A Wider Perspective on Pairs Trading

A TRADING APPLICATION WITH NON-EQUITY ASSETS

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Abstract

Pairs trading is a statistical arbitrage strategy aimed at exploiting temporary divergences in assets that move together. By taking corresponding long and short positions upon divergences, profits can be made if the assets converge. In this study, the pairs trading strategy is applied onto a novel selection of non-equity assets, namely price indices, commodities and currencies. By letting pairs indiscriminately be formed from correlated assets, we examine the possibility of achieving positive excess return using a computerised trading implementation of the strategy. The trading yielded average six-month returns of 1.56 percent (p=0.000). Furthermore, the returns from pairs comprised of same-type and different-type assets were studied, but in this case no significant differences were found.

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1 Introduction

1.1 Background

Investors across the world use a variety of strategies with the common objective of maximizing profits while keeping risk at a minimum. In recent times, many large investment institutions and hedge fund companies have made quantitative and algorithmic trading their focal point, concentrating their efforts in developing increasingly complex strategies. While some of these strategies have been highly successful – yielding large profits by making highly frequent trades – the companies are necessitated to find and exploit new trading tactics to survive. Among these strategies, the pairs trading strategy not only appears elegant in its intuitive simplicity, but is also still widely used despite its age. It was conceived in the early 1980's by a quantitative research group within the investment bank Morgan Stanley. The lifetime of the strategy thus spans at least three decades, making it unusually vital among competitor strategies.

Pairs Trading is a market neutral strategy which is not only used by individual investors but also popular among investment banks and hedge funds. Among its most famous practitioners were Nobel Prize laureates Myron Scholes and Robert C. Merton, who lead the now infamous Long-Term Capital Management hedge fund. It is part of a group of strategies known as risk arbitrage, because unlike pure arbitrage it generates risk for the investor. Another strategy in this category is mergers arbitrage, which may occur when two publicly listed companies merge. The disclosure of merger specifics often reveals a discrepancy between the theoretical price of the merged company and the observed price of its pre-merger parts. The drawback with this strategy is of course that these opportunities rarely occur.

Pairs Trading opportunities on the other hand are plentiful. Also known as statistical arbitrage, the strategy works on the principle of buying one asset while selling another short; hence a pair is formed out of those two assets. By selecting assets which have a history of "moving together", or displaying similar returns in other words, trading positions are opened when the two assets diverge beyond a certain point.

The underperforming asset is bought long while the relative outperformer is sold short, thus speculating in a future convergence generating an arbitrage profit.

Previous research on pairs trading has predominantly been focused on trading equities. In an oft-cited article, Gatev et al. (2006, p.802) describe some of the issues that comes with trading stocks in pairs. The most important caveat is the risk of bankruptcy that stocks carry. Companies defaulting are by no means rare anomalies, but a relatively frequent phenomenon occurring on most markets. If the long part of a trading pair would default, the loss incurred would by far surpass any prospective gains that pair could produce. Increased default probability may also cause unwanted volatility, resulting in non-convergence and consequently negative yields. Stock indices and commodities are on the other hand far less exposed to bankruptcy risk. In the first case this is due to the asset being well-diversified in its construct, while in the latter case the event of a commodity becoming entirely worthless is very unlikely to occur.

Also, commodity market trading has witnessed a considerable expansion in the last two decades, growing at an average annual rate of 19 percent. While this is largely a consequence of the increasing demand produced by developing countries in Asia (foremost China and India), the recent financial crisis has also spurred commodity trade as a safe investment alternative. The increased liquidity stemming from this development furthers the viability of commodities as components of algorithmic trading strategies. (Coxhead and Jayasuriya 2010)

As interest in statistical arbitrage grew, the profits from pairs trading were observed to decrease in the late 1980's as a result of investor saturation (Gatev et al. 2006, p.799). There has been little academic interest in applying the pairs trading strategy onto globally traded "macro" level assets however. With such assets, adjusting the price into equilibrium would require larger amounts of money compared to stocks, and for that reason it should be relatively difficult to saturate arbitrage opportunities.

1.2 Purpose

The aim is to apply the pairs trading strategy as formulated by (Gatev et al. 2006) onto non-equity assets. These are stock indices, commodities and currencies. Our ambition is to examine whether it is possible to achieve significant excess return by selecting pairs using a non-discriminating quantitative method from such a heterogeneous group of assets. We formulate a hypothesis stating that due to the reduction in bankruptcy risk in the assets chosen, we can achieve higher reward-to-variability in comparison with the market as a whole. We also intend to investigate whether there is a difference in profits generated by pairs composed of different categories of assets in comparison to same-category pairs.

1.3 Approach

The methodology used consisted of a two-step trading procedure, where the correlations between the assets of every possible pair were first sampled for twelve months. This screening process was repeated on a monthly basis. Pairs displaying correlations exceeding a threshold value were traded for six months, during which time the pairs were allowed to open and close on multiple occasions. Excess return was calculated using the weighted returns of the two positions constituting a pair.

Transaction costs have not been taken into consideration in this study because of the further complexity it would have added to the implementation of the strategy. A discussion of hypothetical implications of transaction costs is however provided in section 3.6 .

1.4 Outline

The outline of this study is as follows; In section 2, the principles of pairs trading is explained along with the theoretical premises for statistical arbitrage. A summary of previous research in the field is also presented.

In section 3, we provide the methodology used and the details necessary to reproduce the trading application. The results are presented in section 4, followed by our conclusions in section 5.

2 Theory

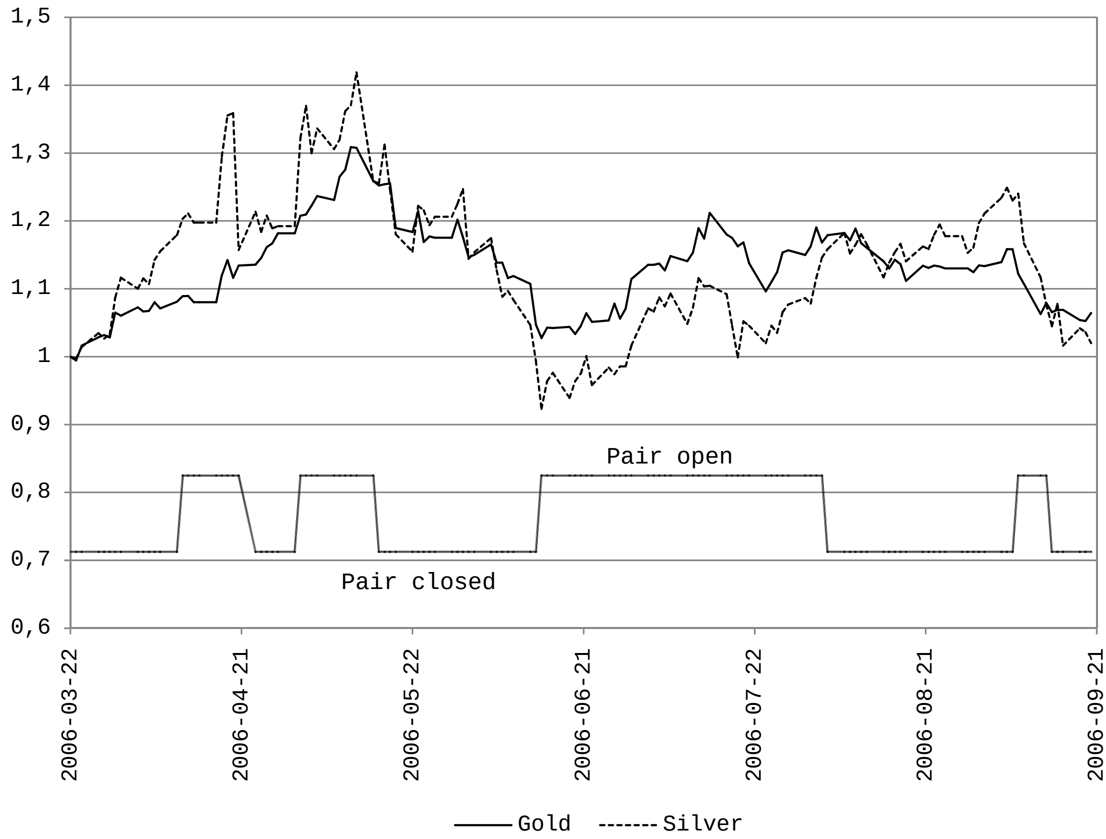
2.1 The basics of pairs trading

There are two commonly used practices for performing pairs trading. One option is to manually select assets based on fundamental a priori assumptions regarding the nature or perceived similarity of the companies. For example, one could argue that General Motors and Ford, two car producing firms co-existing within the same business environment, are supposed to react similarly to external factors and to be equally priced given similar financial circumstances in accordance to the law of one price. By visually comparing the return charts, an investor can take a trading position when the two stocks seem to be drifting apart. This methodology is ill-suited for automated algorithmic trading since it requires the investor to manually assess and select the assets.

Another option is using a quantitative free-formation strategy, where it is possible to define a statistical rule set which a computer can be programmed to act upon automatically. The general procedure of an automated pairs trading strategy as described in most literature is executed in two phases; a screening or formation period where assets are matched up against each other and evaluated according to a specific metric. When a pair meets the predetermined requirements, it is selected for trading during a trading period. In this period an algorithm will decide, usually based on a measure of the spread[1] between the two assets, if and when positions will be opened. Most applications limit the trading period to a certain length in time, allowing positions to be opened and closed multiple times during this time frame.

[1]It is also possible to speculate in the divergence of a pair (Whistler 2004, pp.44). We have chosen to focus on convergence speculation because this methodology has received the most attention in previous research.

Figure 1: A gold–silver pair trading for six months.



Alternatively, one may consider the period closed once one position has successfully opened and closed. In such a case, the trading period might continue without closing for a long period of time if the two assets fail to converge.

2.2 Asymmetry and money management

By definition, the returns of a pairs trade are positive in all cases but one. A loss is incurred if a pair does not close "naturally", i.e. by the convergence of the two assets. Using a time limited trading period, any positions are closed out at the last day of the period thus generating a negative return. Since the buying signal is defined by a certain spread metric, this value also represents the maximum gain attainable with the pair. In contrast, the potential losses of premature closures are virtually unlimited.

The asymmetrical nature of the returns can be problematic because any consequent positive (but small) returns can be cancelled out by a few large losses. For this reason, it is common to apply some sort of money management scheme in order to restrict large shortfalls (Whistler 2004, p.107).

Some implementations of the strategy open positions on convergence as indicated by the second (converging) crossing of a standard deviation limit. A more commonly used technique is the stop-loss policy, where positions are closed when the total loss of the positions exceed a certain limit (Hull 2003, pp.300).

2.3 Market neutrality

In the recent past market neutral strategies have gained the attention of investors because such strategies have the purpose of giving substantial positive gains irrespective of the market condition. The capital asset pricing model (Sharpe 1964, Lintner 1965 and Mossin 1966)(Sharpe 1964, Lintner 1965, Mossin 1966), CAPM, divides total risk into two components; one is systematic risk (the risk of holding the market portfolio) and the other is asset specific risk (the risk tied to the specific asset). The objective of a market neutral strategy is to remove the systematic risk from a portfolio, and thereby subjecting the investor to asset-specific risk only. There are several techniques to achieve this effect. One is to buy undervalued assets while short-selling overvalued asset. When the long asset is affected by the market exposure, it is offset by the short position thus eliminating the systematic risk that the market carries (Beliosi 2002). This is also the basis for the pairs trading strategy, which is therefore characterised as a market neutral strategy as one takes long and short on relatively mispriced assets (Levy and Jacobs 2005).

2.4 The Law of One Price

The law of one price states that that if the returns from two investments are identical in every state then the current value of the two investments must be the same (Ingersoll 1987). Similarly, for markets to be perfectly integrated (which is commonly assumed), two portfolios created from two markets cannot exist with different prices if the payoffs are identical (Chen and Knez 1995). If these conditions are not satisfied, arbitrage opportunities exist thus giving investors opportunities to make risk-free profits by buying underpriced securities and short-selling the overpriced (Lamont and Thaler 2003).

In a perfectly efficient market, the prices "fully reflect" the available information at all times (Fama 1970). The market efficiency hypothesis reached its peak in 1970's, and at that time there was a consensus on the idea that as soon as any news reach the market it spreads quickly and immediately gets reflected in stock prices.

2.5 Mean reversion and market efficiency

Different activities in the market, such as changes in demand and supply, unexpected events and so forth, lead to changes in asset prices away from their equilibrium prices. When prices move away from their "normal" (average) levels and then revert back again, they demonstrate what is known as a mean reversion process. The time it takes for the price of an asset to come back to its normal level is called time to reversion. The length of this time period is variable; it could range from days to months depending on the nature of the event that triggered the deviation. In the case where prices of goods do not come back to their original level after such an event, the process is called a random walk.

De Bondt and Thaler (1985) presented so called contrarian strategies which outperformed the market. This is considered to be one of the earliest evidences of mean reversion. Contrarian means that the short-term losers in a portfolio tend to outperform the stocks that had the highest previous returns. This is also the central idea behind the strategy of selecting stocks with low P/E ratios (Dreman 1998).

This also has the implication that there is no information of predictive qualities in the historical prices or trends of stocks. The dominance of this view declined with time, and behavioural finance[2] appeared. It stood in opposition to the previous widely accepted market efficiency hypothesis (Shiller 2003). The concept of market efficiency can be related to the random walk concept. If prices are assumed to reflect

[2]Behavioural finance incorporates social science perspective including psychology and sociology.

all market information, the latest news will be instantly absorbed by the market which consequently results in random prices because news is random (Malkiel 2003).

According to the efficient market hypothesis, there are three levels of efficiency. The strongest form tests if any investor has private information, whether it is fully reflected in the market or not. The semi-strong form is concerned with market prices adjusting to public information, and the weak form implies that future prices cannot be predicted in any way. According to the weak form there is no use of any kind of technical analysis, and future prices are not dependant on the current price trend as no correlations exist in prices. Out of these three forms of market efficiency, the weak form is of most interest to our work. This form of the efficiency hypothesis cannot hold if positive returns can be achieved by using the pairs trading strategy. The critique has indeed been considerable. Fama and French (1988) and Campbell and Shiller (1988) conducted tests to see whether historical returns may be used for predicting future returns and the result showed that future returns to some extent could be predicted from the dividend yield of the market. Apart from using the dividend yield to forecast returns, also interest rates and price ratios could be used for this purpose.

Campbell (1987) found that information contained in the spreads of interest rates could be used to predict future returns. Campbell and Shiller (1998) showed that P/E ratios could explain a significant part of the variation in future returns. Fama (1965) showed that most of the Dow Jones stocks are correlated. Thus, markets cannot be characterized as perfectly efficient even with the weakest form of the hypothesis. This means that short term arbitrage opportunities might exist in the market allowing investors to make positive returns.

2.6 Previous research

Several authors have published articles concerning pairs trading and the use of different methodologies for the selection of pair assets. Gatev et al. (1998, 2006) pioneered the academic interest in the strategy using a correlation-like metric to rank feasible pairs. Long and short positions were taken when the assets diverged as measured by the historical values of this metric. In the latter and updated article, they used data gathered from four decades and found significant positive excess return of 12 percent yearly. Elliott et al. (2005) proposed a mean reverting process for pairs trading (using stocks from the same sector) known as the Gaussian Markov chain model. They showed that the model could be used to make predictions about the spread between the two stocks. After making these predictions, succeeding observations were compared to the predicted values. If the observed spread were greater than the corresponding expected value, a pair position was opened.

Huck (2009) developed a methodology based on bivariate information sets which were used to forecast returns. A ranking is done for the assets in terms of their expected values which provide information about over- and undervalued assets. The results turned out rather promising, and when applied to stocks from the S&P100 index the method seemed to have a good forecasting ability of future returns. The method was found to produce greater returns the smaller number of pairs was.

Dattasharma et al. (2008) attempted to outline a general framework for the prediction of return dependence among stocks. They transformed the time series of stocks into so called binary strings, a computer science concept, where the dependence of the strings were allowed to be computationally analysed in terms of string distance. The optimal stopping theory is related to an appropriate time to make investment decision based on some observed factors which helps to reduce costs and thus maximising potential profits.

Perlin (2007) introduced a multivariate approach to pairs trading. The main idea behind this approach was to find pairs of stocks using information generated by all other stocks rather than picking pairs randomly. This approach was applied to the Brazilian financial market on 57 assets. The results of adopting multivariate approach came out to be promising. Moreover, if a company has announced bad results then fewer long positions were observed to be taken.

3 Methodology

3.1 Statistical bias and trade parameters

When evaluating quantitative trading methodologies, over-optimising trading parameters is a common temptation. Optimising is one example of where one is exposed to "data snooping bias", which occurs when one derives inference or conclusions from the same set of data more than once. This problem is especially widespread in time-series analysis and hence in the financial field. Because it is possible to evaluate a large number of models on the data set, one or more hypothesises may be adjusted into eventually being accepted. Results of this nature are often worthless in terms of prediction abilities. Not only can the consequences of data snooping be severe, there is also a lack of good methods for identification of such errors and for consequence analysis (White 2000). There are, however, means to avoid the risk of data snooping. Working with time-series data, one option is to save a reasonably large chunk at the end for evaluation once the parameters are settled based on the analysed subset. In this manner, false positives can be detected given that the evaluation subset is substantial. In this case, the dataset covered only twenty years worth of price observations, which left little room for such a fragmentation of the data. Instead, all trading parameters were predetermined in order to avoid alterations of the model.

3.2 Data

We gathered daily price data[3] for 25 assets (displayed in tables 2, 3 and 4 under section 4.1) from a time period spanning twenty years (1990–2010). The assets were chosen from three different non-equity classes of assets; stock market indices, commodities and currencies. A number of the chosen assets are important world economy markers, but this selection was broadened by assets of lesser significance. To get enough useful data, we limited our selection to assets with price information available for the largest part of the study's time period. Nonetheless, it should be noted that some of these assets had a shorter lifespan, but the design of the

[3]Provided by Thomson DataStream.

trading software took these irregularities into consideration. Additional clusters of currencies were included that would have a reasonably good likelihood of correlating (none were however screened numerically). For example, the Danish Krone, Finnish Markka, Norwegian Krone and Swedish Krona were included because the similarities in those economies. For similar reasons, the Polish Zloty and the Czech Koruna were included into the study. All assets were denominated in US Dollars to eliminate currency effects on the trades.

3.3 Formation of pairs

As previously mentioned, different metrics can be used to find and rank feasible pairs. The intricacies of the different formation algorithms and methodologies lay outside the scope of this thesis, and for this reason a computationally straightforward procedure was selected. We adhered, with one exception, to the methodology outlined by Gatev et al. (2006, p.803), where the sum of squared deviances (SSD) of the indexed cumulative returns are calculated for all screened pairs. The twelve month averages of these deviances are sorted ascendingly, and finally a fixed number of pairs are selected for a six month trading period from the top of this list each time the screening is done. The drawback of this practice is that the output disregards the quality of the pairs. If all assets are entirely uncorrelated for one period, one is still left with the same amount of pairs that get traded.

In this study, we chose to use a correlation measure to select the pairs. This way, only pairs displaying correlations greater than the predetermined threshold value 0.95 were traded. For this reason, we know for certain that the traded pairs attain a certain level of quality, and that they do in fact have a history of moving together. This threshold value was selected to give a sufficient number of pairs. The correlations were calculated on the indexed cumulative returns for the 300 possible pairs ($\frac{N(N-1)}{2}$ where $N = 25$) once a month iteratively. Even though the SSD was not used for the pairs selection, it was still calculated since the construction of the trading application required this measure (see section 3.4). As noted, assets were included that lacked price observations for short periods in the beginning or the end of the study period. Thus, for every monthly round of sampling, only assets with observations reaching twelve months back were eligible for matching.

3.4 Trading signals

Once a pair was formed and fulfilled the aforementioned condition, it was traded for a period of six months. The SSD of the two assets was tracked on a daily basis, and a pair was opened as soon as the deviation exceeded two standard deviations (as measured during the formation period) according to our specifications. Upon opening, the asset with the greater cumulative return was sold short while the other asset was bought long. One hundred dollars were invested into these positions respectively.

The opening trigger was programmed to use same-day prices based on the assumption that the program could be instructed to execute purchases near or very near the closing call of the exchange day. Open pairs were closed upon convergence expressed by either the intersection of cumulative price indices or a deviation falling short of 0.1 standard deviations. In the case where assets were unlisted (as was the case with the Finnish Markka), any affected open pair was closed.

As a consequence of the discussion on asymmetrical returns (section 2.2), the trading procedure was supplemented with a twenty percent stop-loss restraint in a second round of execution. The restraint was activated when the spread between the two positions exceeded 2.4 standard deviations, thus restricting the losses to twenty percent by exiting the positions. Re-entry of trading positions was not allowed until the regular conditions for a close were satisfied.

3.5 Excess return

In theory, trading pairs is a zero-investment strategy because the short selling funds the long position. Hence no capital is actually invested in a pair position, and as a consequence, the ordinary arithmetic return model ($r = \frac{V_t - V_0}{V_0}$) is invalid because the denominator is zero in all cases. In practice, however, short-selling investors are subjected to margin requirements. This margin can be used as one way to estimate the capital base of the position, but this adds complexity in that the margin varies with the price of the underlying asset.

Another option is using the weighted average return of the two opposing positions, forming a pair portfolio, as proposed by Gatev et al. (2006, p.805). Since we chose to abide by this work, this model was also used in this study. The rather straightforward calculation is equivalent to using the sum of capital committed in the positions as a capital base. In other words, if the overpriced asset is shorted for a total of one hundred dollars and this amount is used to purchase the underpriced asset, the effective capital base is two hundred dollars. Thus, the return of one pair is calculated on a daily basis in the following fashion;

$$r_{P,t} = \frac{\sum_{i \in P} w_{i,t} r_{i,t}}{\sum_{i \in P} w_{i,t}} \tag{1}$$

where

$$w_{i,t} = w_{i,t-1}(1 + r_{i,t-1}) = (1 + r_{i,1}) \ldots (1 + r_{i,t-1}) \tag{2}$$

The weights $w_{i,t}$ are essentially the previous day cumulated returns for the positions. Due to the self-funding nature of the strategy, the expression in equation 1 has the interpretation of excess return. This notion of return can be considered quite conservative, considering the vastly larger capital base in relation to a realistic margin requirement.

In contrast, the conventional approach dictates denominating returns using only the capital invested in the long position, or one hundred dollars in this example. While we chose to focus on the former method, trading returns were also calculated using the latter. In that case, we found that the payoffs were increased by approximately 0.5 percentage points, and the difference in standard deviations between the no-constraints and the stop-loss trading rounds was particularly pronounced. The stop-loss returns were found to be significantly greater than the no-constraints returns.

In order to further assess the outcome of the pair trades, a benchmark zero-investment portfolio was constructed. The average of the Swedish central bank reference rate over the study period, 4.15 percent, was used to simulate a zero-coupon bond sold short to finance the purchase of the OMXS30 index. This portfolio was marked-to-market on a daily basis in a similar fashion using the method described above.

3.6 Transaction costs

It is important to stress that the model used did not include any transaction costs. The returns generated in the study should therefore be interpreted with caution. While specifically currency trade is normally exempt from commissions, it is still subjected to bid-ask spreads. Bessembinder (2003) studied the bid-ask spreads on the NYSE and NASDAQ exchanges, and found that the average spreads (for all shares) were 0.486 and 0.739 percent of the share price respectively. For large stocks the corresponding figures were 0.212 and 0.238 percent. Thus, it is reasonable to assume that bid-ask spreads alone generate an overhead of roughly half a percent on each transaction. Since positions need to be entered and exited, the returns suffer from these spreads twice.

Another caveat to consider is the extra costs caused by a stop-loss constraint. Hull (2003, p.301) shows that if the limit price is K, purchases must be made at $K + \epsilon$ and sales at $K - \epsilon$. Buying and selling one asset therefore incurs costs of 2ϵ on top of the regular transaction costs.

3.7 Long-horizon PT portfolio

It was also desirable to get an idea of what a practical computerised implementation of the pairs trading strategy could look like. The average profit of one pair has little significance to an investor if there are few arbitrage opportunities to exploit. Two long-horizon portfolios were constructed, one using the unconstrained pair trade returns and the other using the stop-loss strategy returns. The income streams generated by the individual pairs previously described formed the components of the portfolios.

These cash flows were either positive or negative, and when a profit was recorded, interest was accrued on the proceeds. Interest was paid correspondingly on losses. Hence, no money was deposited nor withdrawn with the portfolios, and the portfolio returns were calculated as weighted averages (as above) of the individual income streams marked-to-market daily.

4 Results

4.1 Asset statistics

As previously mentioned, assets of three different types were used in the trading. The distribution of these assets is shown in table 1. The descriptive statistics of the daily returns for these assets are displayed in tables 2, 3 and 4. In appendix A, correlation matrices are provided for these categories, and the price performances are displayed in appendix B.

Table 1: Asset frequencies

Asset class	N	Proportion
Commodities	9	36%
Currencies	10	40%
Indices	6	24%
$\sum$	25	100%

Table 2: Commodities, daily returns.

Asset	N	Average	Median	StDev	StdErr	Min	Max
Copper	5220	0.0333%	0.00%	1.76%	0.0243%	-11.7%	16.7%
Cotton	5220	0.0178%	0.00%	1.75%	0.0242%	-8.32%	9.46%
Gold	5220	0.0240%	0.00%	0.964%	0.0133%	-6.96%	7.66%
Oil	5220	0.0567%	0.00%	2.37%	0.0328%	-35.5%	14.5%
Palladium	5220	0.0458%	0.00%	2.06%	0.0285%	-16.4%	17.2%
Silver	5220	0.0394%	0.00%	1.79%	0.0248%	-14.8%	20.1%
Tin	5220	0.0293%	0.00%	1.38%	0.0191%	-12.9%	20.7%
Uranium	5220	0.0372%	0.00%	1.26%	0.0174%	-19.0%	20.8%
Wheat	5220	0.0181%	0.00%	1.75%	0.0242%	-11.6%	13.4%

4.2 Trade frequencies

The frequencies of pair assets are shown in table 5, arranged by long/short positions and by the three asset categories. Currencies were clearly the most traded assets, and with involvement in 73 percent of the pairs they were also overrepresented in relation to the 40 percent share they held of all assets included. Commodities on the other hand were underrepresented with 15 percent of the pairs compared to

Table 3: Currencies, daily returns.

Asset	N	Average	Median	StDev	StdErr	Min	Max
AUD	5220	0.00654%	0.0130%	0.760%	0.0105%	-8.33%	8.31%
CAD	5220	0.00401%	0.000%	0.474%	0.00656%	-3.35%	3.95%
CZK	4770	0.0115%	0.000%	0.791%	0.0114%	-7.01%	7.05%
DKK	5220	0.00528%	0.000%	0.660%	0.00913%	-3.34%	3.52%
FIM	4830	0.00185%	0.000%	0.696%	0.0100%	-13.3%	3.74%
NOK	5220	0.00476%	0.000%	0.749%	0.0104%	-5.26%	5.66%
PLN	4770	-0.0150%	0.000%	1.10%	0.0160%	-16.9%	13.4%
SEK	5220	-0.000169%	0.000%	0.762%	0.0105%	-6.61%	5.80%
CHF	5220	0.00935%	0.000%	0.723%	0.0100%	-3.70%	4.32%
NZD	5220	0.00634%	0.000%	0.735%	0.0102%	-6.65%	6.14%

Table 4: Stock indices, daily returns.

Asset	N	Average	Median	StDev	StdErr	Min	Max
DAX	5220	0.0325%	0.0360%	1.46%	0.0202%	-9.40%	11.4%
Dow Jones	5220	0.0322%	0.0180%	1.10%	0.0153%	-7.87%	11.1%
FTSE100	5220	0.0242%	0.00%	1.13%	0.0157%	-8.85%	9.84%
NASDAQ	5220	0.0591%	0.0671%	1.87%	0.0259%	-10.52%	18.8%
NIKKEI	5220	-0.00856%	0.00%	1.53%	0.0212%	-11.4%	14.2%
OMXS30	5220	0.0438%	0.00639%	1.51%	0.0209%	-8.17%	11.7%

a 36 percent share among assets. The corresponding numbers for indices were 28 percent among pairs and 24 percent among assets. Also apparent is that for each asset category, the most frequent opposing asset was from the same category. In other words, indices were found to be the best matches for indices, currencies for currencies and so forth. In total, only 17 percent of the pairs contained assets from different categories.

Table 5: Trade frequencies.

		Short			
		Index	Currency	Commodity	$\sum$
Long	Index	250	22	49	*321*
	Currency	39	790	78	*907*
	Commodity	5	23	46	*74*
	$\sum$	*294*	*835*	*173*	*1302*

4.3 Returns

The six month trading returns from the two variations executed, the no-constraints and the twenty percent stop-loss applications, are presented in table 8. Interestingly, the fear of great losses as a consequence of the asymmetrical construction of the trading algorithm was proved somewhat unnecessary. The maximum loss in the unconstrained application was a staggering near 54 percent. However, the maximum profit was almost 67 percent.

To get an understanding of what the pair returns could look like, the five best and five worst trades are illustrated in tables 6 and 7. It was observable that there was an assortment of asset combinations in both extremes.

Table 6: Five best trades.

Long	Short	Return	Date
Nikkei	OMXS30	67%	2008-12-02–2009-06-02
Gold	Silver	43%	2006-03-22–2006-09-20
DAX	NIKKEI	43%	2009-02-02–2009-08-03
NASDAQ	Silver	42%	2001-07-02–2001-12-31
SEK	Tin	41%	2009-03-04–2009-09-02

Table 7: Five worst trades.

Long	Short	Return	Date
DJ	OMXS30	-54%	1999-09-23–2000-03-23
Palladium	Cotton	-42%	2002-01-02–2002-07-03
PLN	Oil	-42%	2009-01-01–2009-07-02
NIKKEI	Copper	-42%	2006-01-19–2006-07-20
OMXS30	Copper	-35%	2006-01-19–2006-07-20

From table 8, it is evident that the introduction of a stop-loss rule altered the extreme values yielded by the trades. While the maximum gain decreased to 32 percent, the worst case set us back merely six percent. Also, the standard deviation using a stop-loss constraint was approximately a third of the unconstrained value. A one-sample t-test was used to test whether the two groups of returns were significantly greater than zero ($\mu_\alpha > 0$ and $\mu_\beta > 0$), or in other words, whether excess return existed. Both variations produced significant p-values of 0.000.

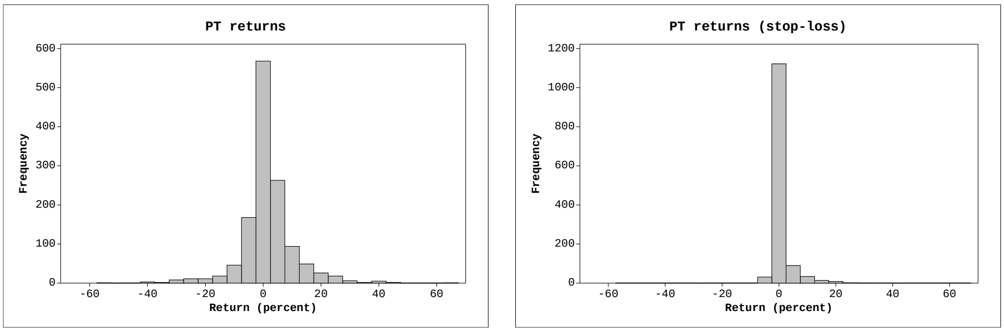
Table 8: Six month returns for two application runs (observations=1302).

	No-constraints	Stop-loss
Average	1.56%	1.41%
Median	0.813%	0.944%
StDev	9.08%	3.11%
StdErr	0.252	0.0863
Min	-53.5%	-6.22%
Max	66.6%	31.9%
Skewness	0.264	3.77
Kurtosis	7.45	21.0
Average trades	1.35	1.35
t	6.21	16.37
p	0.000***	0.000***

The distributional transformation of returns caused by the stop-loss restraint is displayed in figure 2 and is confirmed by the skewness measures in table 8. It is apparent that the stop-loss effectively cut short the negative tail of the distribution while the positive tail remained considerably long. The stop-loss was included in the model hoping to increase the average returns. The two groups were therefore tested for inequality ($\mu_\alpha \neq \mu_\beta$), and the corresponding p-value was 0.572 (t=0.57). Hence, there was no statistical evidence of the stop-loss constraint having an effect in any direction on the average returns.

Figure 2: Distributions of the no-constraint and the stop-loss returns.

(a) No-constraints (b) Stop-loss



4.4 Sharpe ratios

The six-month returns were correspondingly calculated for the benchmark zero-investment portfolio (see section 3.5). Because this portfolio was formed by one short position funding the long part, the portfolio return can be interpreted as excess return analogue to the pairs trading returns. In table 9, we present the Sharpe ratios (Sharpe 1994). The Sharpe ratio quantifies the reward given to an investor for taking risk, and is defined as:

$$S_i = \frac{R_i - R_f}{\sigma_i} \tag{3}$$

The higher the ratio, the higher is the compensation for each unit of risk. The numerator in equation 3 corresponds to excess return or risk premium of an asset. Bearing this in mind, the numerator was replaced by the returns from our trading application runs. While the benchmark portfolio outperformed the no-constraints pair trading strategy, the stop-loss constraint clearly gave the best reward for risk by almost doubling the benchmark Sharpe ratio.

Table 9: Six month Sharpe ratios.

	No-constraints	20% Stop-loss	Benchmark
Excess return	1.56%	1.41%	6.75%
StDev	9.08%	3.11%	27.1%
Sharpe ratio	0.16	0.45	0.25

4.5 Asset category significance

The previously analysed two groups, the no-constraint and the stop-loss strategies, were each divided into two subgroups. The "different" group was defined by pairs where the two assets came from different asset categories, whereas "same" allowed only same-category asset pairs. The purpose of this separation was to test the hypothesis formulated in section 1.2, that is, to examine whether it is possible to attain higher returns by trading pairs with assets of different types. The result is shown in table 10. All four groups yielded returns significantly greater than zero. As can be seen from the table however, in none of the two strategies are there any signs of a significant difference in returns comparing the same-category and different-category pairs.

Table 10: Six month returns grouped by same and different category assets.

	No-constraints		Stop-loss	
	Different	Same	Different	Same
Average	2.02%	1.45%	1.54%	1.39%
Median	1.29%	0.797%	0.536%	0.991%
StDev	14.1%	7.71%	4.83%	2.65%
StdErr	0.959%	0.234%	0.329%	0.0803%
Min	-42.1%	-53.5%	-6.22%	-5.25%
Max	42.5%	66.6%	22.9%	31.9%
N	216	1086	216	1086
$p(\mu > 0)$	0.018^{*}	0.000^{***}	0.000^{***}	0.000^{***}
t	2.10	6.30	4.68	17.29
$p(\mu_{\text{same}} \neq \mu_{\text{diff}})$		0.583^{ns}		0.658^{ns}
t		0.55		0.44

Table 11: Same-category pair returns.

	Index	Commodity	Currency
N	250	46	790
Average	4.28%	2.88%	0.505%
StDev	11.6%	18.6%	4.00%
StdErr	0.732	2.75	1.42
$p(\mu > 0)$	0.000^{***}	0.150^{ns}	0.000^{***}
t	5.84	1.05	3.54

We also compared the returns for the three varieties of same-category pairs. The descriptive statistics are displayed in table 11. Both index and currency pairs showed significant excess return. The commodity pair returns were not significant, but the number of observations was only 46, and the result should therefore be interpreted with caution. When testing for differences, only index-index pairs and currency-currency pairs were significantly different with p=0.000 (t=5.06). The corresponding values for index versus commodity pairs are p=0.625 (t=0.49), and p=0.393 (t=0.86) for commodity versus currency pairs.

4.6 Portfolio returns

In section 3.7, the construction of a long-term portfolio using the pairs trading strategy was described. One portfolio was constructed using the no-constraints trading returns and another using the stop-loss returns. Because no distinctive difference in returns could be observed for the asset class separated groups in the previous section, these were excluded from this treatment.

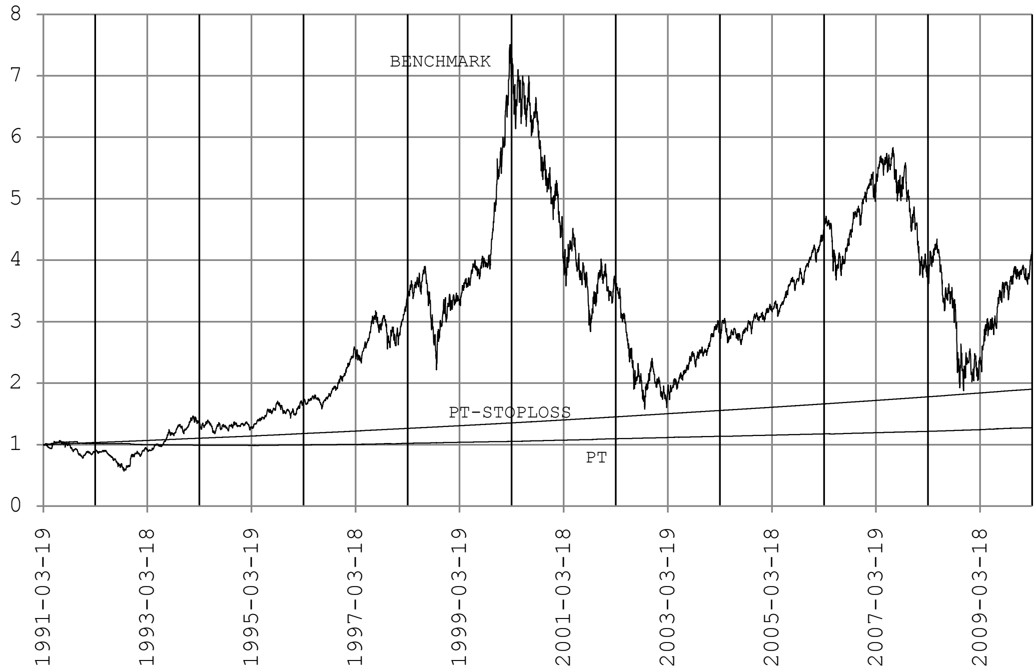
To evaluate the performance of these portfolios, an additional buy-and-hold benchmark portfolio was added consisting of a long position in the Swedish OMXS30 index and a short position in a simulated zero-coupon bond yielding 4.15 percent annually. The performances of the three portfolios are shown in figure 3.

Weekly returns were computed for the portfolios by measuring the percentage increase in the cumulative returns of each portfolio. Descriptive statistics of the portfolios are displayed in table 12. The index-invested portfolio clearly outperformed the trading portfolios in terms of sheer returns but was far more volatile than both of the pair trading portfolios with a standard deviation of 2.9 percent. This compares to 0.47 and 0.13 percent for the no-restrictions and stop-loss strategies correspondingly. It should be noted, however, that the standard deviations of the trading portfolios were not stable over time. This is due to the construction of the portfolios where the returns from trades continue to amass either positive or negative interest. With time the pair returns are hence given smaller weights as more and more of the returns from previous pairs are weighted into the portfolio.

Table 12: Portfolio returns (weekly).

	No-constraints	Stop-loss	Benchmark
Average	0.0377%	0.0773%	0.135%
Median	0.0422%	0.0780%	0.281%
StDev	0.470%	0.125%	2.86%
StdErr	0.0149%	0.00397%	0.0909%
Min	-3.52%	-0.978%	-12.9%
Max	2.48%	1.36%	22.8%

Figure 3: Portfolio development over 19 years.



5 Conclusions

By applying the pairs trading strategy onto a novel selection of non-equity price data, we intended to examine whether positive excess return could be generated. We found that using this strategy, we were able to achieve statistically significant excess return of almost 1.6 percent on a six month basis.

By theoretically skewing the return distribution, we had expected significantly improved returns using a stop-loss constraint. However, adding the constraint yielded a slightly lower average return. While the constraint did provide defence against large shortfalls, it effectively reduced the number of positive gains. It also managed to cut the standard deviation to a third compared to the unconstrained trading run.

When the returns of the two trading runs were regarded with respect to the risks they carried, we recorded a lower reward-to-risk, measured by the Sharpe ratio, for the unconstrained trading compared to a benchmark portfolio (0.16 versus 0.25). The benchmark portfolio consisted of a short position in a theoretical zero-coupon obligation and a long position in the Swedish stock index OMXS30, thus forming a zero-investment portfolio. When the stop-loss was applied, a Sharpe ratio of 0.45 was attained. As a consequence, investors using this strategy are compensated by almost the double return given a certain level of risk compared to the benchmark.

Positive excess returns were also established for pairs comprised of the combinations index-index and currency-currency. We were particularly interested in the latter case, because of two reasons. One is that currency-to-currency arbitrage opportunities were quite plentiful – they constituted almost 61 percent of all pairs. Producing large profits in terms of percentage has little relevancy if there is a lack of opportunities to exploit the arbitrage scheme. The other reason was that usually there are no commissions charged for trading currencies, and hence the transaction costs are limited to the bid-ask spreads. However, the average six month returns from pure currency pairs are a meagre 0.5 percent. Index pairs on the other hand exhibit returns exceeding 4 percent.

While we found many instances of significant excess returns, the model used did not include transaction costs. In section 3.6, we refer to a study estimating bid/ask spreads to the vicinity of half a percent. As was also shown, applying a stop-loss constraint introduces additional costs, which in addition to the relatively fewer positive returns would likely reduce the favourable Sharpe ratio received from the stop-loss trading. On the other hand, the small margin requirements for short selling assets would likely offset these costs by generating greater returns in practice in comparison to our results.

Nonetheless, in this study we have shown that a free-formation pairs trading strategy could indeed generate significant positive excess return using non-equity assets of various types. Constructing long-term portfolios using the strategy were shown to yield small but low-risk arbitrage profits. Furthermore, there were observations that we feel would benefit from further examination. Specifically, it would be interesting to investigate the reasons behind the recorded differences in return achieved from trading the three types of same-category pairs.

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A Correlation matrices

Displayed below are the 20 year correlations for the assets used in the study, grouped by their corresponding asset type.

Table 13: Commodity correlations

	Copper	Cotton	Gold	Oil	Palladium	Silver	Tin	Uranium
Cotton	0.132							
Gold	0.195	0.076						
Oil	0.162	0.078	0.172					
Palladium	0.123	0.036	0.284	0.069				
Silver	0.099	0.032	0.416	0.098	0.365			
Tin	0.249	0.085	0.129	0.090	0.124	0.126		
Uranium	0.004	-0.006	-0.003	-0.022	-0.009	0.007	0.012	
Wheat	0.144	0.116	0.104	0.074	0.062	0.060	0.070	-0.001

Table 14: Currency correlations

	AUD	CAD	CZK	DKK	FIM	NOK	PLN	SEK	CHF
CAD	0.523								
CZK	0.384	0.328							
DKK	0.380	0.286	0.554						
FIM	0.286	0.180	0.438	0.865					
NOK	0.422	0.346	0.505	0.820	0.757				
PLN	0.291	0.261	0.474	0.304	0.190	0.306			
SEK	0.436	0.364	0.499	0.785	0.748	0.769	0.315		
CHF	0.258	0.189	0.457	0.866	0.772	0.710	0.239	0.671	
NZD	0.773	0.478	0.379	0.405	0.310	0.428	0.278	0.437	0.292

Table 15: Index correlations.

	DAX	DJ	FTSE100	NASDAQ	NIKKEI
DJ	0.492				
FTSE100	0.719	0.451			
NASDAQ	0.399	0.718	0.326		
NIKKEI	0.256	0.116	0.281	0.083	
OMXS30	0.698	0.400	0.693	0.334	0.272

B Price charts

Below are three graphs displaying the indexed cumulative relative development of the assets used in the study, grouped by asset type.

Figure 4: Commodity performances.

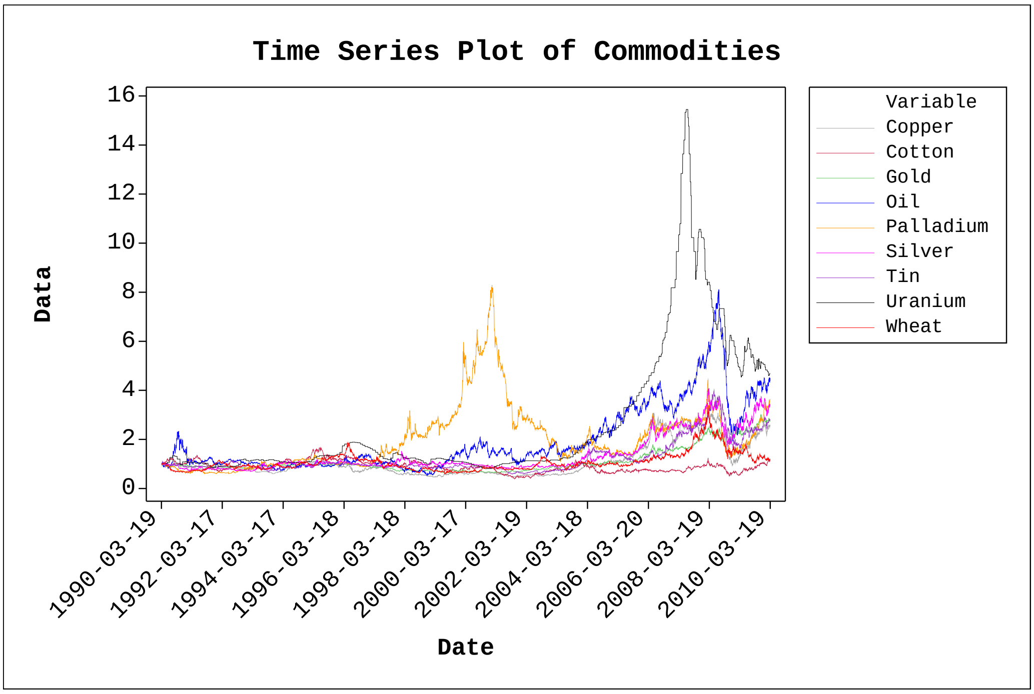

Figure 5: Currency performances.

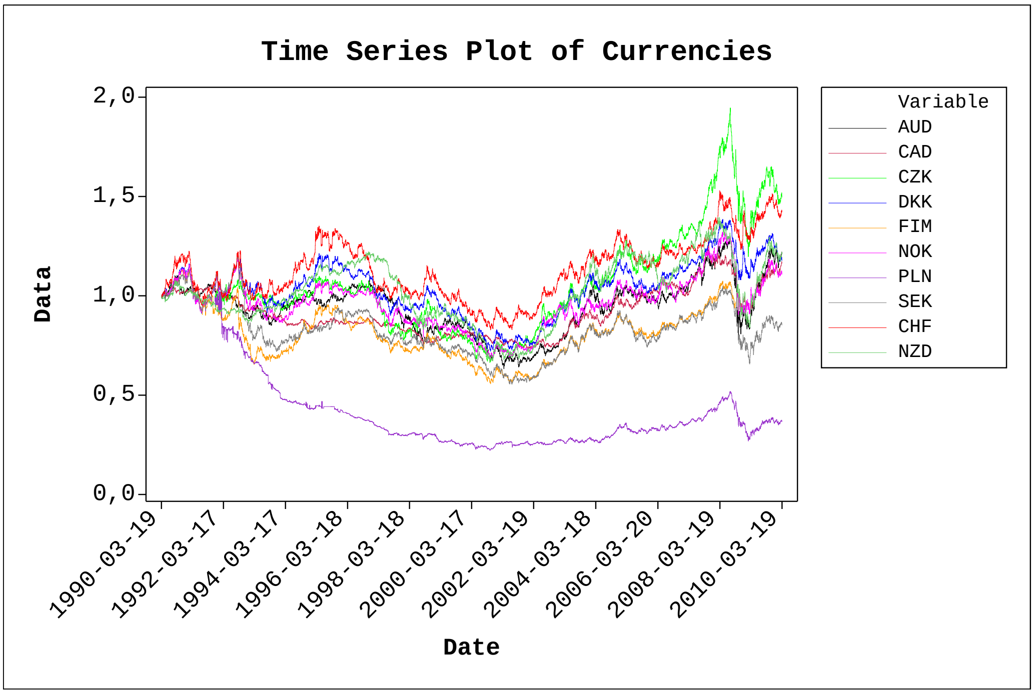

Figure 6: Stock index performances.