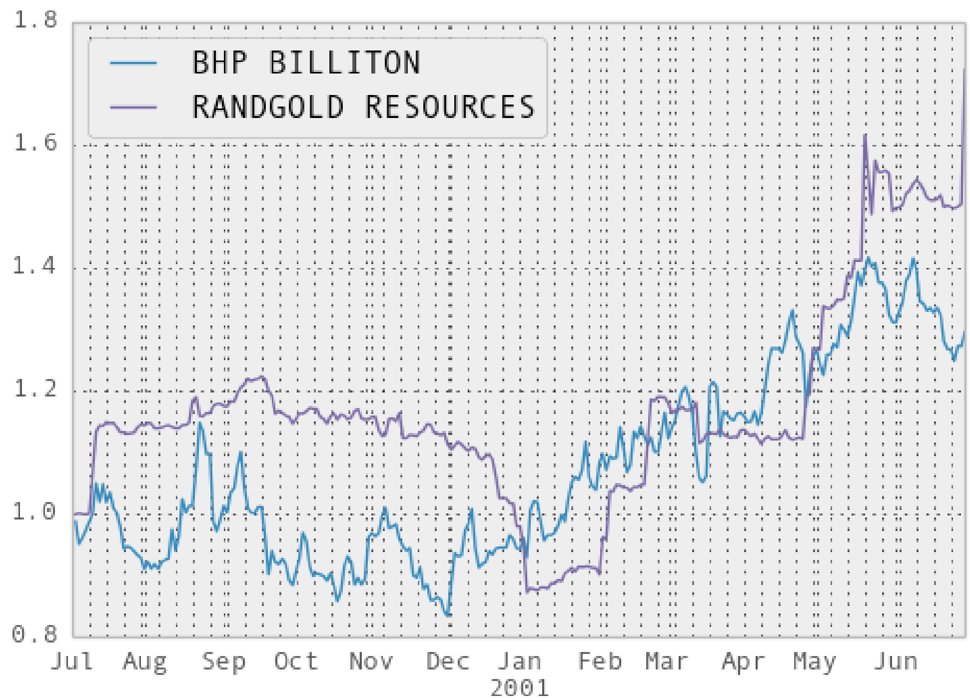
A trading pair may on the other hand diverge and close multiple times within a trading period generating profits over the trading period. **Figure 4** shows the trading period of such stock pairs. The trading period shows that the stocks diverge and close for four cycles.

Figure 4: A pair that diverges and converges multiple times



Prior to the trading period the trading parameters are estimated from the formation window. **Figure 5** shows the preceding formation period for the same pair of stocks.

Figure 5: Example of traded pairs during the formation period



6.1 Portfolio performance without rebalancing

Table 5 shows the results of trading industry-based portfolios without periodically rebalancing the portfolio or changing the constituent pairs of the portfolio. In this approach, all possible pairs that can be formed within a given industry group are traded and held over the entire trading period. The trading parameter 2σ in equation 4 is however updated during the formation period and used in the following trading period. The table shows that all industry groups earn positive and significant daily returns.

The largest portfolios by number of pairs are the Industrials, Financials and Consumer

Services groups with 561, 406 and 253 pairs respectively. Industrials earn a daily average return of 0,07% (t-Statistic = 14.8), Financials get an average daily return of 0,08% (t-Statistic = 11.8) and the Consumer Services portfolio obtains an average daily return of 0.08% (t-Statistic = 13.7). Industrials portfolio has the lowest standard deviation obtained among the portfolios 0.29% indicating the diversification benefit of a highly diversified portfolio. The Industrials portfolio has the highest risk adjusted returns.

Technology and Telecommunications portfolios are the smallest portfolios formed each having three pairs. They obtain the largest average daily returns with 37.5% (t-Statistic = 14) and 12.48% (t-Statistic = 14). The standard deviations are also the highest among the portfolios with the Technology portfolio being 149.5% and Telecommunications 49.8%. The high standard deviation signifies high risk associated with these portfolios and a lack of enough diversification opportunities. Results from these two portfolios can be regarded as unique mainly due to data sample size and time series structure of the period covered in this study. The sample begins right at the downturn of the dot-com bubble that collapsed over the 1999–2001 period leading to large corrections particularly in stock prices in technology related sectors, this is similar to having structural breaks in the data. **Figure 6** and **Figure 7** show the normalized price series for individual stocks that comprise the Technology and Telecommunications groups. The graphs show large price corrections after the dot-com bubble collapse during the period 1999–2001.

Among the technology group, ARM holding and SAGE group undergo the largest corrections over this period. ARMs price recovers after 2010 while SAGE group prices do not recover to their levels pre 2000 period. The collapse in prices and a failure to rebalance the portfolio regularly account for the observed return and standard deviation results.

Figure 6: Normalized price series in the technology group

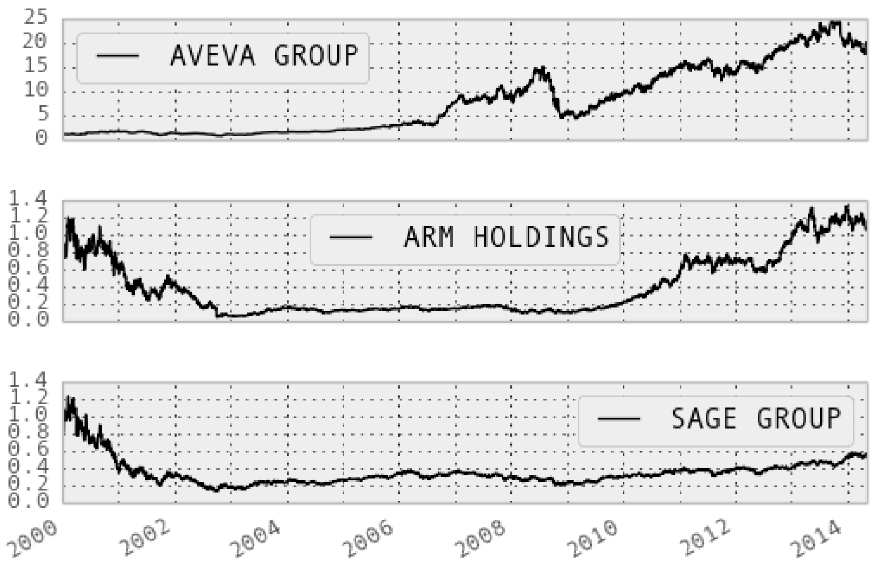


Figure 7: Normalized price series in the telecommunications group

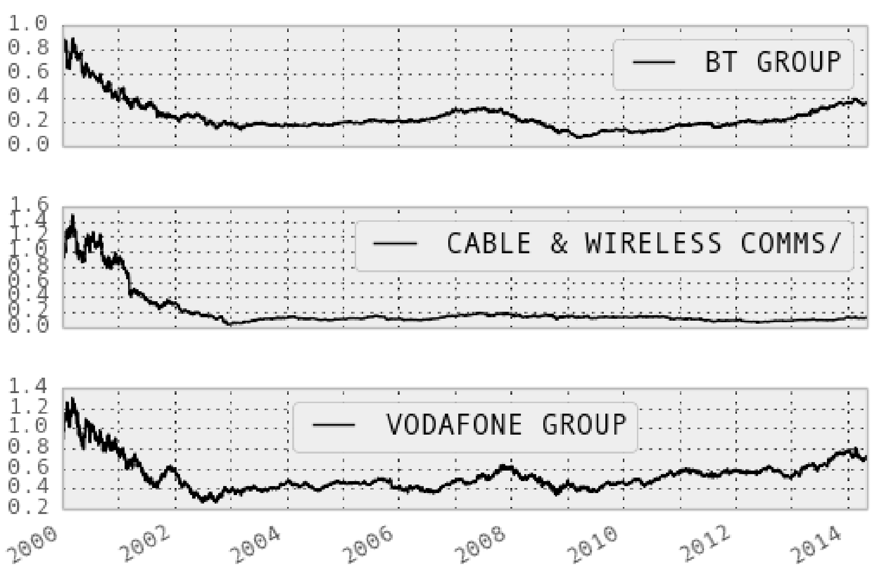


Table 5: Industry based portfolios

	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare
Average daily excess return	0.0007	0.0005	0.0008	0.0008	0.0517
Standard error	0.0001	0.0001	0.0001	0.0001	0.0044
t-Statistic	8.45***	7.73***	13.74***	11.85***	11.87***
Risk-adjusted returns	0.144	0.131	0.233	0.201	0.202
Standard deviation	0.0048	0.0038	0.0033	0.0038	0.2565
Skewness	1.1209	0.5774	2.6220	3.0689	3.0194
Kurtosis	14.0421	35.1367	28.3816	82.9225	84.4343
Minimum	-0.0409	-0.0550	-0.0288	-0.0590	-4.0238
Maximum	0.0450	0.0440	0.0390	0.0744	5.0419
Observations with Excess return < 0	26%	31%	31%	30%	30%
Number of pairs in portfolio	45	91	253	406	10

	Industrials	Oil & Gas	Technology	Telecommunications	Utilities
Average daily excess return	0.0007	0.0250	0.3750	0.1248	0.0248
Standard error	0.0000	0.0017	0.0254	0.0085	0.0017
t-Statistic	14.82***	14.77***	14.76***	14.74***	14.64***
Risk-adjusted returns	0.2518	0.2509	0.2507	0.2504	0.2488
Standard deviation	0.0029	0.0998	1.4957	0.4985	0.0996
Skewness	0.5856	0.5704	0.5628	0.5587	0.4860
Kurtosis	78.3643	82.8319	82.8331	82.8186	82.8817
Minimum	-0.0551	-1.9418	-29.1275	-9.7130	-1.9492
Maximum	0.0480	1.6881	25.2670	8.3945	1.6726
Observations with Excess return < 0	28%	28%	28%	28%	27%
Number of pairs in portfolio	561	21	3	3	15

6.2 Portfolio performance with rebalancing

Rebalancing the portfolio ensures that the trading strategy can be further optimized by selecting new trading pairs in each new trading period. Over each newly started formation period, the pairs in the universe are re-tested for their minimum distance (SSD). A price series may drift apart from its current pair over time, while it begins moving closely to another price series. After rebalancing, the top twenty pairs from the universe are selected for trading. Rebalancing the portfolio provides an opportunity to dynamically allocate trading pairs over trading periods but from the same industry group each time. **Table 6** shows results from trading portfolios with rebalancing over every formation period.

Compared to the returns obtained when portfolios are traded without rebalancing, the average daily returns are slightly reduced across the portfolios after rebalancing. The average daily returns are nonetheless all statistically significant as in the non-rebalanced case. All portfolios have reduced standard deviation indicating that rebalancing reduces the risk exposure in the portfolios. Risk adjusted returns increase for the Basic Materials, Consumer Goods, Consumer Services, Financials, Healthcare and Industrials portfolios. Oil & Gas, Technology, Telecommunications have reduced risk-adjusted returns while they remain unchanged for Utilities portfolio.

The Industrials portfolio has an average daily return of 0,005% (t-Statistic = 15) and continues to have the largest risk-adjusted returns 0,2738 over the sample period and the lowest standard deviation of 0,0002. Outlier portfolios -Technology and Telecommunications noted in the non-rebalanced case continue to have the highest average daily returns 0,486% (t-Statistic = 10,5) and 0,5% (t-Statistic = 10,3) respectively. The reduced standard deviations of these portfolios 0,0268 and 0,0271 respectively are still the highest among all the portfolios. Results also seem to suggest that smaller portfolios may obtain higher returns subject to higher risk as measured by the standard deviation.

Rebalancing allows the trading strategy to stop incurring further losses since positions taken in stock pairs that may take long to converge over a trading period are closed and the stocks can be traded with new partners in the subsequent trading period. This is the trading model followed in the rest of this study.

Table 6: Industry based portfolios rebalanced every formation period

	Basic Materials	**Consumer Goods**	**Consumer Services**	**Financials**	**Healthcare**
Average daily excess return	0.041%	0.021%	0.009%	0.006%	0.190%
Standard error	0.0000	0.0000	0.0000	0.0000	0.0002
t-Statistic	9.64***	13.05***	15.07***	12.04***	11.23***
Risk-adjusted returns	0.1664	0.2254	0.2602	0.2079	0.1939
Standard deviation	0.0025	0.0009	0.0004	0.0003	0.0098
Skewness	1.5616	0.8359	0.8959	1.6251	2.3948
Kurtosis	15.0189	13.5983	11.7386	48.9371	40.3473
Minimum	-0.0186	-0.0090	-0.0036	-0.0034	-0.1197
Maximum	0.0208	0.0089	0.0027	0.0047	0.1362
Observations with Excess return < 0	28%	30%	33%	32%	33%
Number of pairs in traded portfolio	20	20	20	20	10
Number of pairs in universe	45	91	253	406	10

	Industrials	**Oil & Gas**	**Technology**	**Telecommunications**	**Utilities**
Average daily excess return	0.005%	0.073%	0.486%	0.480%	0.060%
Standard error	0.0000	0.0001	0.0005	0.0005	0.0001
t-Statistic	15.86***	9.62***	10.49***	10.27***	11.86***
Risk-adjusted returns	0.2738	0.1660	0.1811	0.1774	0.2047
Standard deviation	0.0002	0.0044	0.0268	0.0271	0.0029
Skewness	1.6502	7.2015	4.6277	4.3360	2.5312
Kurtosis	21.0931	144.0553	61.8114	55.5439	24.3274
Minimum	-0.0013	-0.0322	-0.2288	-0.2510	-0.0189
Maximum	0.0025	0.1116	0.4699	0.4699	0.0383
Observations with Excess return < 0	31%	26%	26%	27%	25%
Number of pairs in traded portfolio	20	20	3	3	15
Number of pairs in universe	561	21	3	3	15

6.3 Performance of finely defined portfolios

To test the effect of constructing smaller finely defined portfolios, new portfolios are formed from a fine-grained classification (39 groups of ICB classification). Following this classification, firms in the same group have a greater degree of homogeneity thereby further increasing the co-movement in stock prices within the group.

Comprehensive trading results are shown in **Table 8**. All the daily excess returns are significant at the 1% level. The *Food & Drug Retailers* portfolio obtains the highest returns 0,549% (t-Statistic = 9,1) but also the highest standard deviation (0,0351) among all the portfolios. *Support Services* has the lowest return (0,016%) with the lowest standard deviation (0,007). The trading results are summarized in **Table 7** and sorted based on $R_{portfolio}$: the average daily excess returns for the portfolio. $\sigma_{portfolio}$ is the standard deviation of a portfolio. P_{traded} represents the number of pairs traded and P_{group} indicates pairs available in the industry group where at most 20 trading pairs are picked from this group for trading.

Table 7: Summary of results for finely defined portfolios

Portfolio	$R_{portfolio}$	$\sigma_{portfolio}$	P_{traded}	P_{group}
Support Services	0.016%	0.0007	20	153
Real Estate Investment Trusts	0.039%	0.0025	20	28
Media	0.053%	0.0032	20	28
Aerospace & Defense	0.064%	0.0054	10	10
Financial Services (Sector)	0.069%	0.0047	20	28
Banks	0.075%	0.0086	10	10
Mining	0.086%	0.0056	15	15
Chemicals	0.099%	0.0090	6	6
Travel & Leisure	0.107%	0.0070	15	15
General Retailers	0.112%	0.0080	15	15
Household Goods & Home Construction	0.118%	0.0098	15	15
Oil & Gas Producers	0.123%	0.0070	10	10
Gas & Water & Multiutilities	0.126%	0.0072	10	10
Life Insurance	0.150%	0.0093	10	10
Pharmaceuticals & Biotechnology	0.188%	0.0114	6	6
Industrial Engineering	0.233%	0.0168	6	6
General Industrials	0.417%	0.0240	3	3
Nonlife Insurance	0.436%	0.0280	3	3
Food & Drug Retailers	0.549%	0.0351	3	3

To further understand the characteristics of the modelled portfolios, **Figure 8** is useful in characterising the relationship between risk versus return among modeled portfolios while **Figure 9** shows how risk is related to the number of pairs available in pair selection universe(P_{group}) as a source of portfolio diversification.

Each dot in the diagram shown in **Figure 8** shows the obtained return and standard deviation to 1 of the 19 portfolios in **Table 7**. The plot indicates a general linear relationship between returns and risk as measured by the standard deviation. A portfolio with high risk profile obtains greater returns. Investors aiming to obtain high returns would hold portfolios with greater risk exposure moving further towards the right upper corner. The pattern is however not fully consistent in the entire set of portfolios, few are clustered towards the lower section indicating potentially more efficient portfolios than others. Investors would choose more efficient portfolios since they offer higher returns with similar or lower risk profiles.

One view to the effect of diversification is shown in **Figure 9**, where each dot represents the standard deviation and number of stocks pairs available in each industry group (P_{group}) for each of the 19 portfolios in **Table 7**. A larger number in P_{group} implies that during the portfolio rebalancing process, there is a larger pool of stocks to choose from when identifying trading pairs in the formation period. A seemingly downward sloping exponential curve is formed by the data points; the standard deviation reduces drastically with the increase in available trading pairs therefore leading to the conclusion that an increase in the stock universe to form pairs does lead to reduction in a portfolio's risk as measured by standard deviation of the portfio ($\sigma_{portfolio}$).

Figure 8: Return (y-axis) vs Standard Deviation (x-axis)

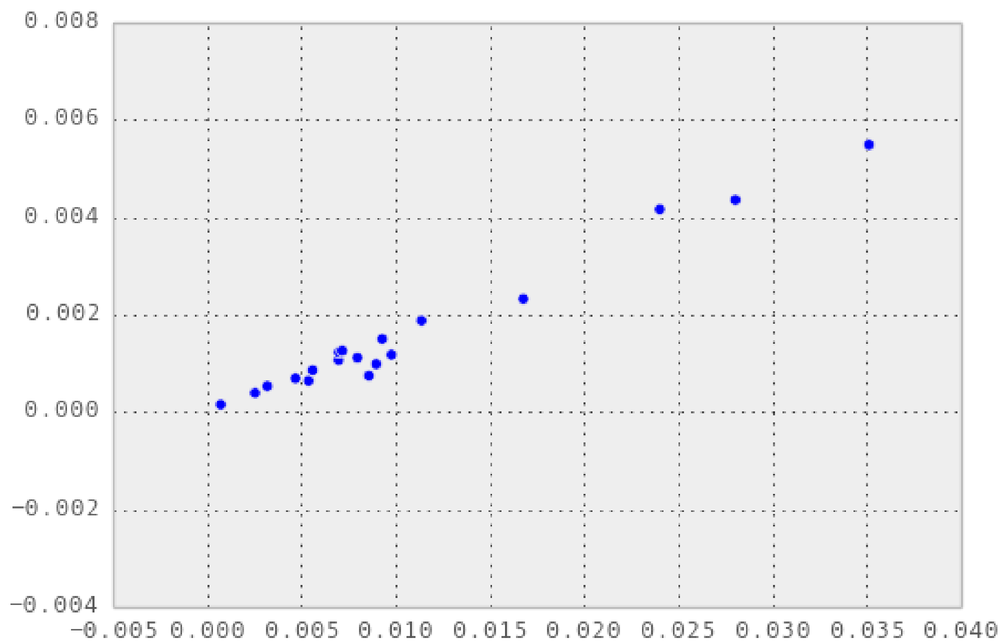
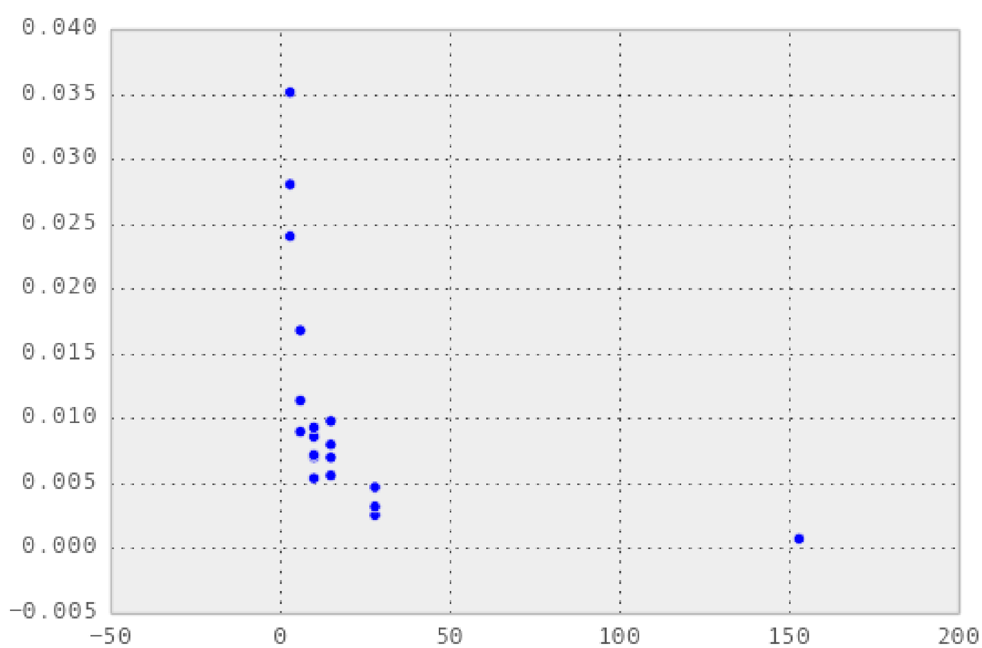


Figure 9: Standard Deviation (y-axis) vs Pairs in group (x-axis)



Another perspective to analyze diversification of the portfolios is by analyzing the effect of increasing the number of traded pairs to a portfolio. In **Table 7**, column P_{traded} shows that there are portfolios with similar number of stocks but obtain different standard deviation. A downward sloping exponential curve is also obtained when P_{traded} is plotted against the standard deviation of the portfolios, this is shown in **Figure 10**. The general idea of increased diversification benefits brought about by an increase in the number of stocks is still apparent, although in this case it is the increase in pairs of stock to a portfolio that drives risk reduction through diversification.

The figure also demonstrates that portfolios with similar number of stocks bear different risk levels which is potentially idiosyncratic industry risk since the portfolios are constructed based on industry classification of the individual stocks. For example three portfolios have each three traded pairs and obtain different standard deviation indicating diverse risk profiles for these portfolios.

Figure 10: Standard Deviation (y-axis) vs Pairs traded (x-axis)

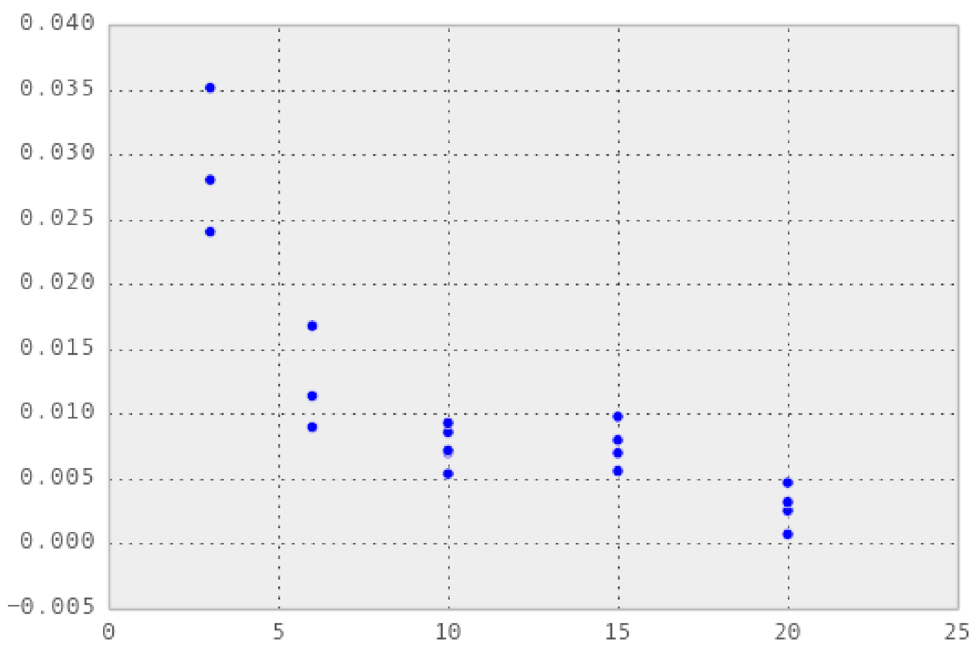


Table 8: Results for portfolios constructed based on refined industry classification

	Aerospace & Defense	Banks	Chemicals
Average daily excess return	0.064%	0.075%	0.099%
Standard error	0.0001	0.0001	0.0002
t-Statistic	6.92***	5.05***	6.38***
Risk-adjusted returns	0.1195	0.0872	0.1102
Standard deviation	0.0054	0.0086	0.0090
Skewness	3.5448	9.0990	6.6702
Kurtosis	54.1052	223.3319	122.8644
Minimum	-0.0478	-0.0767	-0.0549
Maximum	0.0833	0.2356	0.2056
Observations with Excess return < 0	22%	27%	22%
Number of pairs in traded portfolio	10	10	6
Number of pairs in group	10	10	6

	Financial Services (Sector)	Food & Drug Retailers	Gas & Water & Multiutilities
Average daily excess return	0.069%	0.549%	0.126%
Standard error	0.0001	0.0006	0.0001
t-Statistic	8.56***	9.06***	10.19***
Risk-adjusted returns	0.1479	0.1564	0.1760
Standard deviation	0.0047	0.0351	0.0072
Skewness	1.2936	1.1553	1.9077
Kurtosis	34.1558	30.3272	31.2573
Minimum	-0.0555	-0.4253	-0.0550
Maximum	0.0642	0.4406	0.1144
Observations with Excess return < 0	27%	28%	28%
Number of pairs in traded portfolio	20	3	10
Number of pairs in group	28	3	10

	General Industrials	General Retailers	Household Goods & Home Construction
Average daily excess return	0.417%	0.112%	0.118%
Standard error	0.0004	0.0001	0.0002
t-Statistic	10.04***	8.13***	6.97***
Risk-adjusted returns	0.1734	0.1403	0.1204
Standard deviation	0.0240	0.0080	0.0098
Skewness	1.5813	1.6938	-2.4204
Kurtosis	25.4051	43.8161	160.7801
Minimum	-0.1788	-0.1028	-0.2467
Maximum	0.3349	0.1111	0.1460
Observations with Excess return < 0	26%	27%	23%
Number of pairs in traded portfolio	3	15	15
Number of pairs in group	3	15	15

	Industrial Engineering	Life Insurance	Media
Average daily excess return	0.233%	0.150%	0.053%
Standard error	0.0003	0.0002	0.0001
t-Statistic	8.03***	9.37***	9.67***
Risk-adjusted returns	0.1387	0.1618	0.1670
Standard deviation	0.0168	0.0093	0.0032
Skewness	0.6882	1.6121	1.5192
Kurtosis	66.3943	25.8335	21.7999
Minimum	-0.3123	-0.0923	-0.0339
Maximum	0.2253	0.0995	0.0357
Observations with Excess return < 0	25%	26%	29%
Number of pairs in traded portfolio	6	10	20
Number of pairs in group	6	10	28

	Mining	Nonlife Insurance	Oil & Gas Producers
Average daily excess return	0.086%	0.436%	0.123%
Standard error	0.0001	0.0005	0.0001
t-Statistic	8.92***	9.00***	10.18***
Risk-adjusted returns	0.1540	0.1555	0.1757
Standard deviation	0.0056	0.0280	0.0070
Skewness	2.0216	2.2843	7.2912
Kurtosis	22.3294	24.4319	158.3748
Minimum	-0.0325	-0.1613	-0.0355
Maximum	0.0805	0.3594	0.1851
Observations with Excess return < 0	27%	27%	26%
Number of pairs in traded portfolio	15	3	10
Number of pairs in group	15	3	10

	Pharmaceuticals & Biotechnology	Real Estate Investment Trusts	Support Services
Average daily excess return	0.188%	0.039%	0.016%
Standard error	0.0002	0.0000	0.0000
t-Statistic	9.57***	8.96***	12.67***
Risk-adjusted returns	0.1653	0.1548	0.2187
Standard deviation	0.0114	0.0025	0.0007
Skewness	3.0946	4.2504	4.5812
Kurtosis	33.5332	110.5507	83.1886
Minimum	-0.0599	-0.0353	-0.0055
Maximum	0.1801	0.0544	0.0156
Observations with Excess return < 0	27%	26%	32%
Number of pairs in traded portfolio	6	20	20
Number of pairs in group	6	28	153

	Travel & Leisure
Average daily excess return	0.107%
Standard error	0.0001
t-Statistic	8.88***
Risk-adjusted returns	0.1533
Standard deviation	0.0070
Skewness	1.2768
Kurtosis	136.6434
Minimum	-0.1466
Maximum	0.1509
Observations with Excess return < 0	30%
Number of pairs in traded portfolio	15
Number of pairs in group	15

6.4 Performance during different sub-periods

Do and Faff (2010) indicate that pairs trading tends to be more profitable during bear markets, this is supported by superior returns they obtained during bear markets January 2000–December 2002 and July 2007–June 2009 compared to other periods investigated.

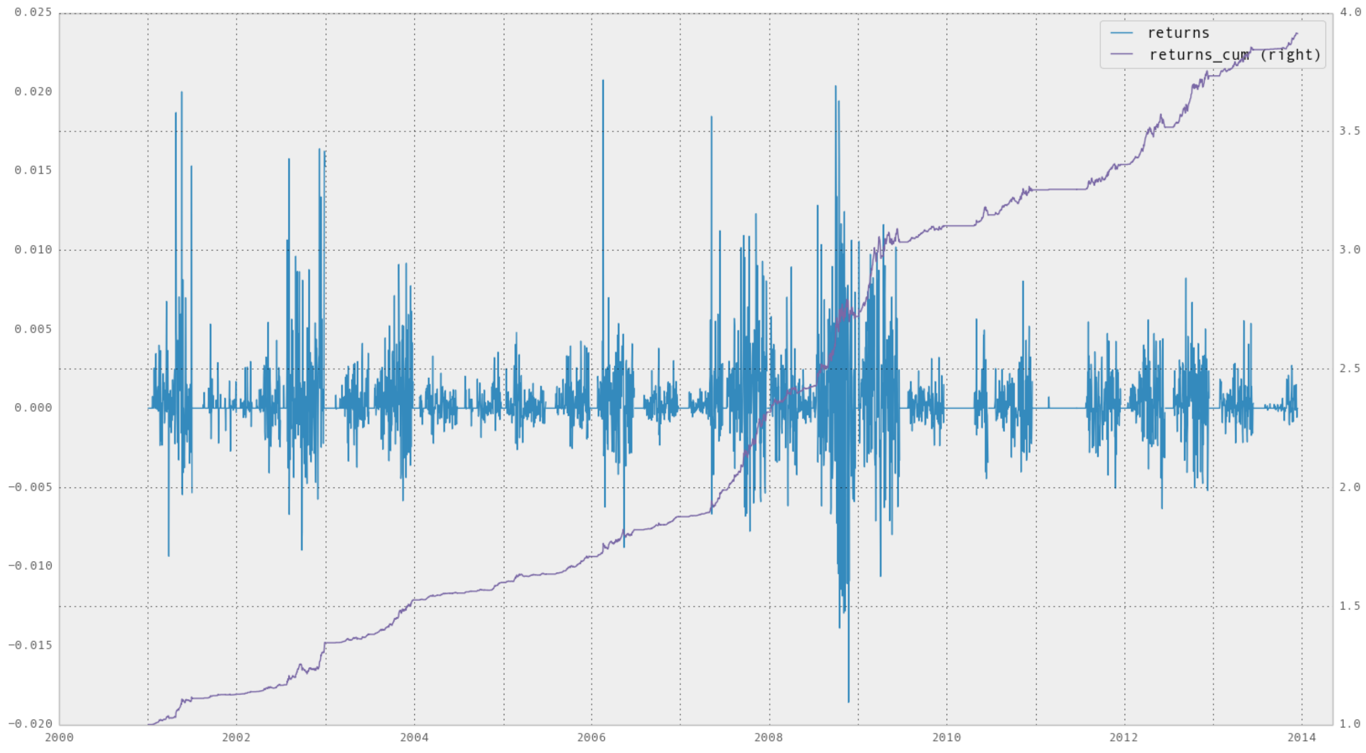
Plotting the returns and the cumulative returns of the Basic Materials as shown in **Figure 11** indicates that indeed during period of increased volatility, the cumulative returns tend to increase. To test this assertion, the sample data is divided into four sample periods.

The sample period January 2000–December 2002 is one bear market following the collapse of the dotcom bubble. The period January 2003–June 2007 is considered a stable period in the markets. July 2007–June 2009 is another bear market covering the financial crisis emanating from the housing market collapse in the USA. The last sub period is July 2009–May 2014. **Table 9** shows a summary of sub-periods trading setting. Bear markets are short lived and therefore the number of observations as indicated by the "Obs"column is smaller compared to other non-turbulent periods in the equity markets.

Table 9: Summary of sub-period trading setup

Period	**Description**	**Trading periods**	**Obs**
January 2000 - December 2002	Bear Market	4	782
January 2003 - June 2007	Stable Market	7	1173
July 2007 - June 2009	Bear Market	2	522
July 2009 - May 2014	Stable Market	7	1267

Figure 11: Returns and cumulative returns of the Basic Materials portfolio over the sample period



Results obtained lead to similar conclusions as outlined in Do and Faff (2010); pairs trading tends to be more profitable during bear markets or over periods of increased volatility. To facilitate comparison, this section is reported only for portfolios with at least 20 tradable pairs over the trading period. Other portfolios such as technology, telecommunications, healthcare and utilities were eliminated since they did not meet this criteria.

Performance during Dot-Com bubble collapse and post bubble periods

Table 10 and panel A shows results covering the collapse of the dotcom bubble during the period January 2000 to December 2002. While panel B shows results over the period January 2003 to June 2007, a period considered to be stable compared to the period covered in panel A.

Returns in both panels are positive and significant at the 1% level. However, each portfolio obtains higher daily average returns during the bear market in panel A compared to the period covered in panel B. Returns of portfolios in panel A are also associated with higher volatility as indicated by a higher standard deviation compared to the standard deviation estimated during the stable period.

Basic Materials portfolio obtains double the average daily return during the bear market in panel A. This is an average daily excess return of 0,058% (t-Statistic = 4,42) during the collapse of the bubble while the same portfolio has a daily average return of 0,029% (t-Statistic = 5,87) when the markets stabilize, a difference of 2,9 basis points. Consumer Goods portfolios have a difference of 0,9 basis points, Consumer Services a difference of 0,5 basis points, Financials a difference of 0,1 basis points, Industrials a difference of 0,4 basis points and lastly Oil & Gas portfolios have a difference of 4,9 basis points. The largest difference between the two market conditions clearly occurs in the Oil& Gas portfolios.

Consumer Services portfolio reports the highest risk adjusted returns -a Sharpe ratio of 0,3130 over the bear market in panel A of **Table 10**. This high Sharpe ratio is driven by a low risk value as measure by the standard deviation. The Basic Materials portfolio has the highest return over the period but the high standard deviation reduces the Sharpe ratio for the portfolio in fact making it the lowest among the portfolios.

During the post bubble period as reported in panel B of **Table 10**, the Financials portfolio has the highest Sharpe ratio of 0,3237 also driven by lower risk than other portfolios that record higher average daily excess returns. Oil & Gas portfolio on the other hand records the lowest Sharpe ratio of 0,1493 over the post bubble period. Despite the high average daily excess return, the risk is also the highest recorded over this period.

Portfolios in panels A and B of **Table 10** are tested for differences in the means of their returns to ascertain whether the difference is statistically significant. The null hypothesis of the mean test asserts that the samples have identical average (expected) values. The results are reported in panel A of **Table 12**. We can reject the null hypothesis in favor of different means for the following portfolios: Basic Materials, Consumer Goods, Consumer Services, Industrials and utilities with the t-Statistics (2.4, 2.11, 2.94, 4.22 and 2.43) respectively.

Performance during financial crisis and post crisis periods

Portfolio performance during the recent financial crisis is tested over the period July 2007–June 2009 and results are reported in **Table 11** panel C while the post crisis period is reported in panel D of the same table.

Average daily excess returns are positive and highly statistically significant (at the 1% level) in both panel C and D. Each portfolio in panel C reports higher average daily excess returns than the counterpart in panel D. The standard deviation is considerably higher in panel C than observed in panel D owing to increased volatility associated with the crisis period.

Portfolios earn more than double the daily average return over the crisis period as reported in panel C in comparison to panel D, the only portfolio that does not earn more than double is the Oil & Gas portfolio whose returns are nonetheless higher during the crisis period as opposed to the post crisis period. Basic Materials portfolio earns the highest returns over the crisis period 0,093% (t-Statistic = 3,05).

The difference between returns over the two sub-periods is larger compared to the previously studied two sub-periods. Basis Materials portfolios have a difference of 6.6 basis points, Consumer Goods 3 basis points, Consumer Services 2 basis points, Financials 1.5 basis points, Industrials 0.4 basis points a difference similar to that observed in sub-periods presented in **Table 10**. Finally Oil & Gas portfolios have a difference of 2.6 basis points. Based on this analysis, the Basic Materials portfolios have the largest difference in average daily excess returns

Consumer Services record the highest Sharpe ratio (0.3336) during the financial crisis period as reported in panel C of **Table 11**. This risk adjusted return is driven by a lower risk value as compared to other portfolios that record higher returns with corresponding high standard deviation values therefore reducing their Sharpe ratios. Oil & Gas portfolio records the lowest risk adjusted returns (0.1756) due to a high standard deviation of 0.0041.

In the post crisis period, Financials portfolio has the highest Sharpe ratio of (0.2879) while Oil & Gas portfolio has the lowest with 0.1673. The high Sharpe ration in the Financials portfolio is once again mainly driven by low standard deviation while Oil & Gas records high standard deviation.

The portfolios in panels C and D of **Table 11** were also compared for differences in the means of their returns. Results are reported in panel B of **Table 12**. The null hypothesis of similarity in expected values can be rejected at the 1% level for all portfolios except the Oil& Gas portfolio that indicates no significant difference in means between the two sub-periods represented in panels C and D of table.

Panel C of **Table 12** shows a test on difference of means for the data sample covering both bear market periods, that is, the dot-com bubble collapse and the financial crisis. Results indicate that for Basic Materials, Consumer Goods, Industrial, Oil & Gas and Utilities portfolios the null hypothesis for a similar expected value cannot be rejected. This result is an indication of the similarity in market reaction between these two periods. Consumer Services and Financials portfolios however have significant t-Statistics (3.12, 3.46) respectively. For these portfolios, the null hypothesis of similar expected values is rejected. This indicates a difference in market reaction over the two bear markets in these industries .

In summary, during both bear market periods reported in panel A **Table 10** and panel C of **Table 11** the Consumer Services portfolio consistently records that highest Sharpe ratio. But the lowest Sharpe ratios are Basic Materials (panel A) and Oil & Gas (panel C). In both post crisis/stable market periods, the Financials portfolios record the higher Sharpe ratios while Oil & Gas produce the lowest Sharpe ratios in both post crisis periods.

Notably too is the fact that risk as measured by standard deviation for the portfolios falls by close to half of their crisis value during post crisis periods, however there is an exception to the Oil & Gas portfolio whose high standard deviation persists across periods. In the case of the dotcom bubble (**Table 10** panel A) and post dotcom bubble period (**Table 10** panel B), 84% of the previously observed standard deviation is still recorded. From the financial crisis period (**Table 11** panel C) to the post crisis period (**Table 11** panel D) the standard deviation still records 66% of the crisis period value.

Table 10: Performance in bear market (Panel A) and stable market (Panel B)

Panel A: Period 01/2000 - 12/2002

	Basic Materials	**Consumer Goods**	**Consumer Services**	**Financials**	**Industrials**	**Oil & Gas**
Average daily return	0.058%	0.025%	0.012%	0.005%	0.007%	0.130%
Standard error	0.0001	0.0000	0.0000	0.0000	0.0000	0.0003
t-Statistic	4.42***	5.40***	7.11***	5.10***	6.81***	4.68***
Risk-adjusted returns	0.1946	0.2376	0.3130	0.2245	0.2997	0.2060
Standard deviation	0.0030	0.0011	0.0004	0.0002	0.0002	0.0063
Skewness	2.6245	0.1145	0.6681	0.3824	2.1908	1.9139
Kurtosis	13.2368	3.4244	2.6179	2.9049	18.5296	16.6743
Minimum	-0.0094	-0.0052	-0.0012	-0.0009	-0.0007	-0.0322
Maximum	0.0200	0.0045	0.0019	0.0011	0.0025	0.0538
Observations with Excess return < 0	26%	29%	32%	36%	32%	22%
Number of pairs in traded portfolio	20	20	20	20	20	20

Panel B: Period 01/2003 - 06/2007

	Basic Materials	**Consumer Goods**	**Consumer Services**	**Financials**	**Industrials**	**Oil & Gas**
Average daily return	0.029%	0.016%	0.007%	0.004%	0.003%	0.081%
Standard error	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002
t-Statistic	5.87***	7.92***	9.17***	9.73***	9.30***	4.49***
Risk-adjusted returns	0.1953	0.2634	0.3050	0.3237	0.3095	0.1493
Standard deviation	0.0015	0.0006	0.0002	0.0001	0.0001	0.0054
Skewness	4.5064	4.6054	1.3729	2.9228	1.3184	11.6236
Kurtosis	52.4427	52.8556	7.9288	-3.0100	-3.0100	212.6190
Minimum	-0.0067	-0.0016	-0.0009	-0.0004	-0.0005	-0.0177
Maximum	0.0206	0.0089	0.0017	0.0015	0.0010	0.1116
Observations with Excess return < 0	32%	29%	33%	32%	29%	25%
Number of pairs in traded portfolio	20	20	20	20	20	20

Table 11: Performance in bear market (Panel C) and stable market (Panel D)

Panel C: Period 07/2007 - 06/2009	Basic Materials	Consumer Goods	Consumer Services	Financials	Industrials	Oil & Gas
Average daily return	0.093%	0.044%	0.025%	0.018%	0.007%	0.072%
Standard error	0.0003	0.0001	0.0000	0.0000	0.0000	0.0003
t-Statistic	3.05***	4.58***	5.36***	3.71***	4.26***	2.82***
Risk-adjusted returns	0.1901	0.2854	0.3336	0.2311	0.2653	0.1756
Standard deviation	0.0049	0.0015	0.0007	0.0008	0.0003	0.0041
Skewness	-0.0085	-0.6667	0.2061	0.1222	-0.1466	0.8441
Kurtosis	1.3142	9.8940	8.4039	6.8284	1.4628	3.9633
Minimum	-0.0152	-0.0088	-0.0042	-0.0034	-0.0011	-0.0148
Maximum	0.0181	0.0080	0.0040	0.0047	0.0009	0.0198
Observations with Excess return < 0	0.3876	0.3372	0.3062	0.3295	0.3643	0.3488
Number of pairs in traded portfolio	20	20	20	20	20	20

Panel D: Period 07/2009 - 05/2014	Basic Materials	Consumer Goods	Consumer Services	Financials	Industrials	Oil & Gas
Average daily return	0.027%	0.014%	0.005%	0.003%	0.003%	0.046%
Standard error	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001
t-Statistic	5.26***	6.75***	6.98***	8.65***	8.26***	5.03***
Risk-adjusted returns	0.1752	0.2248	0.2323	0.2879	0.2749	0.1673
Standard deviation	0.0015	0.0006	0.0002	0.0001	0.0001	0.0027
Skewness	0.6145	1.5634	2.6606	0.9769	3.0206	4.3474
Kurtosis	7.6197	9.8873	28.6977	-3.0100	-3.0100	56.9757
Minimum	-0.0072	-0.0025	-0.0009	-0.0004	-0.0005	-0.0126
Maximum	0.0104	0.0053	0.0029	0.0008	0.0015	0.0408
Observations with Excess return < 0	25%	33%	32%	31%	32%	27%
Number of pairs in traded portfolio	20	20	20	20	20	20

To test that indeed the returns of the same portfolios represent different returns in various subperiods and contain different variability in returns and hence market behavior, **Table 12** below show the results of carrying out mean tests for the portfolios in **Table 10** and **Table 11**.

Panel A of this table indicates results for testing the means of portfolios in panel A and B of **Table 10** ;the mean of a portfolio in panel A is compared to the corresponding portfolio in panel B in the same table. In a similar manner, Panel B shows the results from testing the means of portfolios in panel C and D of **Table 11**. Panel C shows results obtained by comparing portfolio means during the two bear markets represented by panels A (**Table 10**) and C (**Table 11**).

Table 12: Difference in means between portfolios

Panel A:

Portfolios	**t-Statistic**	**P-Value**
Basic Materials	2.40	0.02
Consumer Goods	2.11	0.03
Consumer Services	2.94	0.00
Financials	1.54	0.12
Industrials	4.22	0.00
Oil & Gas	1.55	0.12
Utilities	2.43	0.02

Panel B:

Portfolios	**t-Statistic**	**P-Value**
Basic Materials	3.48	0.00
Consumer Goods	4.67	0.00
Consumer Services	6.77	0.00
Financials	5.35	0.00
Industrials	3.23	0.00
Oil & Gas	1.19	0.23
Utilities	4.26	0.00

Panel C:

Portfolio	**t-Statistic**	**P-Value**
Basic Materials	-1.23	0.22
Consumer Goods	-1.99	0.05
Consumer Services	-3.12	0.00
Financials	-3.46	0.00
Industrials	0.22	0.83
Oil & Gas	1.36	0.18
Utilities	-0.87	0.39

7 CONCLUSION

The main purpose of this study was to test the profitability of pairs trading using a less documented data sample; an extract of Pound (£) denominated series was extracted from the StoxxEurope600 index for this purpose.

Using this data, the stocks were grouped into their respective industry categories that are further used as the basis of portfolio formation. Stocks with similar time series characteristics are identified from the formed industry groups. The SSD approach is applied to identify similarity between the stocks over a 12-month formation period and trading positions are opened whenever the spread between normalized prices diverge beyond its historical two standard deviations. The positions are closed when the prices converge or at the end of a trading period.

Empirical testing begins with trading all the formed pairs from a given industry group where the portfolio is not regularly rebalanced. Results from this approach indicate positive and significant average daily excess returns. It is however observed that this approach bears significant risk as implied with the high standard deviations obtained from the portfolios.

Further tests are conducted on the same pairs where the portfolio is rebalanced by selecting new stock pairs over each new trading period. In addition, only the top 20 pairs are traded for those industry groups with a large pool of stocks to choose from. The returns are also positive and significant. However, the results from this approach indicate reduced profitability but also significantly reduced risk for the portfolios. This second approach forms the trading model applied to the rest of the study. Results obtained from this test are similar to the industries based results obtained by Gatev, Goetzmann, and Rouwenhorst (2006), they observed that utilities obtained higher returns than financials. In this study returns recorded for utilities are 0,060% (t-Statistic = 11,8) and financials 0,006% (t-Statistic = 12).

Findings of this study indicate that addition of pairs in the portfolio reduces the risk of the portfolio indicated by a reduction in the standard deviation as more pairs are added into the portfolio. Further diversification benefits are obtained by having a larger pool of stocks to choose from in order to form trading pairs.

In order to study the trading strategy's performance over different market conditions -declining and stable, the sample data is divided into four sub-periods covering the dotcom bubble collapse and a corresponding post bubble period, the financial crisis period and the corresponding post crisis period. To make the results comparable, only the industry groups with the potential to make 20 trading pairs are traded. Results from this study indicate pairs trading to be more profitable during the dot-com bubble collapse as compared to the stable period following the collapse. The highest return obtained in the dot-com bubble period is an average daily excess return of 0,058% (t-Statistic = 4,42) and the highest return post bubble period is a daily average return of 0,029% (t-Statistic = 5,87). Similarly, portfolios are more profitable over the financial crisis period than the post crisis period. The highest daily average return is 0,093% (t-Statistic = 3,05) while the highest return post financial crisis period is 0,046% (t-Statistic = 5,03). These findings are consistent to those obtained by (Do and Faff 2010) for US market.

This study shows that applying pairs trading strategies in selected pairs within the UK stock market would yield economically positive results that are statistically significant. Based on this results, it can therefore be stated that the UK market is not fully efficient since past price dynamics can be utilized to profit from arising arbitrage opportunities. Additionally, analyzing the assets from a risk perspective indicate that investors would benefit from active management of investments since selecting a portfolio that maximizes the wellbeing of an investor requires optimizing of a portfolio before an optimimum portfolio is identified.

While the results of this study are positive a few issues still stand out that require further research and thought. The first major issue that follows as a next step for this study is to identify key factors that explain or drive the profitability of pairs trading strategy. Early studies based on US data indicate that factors in the Fama-French three factor model are insignificant when tested against returns from this strategy.

From a practitioner perspective, pairs trading strategy's profitability should be assessed cognisant of the assumptions applied on the onset of this study. Relaxing the zero transaction costs assumptions means reduced profitability and not to mention capital/margin requirements associted with entering short positions. Moreover, depending on market specific regulations, short positions may only be entered on an uptick of the stock, such implementation details are not modeled in this study.

Modeling this strategy assumes sufficient market liquidity for any identified tradable pair. If some stocks are not available for purchasing or selling, then the trades cannot be completed as modeled. Further studies are therefore needed to generate the much needed insight towards pairs trading strategy.