Dynamic ETF Pairs Trading System
Evidence From Australia

N. Robert Enemuwe

Banking & Finance, University of New South Wales

Abstract

This study evaluates the profitability of dynamic pairs trading strategies using a proposed 3-step pairs selection approach. We extend the pairs trading methodology employed by Miao (2014) to the broad-based exchange traded funds (ETFs) listed on the Australian Securities Exchange (ASX). The 3-step approach incorporates the correlation, cointegration and error correction coefficient as the pre-selection criteria during the formation period. In the subsequent trading period, we employ a daily re-calibration of the parameters using a 252-day rolling window from January 1, 2013 to September 30, 2015. We developed a real-time trading system using the Java programming language and KDB+ database, and back test the strategies using tick-by-tick historical quotes during the trading period. The back testing of the top five ETF pairs: ISO-SSO, IOZ-VAS, IOZ-STW, STW-VAS and STW-SFY yield cumulative returns of 10.08%, 4.41%, 19.70%, 62.27%, 46.60% and Sharpe ratios of 2.21, 1.00, 9.29, 15.12, 11.17 respectively. The maximum draw down is -32.47% over the trading period.

Corresponding Author

N. Robert Enemuwe, Banking & Finance, University of New South Wales, Sydney, Australia

Email: robert.enemuwe@student.unsw.edu.au

1. *Introduction*

The concept of pairs trading is rather simple; one identifies a pair of securities that exhibit historical co-movement in prices. Subsequently, if significant deviation from the historical relationship is observed, a trading position is opened. The position is opened by simultaneously selling the over-valued security and buying the under-valued security. The position is closed-out when the prices eventually converge. The strategy builds upon the notion that the relative prices in a market are in equilibrium, and that deviations from this equilibrium eventually will be corrected. Applying a pairs trading strategy is therefore an attempt to profit from temporary deviations from this equilibrium (Gundersen, 2014).

Pairs trading was pioneered by the Wall Street quant Nunzio Tartaglia of Morgan Stanley in the early 1980s. He assembled a team of physicists, mathematicians and computer scientists to uncover arbitrage opportunities in the equities markets. Tartaglia's group of academics used sophisticated statistical methods to develop high-tech trading programs to execute pairs trading strategies. Pairs trading has since become an increasingly popular market-neutral investment strategy used by individual and institutional traders as well as hedge funds (Gatev et al., 2006).

Gatev et al. (2006) is perhaps the most cited paper on pairs trading, laying the foundation for much of the subsequent research. They investigated the profitability of pairs trading using the distance method for US stocks between 1999 and 2002. The strategy generated an average excess return of 10.4% per annum. But they noted that lower transaction costs and large inflows of investment capital into arbitrage strategies by hedge funds may have decreased the rate of return on pairs trading.

Perlin (2009) replicated the pairs trading strategies developed by Gatev et al. (2006) and his strategy generated significant returns for daily trading frequency on the Brazilian stock exchange. Do and Faff (2010, 2012) also replicated Gatev et al. (2006) pairs trading strategies using US equities, but found that the returns from the strategy has declined possibly due to changes in the underlying relationship between the pairs.

Bogomolov (2010) compared the profitability of the distance method, the cointegration method and the stochastic spread approach on stocks listed on the Australia Securities Exchange

(ASX). His strategy produced significant monthly excess returns before transaction cost, but highlights the impact of transaction cost on the overall returns from the strategy.

Despite the reduction in trading returns experienced in earlier years, the introduction of sophisticated trading technologies and networks in recent years, and the rapid reduction in transaction costs have lead to sustained profitability of pairs trading strategies. For example, Galenko et al. (2012) evaluated pairs trading strategy using the cointegration approach with 4 ETFs that track world stock market indexes. The strategy outperforms a naïve buy-and-hold strategy and produced positive returns during the subprime mortgage crisis.

Broussard and Vaihekoski (2012) also implemented Gatev et al. (2006) pairs trading strategy using data from the Finnish stock market between 1987 and 2008. They found the strategy to be profitable even after allowing for a one-day delay in the trade initiation after the signal. On average the strategy generated annualized return of approximately 12.5%.

Sipila (2013) also investigated the profitability of pairs trading strategy using over 66,000 possible pairs of ETFs worldwide from 2004 to 2012. The strategy generated cumulative returns of 105.43% and an annual excess return of 27.29% with volatility of 10.57%. Furthermore, his results confirmed market neutrality with no significant correlation with the MSCI World index.

Caldeira and Moura (2013) investigated the performance of pairs trading on stocks listed on the Sao Paulo stock exchange (Ibovespa) using the cointegration approach. The pairs were traded out of sample for a period of four years yielding a cumulative net return of 189.29%, with an annual mean of 16.38%. Furthermore, the strategy showed relatively low levels of volatility and no significant correlation with the market index confirming the market neutrality of pairs trading strategy.

Marshall et al. (2013) investigated the profitability of pairs trading strategy using the SPDR Trust (ticker SPY) and iShares (ticker IVV) within a high frequency environment. They found that the price deviations between the ETFs returned back to parity following mispricing with a median durations of approximately 1–2 minutes. The result provides evidence that arbitrageurs act to profit from the mispricing and their actions lead to short-lived mispricing. The average profit was 0.33% and 0.32% for the SPY (IVV) and IVV (SPY) pairs respectively.

Miao (2014) applied a two-stage correlation and cointegration approach to pairs in the U.S. equity markets from 2012 to 2013. The strategy yield cumulative returns of up to 56.58% well exceeding the S&P 500 index performance by 34.35% over the 12-month trading period. Furthermore, the pairs trading system performed well during the two months in which the S&P 500 index had negative returns highlighting the market-neutrality of the strategies.

Algorithmic trading and high frequency trading (HFT), which encompass pairs trading has seen significant growth in the United States and Europe. This is also evident in Australia where HFT strategies are dominated by a small group of trading entities, with the 20 largest high-frequency trading entities accounting for approximately 27% of total equity market turnover in 2013 (See ASIC Report 331[1]).

Given the sustained profitability of pairs trading strategies in recent years, the objective of this study is to investigate the profitability of pairs trading in Australia after accounting for real-time transaction cost, market liquidity and risk management controls within a high frequency environment. We focus on exchange traded funds (ETF) listed on the ASX, given the significant growth and size of assets invested in ETFs since the introduction in 1999.

This study builds upon the pairs trading methodology proposed by Miao (2014), which employs a two-step correlation and cointegration approach. The first step, which is referred to as the pre-selection step, is used to identify potential pairs with correlation coefficients greater than or equal to 90%. The second step is used to determine if the pre-selected pairs are cointegrated.

Miao (2014) ranked the pairs based on the cointegration test statistics. The smaller the cointegration test statistics was, the higher the rank the stock pair was assigned to. The final selection of pairs from the top rank is used for the out-of-sample trading. He used a 3-month in-sample training period for parameter estimation followed by a 1-month trading window. He subsequently applied a dynamic forward rolling window of 1 month using high frequency data from 2012 to 2013.

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[1] Refer to the website at http://asic.gov.au/regulatory-resources/find-a-document/reports/rep-331-dark-liquidity-and-high-frequency-trading/

We extend Maio (2014) 2-step approach to include an addition pre-selection criterion. Our 3-step approach incorporates the correlation, cointegration and error correction coefficient as the pre-selection criteria during the formation period. Next during the subsequent trading period, we employ a daily re-calibration of the parameters using a 252-day rolling window.

We estimate the standardize spreads (z-score) from the cointegrating equation and generate trading signals using the z-score, the bid-ask spread, transaction cost, profit potential, profit threshold, trade duration and stop-loss threshold as indicators for trade entry and exit.

We developed a real-time trading system using the Java programming language and KDB+ database and back test the strategies using tick-by-tick quotes from January 1, 2013 to September 30, 2015 using high frequency (100 milliseconds) trading interval.

And finally we report the results of the trading strategies for each ETF pairs using the cumulative returns, Sharpe ratio and the maximum draw down as performance criteria.

Therefore the study is structured as follows; Section 2 provides the institutional details of the ETF market in Australia and Section 3 provides description of the data. Section 4 presents the concepts of stationarity, correlation and cointegration. Section 5 presents the pairs selection methodology and Section 6 presents the pairs trading rules and methodology. Section 7 provides description of the real-time trading system and Section 8 provides the performance evaluation criteria for these strategies. Section 9 presents the result of the trading strategies and finally Section 10 concludes and provides suggestions for future research.

2. ETF Institutional Details

2.1. ETF Structure

An exchange-traded fund (ETF) is a pooled investment fund with shares that are traded on stock exchanges at prices determined by market demand and supply.

In the United States, the Standard and Poor's Depository Receipt (SPDR) Trust was the first commercial ETF listed on the American Stock Exchange (AMEX) in 1993. ETFs accounts for more than $1.2 trillion in assets under management and are growing at a pace greatly exceeding that of traditional mutual funds (Arnerich et al., 2012).

ETFs were almost non-existent in Australia until 1999 and from this point on ETFs have seen consistent record inflows year after year. According to the Australian Securities Exchange, as of 31 March 2015, there are 110 ETF products listed on the ASX with a market capitalization of over $17 billion. Most of the transactions are done by self-managed superannuation funds, attracted to the low-cost and transparent structure of exchange-traded funds and the easy access they provide for investments diversification (Neiron, 2014).

Exchange traded funds are created by fund managers who are referred to as the ETF "Sponsor". The Sponsor outlines the investment and operational plans for the ETF in a registration statement filed with the regulatory authority. ETF shares are created in large blocks of shares known as "creation/redemption units."

Large institutional investors called "Authorized Participants" (APs) purchase creation units with a "portfolio deposit" equal in value to the aggregate net asset value of the ETF shares in the creation unit. The portfolio deposit generally consists of a basket of securities that mirrors the composition of the ETF's portfolio. The authorized participants then offer the ETF shares for sale on the secondary market (Arnerich et al., 2012).

There are several different types of ETFs offered for sales by ETF sponsors in Australia. These include Index Based ETFs, Rules Based ETFs, Active ETFs, Leveraged ETFs, Inverse ETFs, Sector ETFs, Commodity ETFs, Currency ETFs and Country Specific ETFs.

ETFs generally take the form of either physical or synthetic ETFs. Physical ETFs own actual shares of the underlying securities that comprise the ETF mandate. Whereas synthetic ETFs own derivatives rather than physical assets, such as forwards, futures, options, and swaps, which simulate the return of the index (Arnerich et al., 2012).

Advantages of ETFs compared to traditional open-end mutual funds include; intraday trading and immediate liquidity, ability to short sell ETF shares in order to benefit from potential decreases in the prices, tax efficiency, transparency and low transaction fees (Arnerich et al., 2012).

2.2. How ETFs are traded in Australia

In Australia, ETFs are quoted under the ASX Listing Rules or the AQUA rules. ASX created the AQUA market to specifically manage the admission of ETF securities, managed fund products and structured products on the ASX market, and to provide access to clearing and settlement services. In addition, ETF securities are also traded through the exchange market operated by Chi-X (ASIC, 2012).

According to ASX AQUA rules, ETF issuers are required to publicly disclose the fund's NAV on a daily basis (typically in the morning before trading commences). The ETF issuers are also under an obligation to disclose to the market any information that would suggest a false market exists in the AQUA products. Nearly all ETF issuers produce an intraday net asset value for their fund and the index it tracks, which is updated every 15 seconds during trading hours (ASIC, 2012).

2.3. ASX and CHI-X Market Structure

The Australian Securities Exchange is Australia's largest securities exchange market. With a total market capitalization of approx. $1.5 trillion, ASX is one of the world's largest financial securities exchanges, offering a full suite of services, including listings, trading, clearing and settlement, across a range of asset classes including cash equities, futures and derivatives. Normal trading takes place from 10:00 am to 4:00 pm, Sydney time whereby brokers enter orders into the ASX trading system. The system automatically matches all trades in price/time

priority on a continuous basis. The ASX conducts an opening and closing auction process, but the vast majority of trades take place during normal trading hours (ASX, 2015).

Chi-X Australia, an alternative-trading venue for ASX listed securities was introduced in 2011. On May 3, 2013, Chi-X expanded trading to encompass the entire universe of ASX listed securities. No opening or closing auction occurs on Chi-X, with order entry only possible from 10:00am (Aitken et al., 2013).

3. Data Summary

To investigate the profitability of the pairs trading in the Australian ETF market, we obtained historical data from Australian Equities database, which is provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA).

The data for our study is categorized into two groups: the first dataset is used to estimate the correlation coefficients, cointegration test and the error correction model (ECM). The second dataset is used to back test our pairs trading strategies during the trading period.

To create our first dataset, we obtained 1-minute interval historical quotes data for the 11 broad-based ETFs listed on the ASX for the period between January 1, 2012 and September 30, 2015. The quotes data include the open, high, low, close, date and timestamp in milliseconds. Quotes prior to 10:00am and after 4:00pm are removed from our dataset. We further eliminated all anomalous data possibly caused by human and system errors, such as quotes with negative spreads. The resulting dataset consists of approximately 3.03 million records.

To create our second dataset for back testing, we obtained tick-by-tick historical quotes data for the 11 ETFs for the period between January 1, 2013 and September 30, 2015. The quotes data include the bid price, ask price, bid size, ask size, date and timestamp in milliseconds. Quotes prior to 10:00am and after 4:00pm are removed from our dataset. We also eliminated all anomalous data possibly caused by human and system errors, such as quotes with negative spreads. The resulting dataset consists of approximately 14.87 million records.

The transaction costs pricing scheme used in our trading strategies are obtained from Interactive Brokers (IB)[2]. IB offers a fixed rate-pricing scheme for the Australian market, which is set at 0.08% of trade value with a minimum transaction cost of $6.00 per trade. The average daily short selling cost is approximately 0.025% for each of the ETFs.

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[2] Visit www.interactivebrokers.com for details

4. Methodology

This section introduces the concepts of stationarity, correlation, cointegration and the error correction model and outlines the details of how these concepts are used in selecting the pairs of ETFs for our trading strategy.

4.1. Stationarity

The concept of stationarity is important for pairs trading using the cointegration method. A stationary time series is defined as a stochastic process in which the mean and variance of the process do not change over time. A stationary time series y_t is characterized by the following properties for all time t and t-s.

$$E(y_t) = E(y_{t-s}) = \mu \tag{1}$$

$$E[(y_t - \mu)^2] = E[(y_{t-s} - \mu)^2] = \sigma^2 \tag{2}$$

$$E[(y_t - \mu)(y_{t-s} - \mu)] = E[(y_{t-s} - \mu)(y_{t-s-1} - \mu)] = \lambda \tag{3}$$

where $\mu, \sigma^2 \ and \ \lambda$ are all constants. The equations imply that a stationary series has a constant mean, variance and auto correlation (Enders 2010).

Property (2) is regarded as the most important property for pairs trading. If there is a spread between two assets, property (2) ensures the reversion to mean of the spreads. Property (3) is perhaps of lesser importance for pairs trading, although a changing variance may affect profit potential through the magnitude of the oscillations about the mean (Hoel, 2013).

Most non-stationary time series can be transformed into a stationary series using differencing, so that the values represent changes and not levels. A time series that becomes stationary after d number of differencing is referred to as integrated of order d, i.e. I(d).

One popular test for determining whether a time series is stationary is the Augmented Dickey-Fuller test (ADF-test). The ADF-test uses regression analysis to test for a unit root, i.e. non-stationarity in an assumed underlying data generating process.

Consider the following p order Autoregressive process AR(p) in equation (4):

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_1 y_{t-2} + \cdots + \alpha_p y_{t-p} + \emptyset t + \epsilon_t \tag{4}$$

Equation (4) can be rewritten as:

$$\Delta y_t = \alpha_0 + \lambda y_{t-1} + \sum_{i=2}^{p} \beta_i y_{t-i+1} + \emptyset t + \epsilon_t \tag{5}$$

where $\qquad \lambda = -(1 - \sum_{i=1}^{p} \alpha_i)$ and $\beta = -\sum_{j=i}^{p} \alpha_j$

Equation (5) is employed in the Augmented Dickey-Fuller test (ADF-test), where α_0 and $\emptyset$ are the constant and trend terms respectively. The constant and trend term can be set equal to zero depending on the assumptions behind the data generating process. We therefore test the following hypothesis:

$$H0: \lambda = 0, \text{ which implies the series is non-stationary} \tag{6}$$

$$H1: \lambda < 0, \text{ which implies the series is stationary} \tag{7}$$

According to Ng and Perron (1995), an important practical issue for the implementation of the ADF test is the specification of the lag length p. If p is too small then the remaining serial correlation in the errors will bias the test. If p is too large then the power of the test will suffer. They suggest the following data dependent lag length selection procedure that results in stable size of the test and minimal power loss. The steps are described below:

First, set an upper bound p_{max} for p. Next, estimate the ADF test regression with $p = p_{max}$. If the absolute value of the t-statistic for testing the significance of the last lagged price deviation is greater than 1.6 then set $p = p_{max}$ and perform the unit root test. Otherwise, reduce the lag length by one and repeat the process. A useful rule of thumb for determining p_{max}, suggested by Schwert (1989) is given by equation (3) where T is the sample size.

$$P \max = [12.(\frac{T}{100})^{1/4}] \tag{8}$$

4.2. Correlation

Correlation is a statistical term that describes the strength of a relationship between two variables. The correlation coefficient ρ between asset X and asset Y is calculated as follows:

$$\rho = \frac{\sum_{i=1}^{T}(X_i - \bar{X}) - (Y_i - \bar{Y})}{\sum_{i=1}^{T}(X_i - \bar{X})^2 \ \sum_{i=1}^{T}(Y_i - \bar{Y})^2} \tag{9}$$

where $\bar{X}$ and $\bar{Y}$ are the mean prices of asset X and Y respectively. The mean is calculated as:

$$\bar{X} = \frac{1}{T} \sum_{i=1}^{i=T} X_i \tag{10}$$

$$\bar{Y} = \frac{1}{T} \sum_{i=1}^{i=T} Y_i \tag{11}$$

where T is the number of periods and the value of ρ ranges between -1 and 1.

4.3. Cointegration

Economic theory often suggests that certain variables are linked by a long-run equilibrium relationship. Although the variables under consideration may drift away from equilibrium for a while, market forces may be expected to restore equilibrium.

Engle and Granger (1991) defines the concept of cointegration as follows: If two time-series x_t and y_t are integrated of order one I(1), then if there is a linear combination of the two series that is stationary, then the two series are said to be cointegrated. This implies that the two non-stationary series share a common stochastic trend.

To estimate the parameters of the cointegration equation, we consider a simple time series regression equation:

$$y_t = \alpha x_t + u_t \tag{12}$$

where x_t is an I(1) variable given by

$$x_t = x_{t-1} + \epsilon_t \tag{13}$$

Since x_t is I(1), it follows that y_t is I(1). But for x_t and y_t to be cointegrated, their linear combination $u_t = y_t - \alpha x_t$ must be stationary under the following assumptions:

Assumption 1 u_t is an iid[3] process with zero mean and variance σ_u^2

Assumption 2 $\in_t$ is stationary and independently distributed of u_t

Assumption 1 ensures that there exists a stationary cointegrating relationship between y_t and x_t and assumption 2 implies that x_t is exogenous.

One of the most popular tests for cointegration is the 2-step Engle-Granger (1987) test. There are two main issues attributed to the 2-step Engle-Granger procedure. Firstly, the cointegration results are sensitive to the ordering of variables; therefore the residuals may have different sets of statistical properties. Secondly, if the bivariate series is not cointegrated, the end result may turn out to be a set of spurious regressions.

Therefore this study employs the alternative test for cointegration using the Johansen's (1991) cointegration technique. The Johansen technique for cointegration can be described within the context of an error correction model as follows:

In a bivariate model, where x_t and y_t are both non-stationary variables in their levels, and suppose there exist an α_1 such that $y_t - \alpha_1 x_t - \alpha_0$ is a stationary process, this implies that the two variables are cointegrated or have a stationary long-run equilibrium relationship even though individually they are stochastic.

Consider a vector autoregressive model (VAR) with p lags, which can be represented with the following equation:

$$y_t = a_0 + \delta_1 y_{t-1} + \delta_2 y_{t-2} + \cdots + \delta_p y_{t-p} + \varepsilon_t \tag{14}$$

$$x_t = c_0 + \gamma_1 x_{t-1} + \gamma_2 x_{t-2} + \cdots + \gamma_p x_{t-p} + v_t \tag{15}$$

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[3] iid: Independent and identically distributed

where

a_0 and c_0 are the constants (intercepts) term

δ_i (i=1..p) and γ_i (i=1..p) are the coefficients of the AR term

ε_t and v_t are the error terms

and the error term satisfies the following conditions:

$E(\varepsilon_t) = 0$ and $E(v_t) = 0$, error term has zero mean

$E(\varepsilon_t \varepsilon_t') = \Omega$ and $E(v_t v_t') = \Omega$ are the covariance matrix

$E(\varepsilon_t \varepsilon_{t-1}') = 0$, and $E(v_t v_{t-1}') = 0$ implies no serial correlation

Given that the variables are cointegrated, equation (14) and (15) can be written as an Error Correction model (ECM) as shown below:

$$\Delta y_t = \beta_{y0} + \lambda_y(y_t - \alpha_0 - \alpha_1 x_t) + \sum_{i=1}^{i=p-1} \beta_{y1i}\Delta y_{t-i} + \sum_{i=1}^{i=p-1} \beta_{y2i}\Delta x_{t-i} + v_t \qquad (16)$$

$$\Delta x_t = \beta_{x0} + \lambda_x(y_t - \alpha_0 - \alpha_1 x_t) + \sum_{i=1}^{i=p-1} \beta_{x1i}\Delta y_{t-i} + \sum_{i=1}^{i=p-1} \beta_{x2i}\Delta x_{t-i} + w_t \qquad (17)$$

where

λ_y and λ_x are the adjustment coefficients or error correction terms

α_1 is the long-run cointegrating coefficient

$\beta_{y1i}, \beta_{y2i}, \beta_{x1i}$ and β_{x2i} (i=1...p-1) measures the short-run dynamics

The cointegration vector have reduced rank r, where r < 2 and r is the number of cointegrating relationships. The identification of the cointegrating vector uses the maximum likelihood estimation method developed by Johansen (1991).

Johansen (1991) proposed two likelihood ratio tests for the identification of the cointegrating relationship, these are the trace test and the maximum eigenvalue test, shown in (18) and (19):

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln(1 + \rho_i) \qquad (18)$$

$$J_{Max} = -T \ln(1 - \rho_{r+1}) \qquad (19)$$

where T is the sample size and ρ_i is the ith largest canonical correlation. The trace test evaluates the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating

vectors. The maximum eigenvalue test evaluates the null hypothesis of r cointegrating vectors against the alternative hypothesis of r+1 cointegrating vectors. In other words, the test begins from *r=0* where there is no cointegration amongst the variables and accepts the first null hypothesis that is not rejected.

The number of lags for the VAR is selected using the Schwarz's Bayesian information criterion (SBIC). Johansen and Juselus (1990) provide critical values for the test statistics, which are obtained from simulation studies.

The spread for the pairs trading strategy is defined as the residuals from the cointegration equation:

$$spread_t = y_t - \alpha_0 - \alpha_1 x_t \qquad (20)$$

where α_1 is the cointegrating coefficient and α_0 is a constant/intercept term.

We subsequently define the standardize spread (z-score) as follows:

$$z_t = \frac{spread_t - \mu}{\sigma} \qquad (21)$$

where

$$\mu = \frac{1}{T} \sum_{t=1}^{t=T} spread_t \qquad (22)$$

$$\sigma = [\frac{1}{T-1} \sum_{t=1}^{t=T} (spread_t - \mu)^2]^{1/2} \qquad (23)$$

and T is the sample size.

4.4. Error Correction Model

The fact that the ETF pairs are cointegrated implies that there is a common stochastic trend binding together the ETF pairs. Therefore the spreads can be considered short-term movements away from the long-run relationship.

In order to explore the intraday short-term dynamics between the ETF pairs, we estimate the ECM in equation (16) and (17). We are particularly interested in the adjustment coefficients or

the error correction coefficients (λ_y and λ_x) from the ECM equation. The adjustment coefficients provide us with the rate of correction of the spreads back to the long run equilibrium.

The coefficient λ_y and λ_x represents the amount of correction of the prior period (t − 1) disequilibrium that happens in period t. For example, if λ_y is − 0.10, then 10% of the disequilibrium in the prior period would tend (all else equal) be reversed in period t. A higher adjustment coefficient implies a faster rate of mean-reversion.

Since the success of pairs trading depends on the rate of mean-reversion, we therefore incorporate the error correction coefficient as part of our ETF pairs selection procedure.

5. Pairs Formation Period

5.1. 3–Step Selection Process

We employ a 3-step pairs selection process during the formation period. In Step 1, we estimate the correlation coefficients for the pairs of ETFs and select the pairs with correlation greater than or equal to 90%.

In Step 2, we test for cointegration between the remaining pairs using the Johansen (1991) technique. We further eliminate the pairs that fail both the Johansen Trace Test and Maximum Eigen value test for cointegration.

In Step 3, we estimate the ECM in order to obtain the error correction coefficients for the pairs. The remaining pairs are ranked in ascending order of the error correction coefficient and we select the top highly ranked pairs for the subsequent trading period.

In this study, our pairs formation period commences from January 1, 2012 to December 31, 2012. We start by forming pairs of ETFs from the 11 broad-based ETFs listed on the ASX. We select the 9 ETFs with an inception date prior to January 1, 2012. The selected ETFs are listed in Table 1 with brief product details.

Table 1: ETF Details

ETF Name	ASX Code	Benchmark	MER (%)	Inception
iShares MSCI Australia 200 ETF	IOZ	MSCI Australia 200	0.19	Dec-10
iShares S&P/ASX 20 ETF	ILC	S&P/ASX 20	0.24	Dec-10
iShares S&P/ASX Small Ordinaries ETF	ISO	S&P/ASX Small	0.55	Dec-10
SPDR 200 Fund	STW	S&P/ASX 200	0.28	Aug-01
SPDR 50 Fund	SFY	S&P/ASX 50	0.28	Aug-01
SPDR S&P/ASX Small Ordinaries Fund	SSO	S&P/ASX Small	0.50	Apr-11
Vanguard Australian Shares Index	VAS	S&P/ASX 300	0.15	May-09
Vanguard MSCI Australian Large	VLC	MSCI Large Cap Index	0.20	May-11
Vanguard MSCI Australian Small	VSO	MSCI Small Cap Index	0.30	May-11

Given the importance of stationarity assumption in our models, we proceed to test whether the ETFs are stationary using the Augmented Dickey Fuller (ADF) test.

5.2.   Stationarity Test

We test the selected ETFs for stationarity using the Augmented Dickey Fuller (ADF) test. We perform the ADF test using the 1-minute interval historical data between January 1, 2012 and December 31, 2012. This is the 252-day in-sample formation period for the pairs selection process.

Based on Ng and Perron (1995) lag selection procedure, we estimate the maximum number of lags using equation (8), where $N = 246,026$. We test for unit root using a lag of 85 periods. The results of the ADF test are listed in Table 2. The results show that the ETF prices are non-stationary in levels but stationary in first differences at the 1% level of significance.

Table 2: Augmented Dickey Fuller Test

ETF	Lags	Price Series		First Difference	
		T-Statistics	1% Crit. Value	T-Stats	1% Crit. Value
IOZ	85	-1.7729	-3.1277	-59.4671***	-3.1277
ILC	85	-1.7950	-3.1277	-55.9804***	-3.1277
ISO	85	-2.4141	-3.1277	-55.1522***	-3.1277
STW	85	-2.2968	-3.1277	-52.6688***	-3.1277
SFY	85	-2.1639	-3.1277	-54.0048***	-3.1277
SSO	85	-2.4395	-3.1277	-53.8054***	-3.1277
VAS	85	-2.2281	-3.1277	-53.4629***	-3.1277
VLC	85	-1.7787	-3.1277	-54.1774***	-3.1277
VSO	85	-2.5678	-3.1277	-53.6127***	-3.1277

*** Indicates the rejection of the null hypothesis of unit root at the 1% level of significance.

We therefore proceed to form the list of potential pairs of ETFs. The number of potential pairs is given by the following equation:

$$P = \frac{N!}{2!\,(N-2)!} \qquad (24)$$

where N is the number of the remaining ETFs. Given that N = 9, the number of potential pairs for our selection process is 36. We now proceed to estimate the correlation coefficients between the pairs.

5.3.   Step 1: Correlation

The first step in our 3-step pairs selection process is to select from the list of 36 available pairs, the pairs with correlation coefficient greater than or equal to 90%. The process results in a list of 16 ETF pairs, which are presented in Table 3.

Table 3: Correlation Coefficients

ETF Pairs	Correlation	ETF Pairs	Correlation
ILC-VLC	0.9973866	SFY-VAS	0.9885885
IOZ-VAS	0.9967398	VAS-VLC	0.9884803
ILC-SFY	0.9938031	ILC-VAS	0.9882902
SFY-VLC	0.9923301	IOZ-STW	0.9876779
STW-VAS	0.9904406	STW-SFY	0.9843019
IOZ-ILC	0.9898337	ISO-SSO	0.9832574
IOZ-VLC	0.9888663	STW-VLC	0.9820718
IOZ-SFY	0.9886190	STW-ILC	0.9807842

There are stability issues with pairs trading strategies based on correlation. Correlation coefficients do not necessarily imply mean-reversion between the prices of the two ETFs. This is because the correlation approach is sensitive to minor deviations (Lin et al., 2006), especially in high frequency trading. As in Maio (2014), in order to overcome these issues, a cointegration approach is used as the second-stage of the selection process.

5.4. Step 2: Cointegration

In step 2 we apply the cointegration test to the pairs selection process. Following Maio (2014), we test the 16 selected ETF pairs for cointegration, but we differ from Maio (2014) by using the Johansen cointegration technique. We estimate the Trace test statistics and the Maximum Eigenvalue test statistic for each selected pairs. The estimated test statistics for each pair are compared to the Johansen critical values at the 1% level of significance. The results of the cointegration test are presented in Table 4.

Table 4: Johansen Cointegration Test

ETF Pairs	Ranking	Trace Test Rank = 0	Trace Test Rank = 1	Max Eigen Value Rank = 0	Max Eigen Value Rank = 1
ILC-VLC	1	579.1743***	3.5858---	575.5885***	3.5858---
ISO-SSO	2	552.4473***	2.8794---	549.5679***	2.8794---
ILC-SFY	3	481.4052***	3.6833---	477.7218***	3.6833---
IOZ-VAS	4	376.1177***	3.7454---	372.3723***	3.7454---
SFY-VLC	5	342.5929***	3.6762---	338.9167***	3.6762---
STW-VAS	6	323.1521***	3.8743---	319.2778***	3.8743---
IOZ-ILC	7	307.7347***	3.7341---	304.0006***	3.7341---
IOZ-STW	8	268.3911***	3.9326---	264.4586***	3.9326---
ILC-VAS	9	265.6154***	3.7819---	261.8336***	3.7819---
VAS-VLC	10	262.6676***	3.8013---	258.8663***	3.8013---
IOZ-SFY	11	259.3849***	3.9973---	255.3875***	3.9973---
SFY-VAS	12	258.3328***	4.0355---	254.2973***	4.0355---
IOZ-VLC	13	256.4861***	3.7044---	252.7817***	3.7044---
STW-SFY	14	180.9548***	4.0420---	176.9129***	4.0420---
STW-VLC	15	150.6952***	3.7218---	146.9734***	3.7218---
STW-ILC	16	144.7155***	3.6770---	141.0385***	3.6770---

--- Indicates we fail to reject the null hypothesis of one cointegration at the 1% level of significance

*** Indicates the rejection of the null hypothesis of zero cointegration at the 1% level of significance

The maximum number of lags for the VAR are selected based on the SBIC

We test the null hypothesis of no cointegration at the 1% level of significance and reject the null hypothesis if the test statistics is greater than the critical value. Furthermore we also test the null hypothesis of one cointegrating equation at the 1% level of significance and reject the null

hypothesis if the test statistics is greater than the critical value. The result of the cointegration test implies that all 16 ETF pairs are cointegrated.

5.5.   Step 3: Error Correction Model

In step 3, we estimate the error correction model for each of the 16 remaining ETF pairs and select the pairs with statistically significant error correction coefficients at the 1% level of significance. We rank the pairs in ascending order of the error correction coefficient and select the top five highly ranked ETF pairs from the list of 16 ETF pairs. The results from the ECM are presented in Table 5.

Table 5: Error Correction Model

ETF Pairs	Long-Run Equation		Short-Run Equation	
	Constant	Beta	Error Correction Coeff.	Ranking
ISO_SSO	0.1661356	-0.3550208***	-0.0042001***	1
IOZ_VAS	0.1357624	-0.3413781***	-0.0040130***	2
IOZ_STW	-0.079756	-0.4585560***	-0.0029489***	3
STW_VAS	0.3295752	-0.7422068***	-0.0002301***	4
STW_SFY	3.041014	-1.0039670***	-0.0000405***	5

*** Indicates 1% level of significance

Therefore the remaining 5 ETF pairs have a correlation coefficient greater than 90% and satisfy both the Johansen Trace test and Maximum Eigenvalue test at the 1% level of significance. The cointegrating coefficients and the error correction coefficients are statistically significant at the 1% level of significance.

We now proceed to the trading period, where we specify the rules and conditions for trade signal generation.

6. Pairs Trading Period

6.1. Daily Rolling Window

In order to implement our trading strategies, we re-estimate the cointegrating vectors on a daily basis using a rolling window of historical data. Figure 1 depicts the rolling window used in estimating the daily cointegrating vectors. We define a 252-day rolling window using a 1-minute interval data for the parameter estimation. The cointegrating vectors are re-estimated daily at 7:00am prior to the opening of the trading session from January 1, 2013 to September 30, 2015

Figure 1: Daily 252-Day Rolling Window
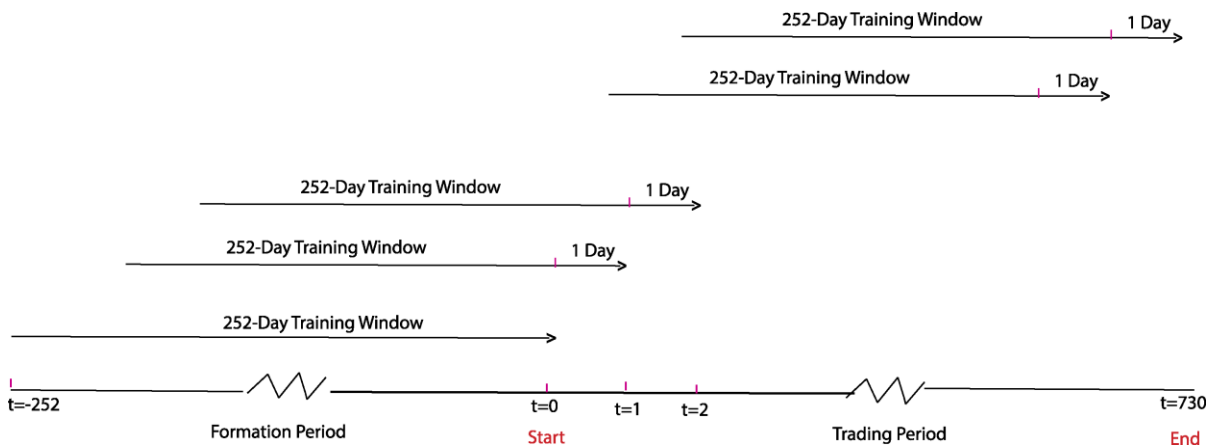
6.2. Trading Rules

One of the most important aspects of the pairs trading strategy is the specification of the trading rules. In this study, the primary criteria for position entries are the z-score, the quoted bid-ask spread, transaction cost and the profit potential. Similarly, the criteria for position exits are the z-score, the quoted bid-ask spread, transaction cost, profit threshold, trade duration and the stop-loss threshold.

The flow chart for the pairs trading strategy is shown in Figure 2. Detail description of the strategy is presented below:

Figure 2: Flow Chart For Pairs Trading Strategy
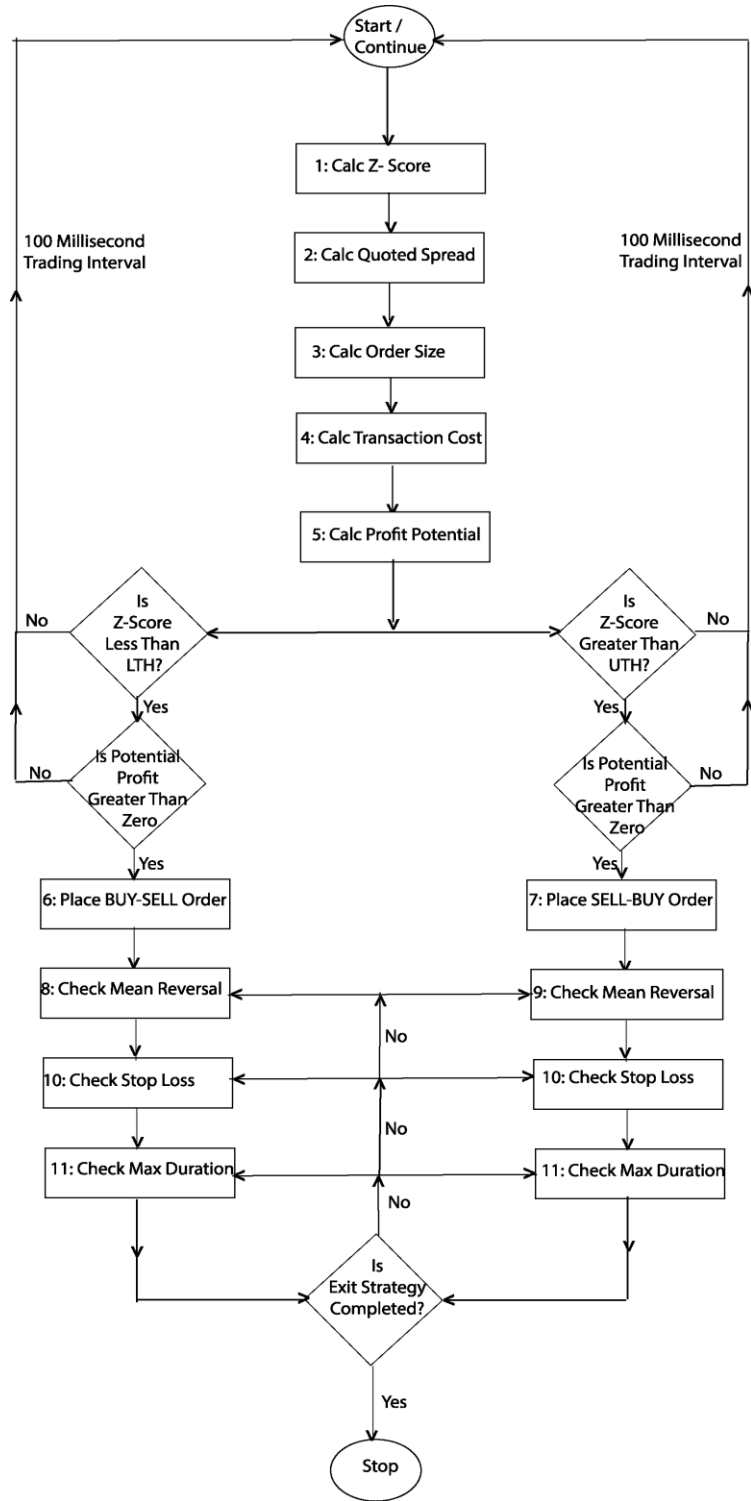
1. We estimate the z-score using the most recent cointegrating vectors estimated for that particular day at 7am.

2. We calculate the real-time quoted bid-ask spread in order to account for market liquidity. The bid-ask spread is used in estimating the potential profit in step (5).

3. We calculate the order size using the cointegrating coefficient. The number of shares of asset A is N, where N is the default order size specified by the trader. The number of shares of asset B is $\beta * N$ where β is the cointegrating coefficient.

4. We calculate the transaction cost and short selling cost based on Interactive Brokers fees schedule and the trade order size estimated in step 3 above.

5. As in Gundersen (2014), we protect the strategy from entering a trade that may result in an immediate loss due to excessive transaction cost and bid-ask spread. We therefore calculate the potential profit using equation (26).

6. If the potential profit is greater than zero and the z-score is greater than or equal to the upper-threshold (UTH) specified by the trader, the system will sell N number of shares of asset A and buys *Beta * N* number of shares of asset B. This position is referred to as a BUY-SELL position.

7. Likewise If the potential profit is greater than zero and the z-score is less than or equal to the lower-threshold (LTH), the system will buy N number of shares of asset A and sells *Beta * N* number of shares of asset B. This position is referred to as a SELL-BUY position.

8. For an existing BUY-SELL position, if the z-score is greater than or equal to zero and the calculated profit is greater than or equal to the profit threshold, the system will enter a SELL-BUY trade to closeout the position.

9. Likewise for an existing SELL-BUY position, if the z-score is less than or equal to zero and the calculated profit is greater than or equal to the profit threshold, the system will enter a BUY-SELL trade to closeout the position.

10. As in Caldeira and Moura (2013) and Maio (2014), a stop-loss is used to close out the position whenever the loss from the strategy is greater than a specified loss threshold, otherwise the system will continue to monitor the active position.

11. The system calculates the duration since trade entry and checks whether the duration is greater than the max duration threshold set by the trader. If the duration is greater than or equal to the

max duration threshold, the system will enter reverse orders to closeout the open positions, otherwise the system will continue to monitor the active position.

6.3.   Pairs Trading Implementation

6.3.1.   Time Varying Cointegrating Coefficients

Figure 3 shows the time varying cointegrating coefficients for the selected ETF pairs between January 1, 2013 and September 30, 2015. The charts highlight the importance of the daily re-calibration of the coefficients and reflect the dynamic changes in the long-run relationship between the ETF pairs.

Figure 3: Time Varying Cointegrating Coefficients
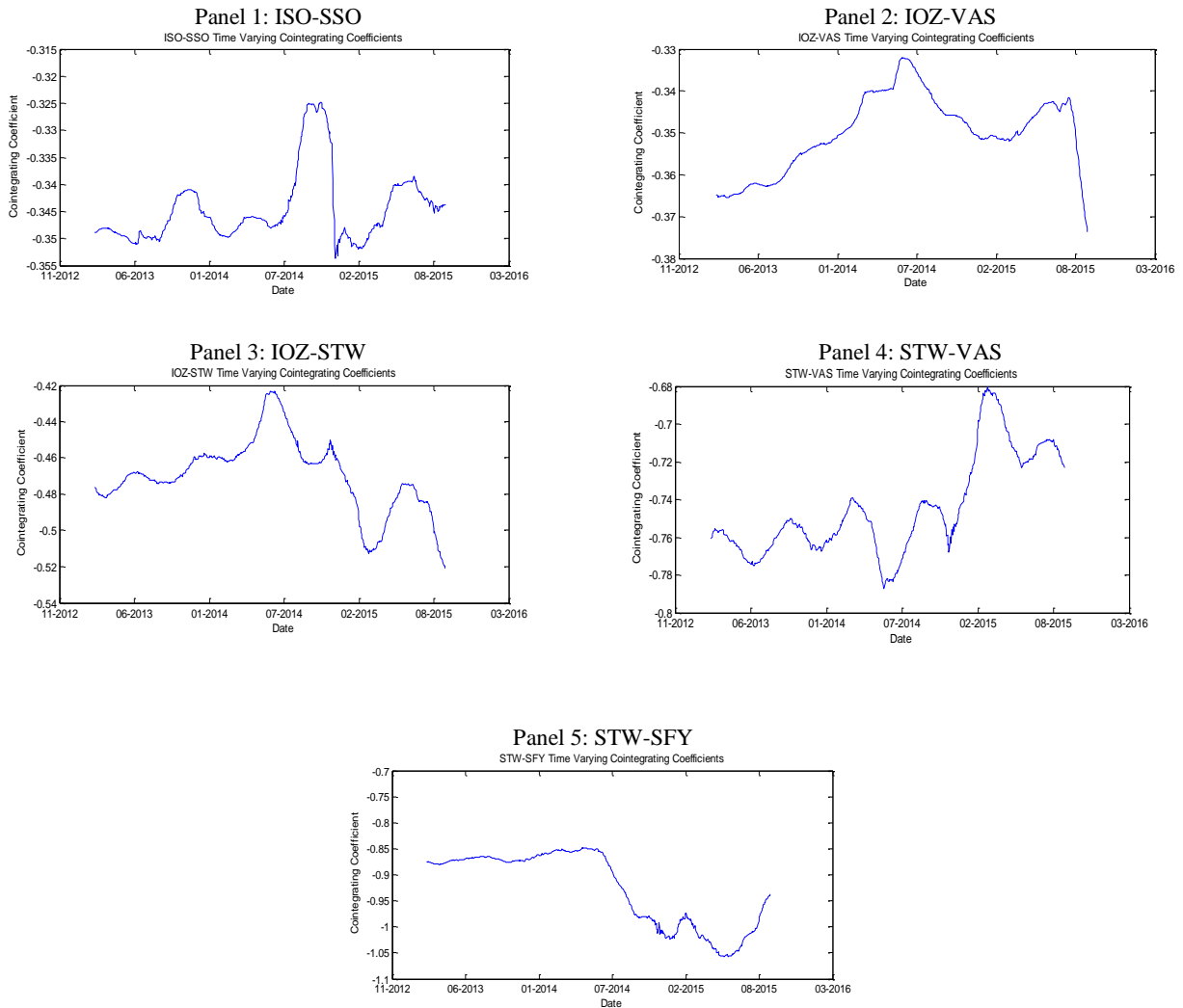
6.3.2. Cointegrated Price & Spread Series

Figures 4-8 depict the evolution of the ETF prices and the spread between January 1, 2013 and September 30, 2015. The charts confirm that the ETF pairs do indeed move together with temporary price deviations. We also present the summary statistics for the spread in Table 6.

The spread series for ISO-SSO ranges from a minimum of -0.4786 to a maximum of 0.2943 and the mean of the spread is -0.0523 with a standard deviation of 0.073.

Figure 4: ISO-SSO Cointegrating Price & Spread Series
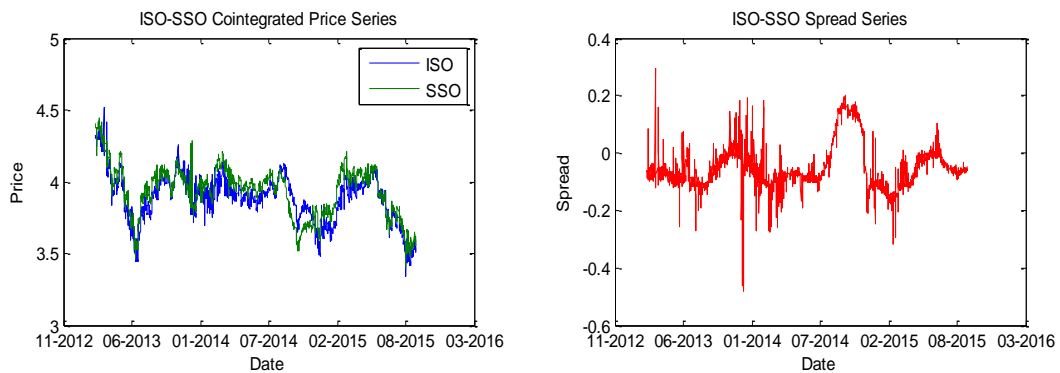
The spread series for IOZ-VAS ranges from a minimum of -2.8846 to a maximum of 4.4884 and the mean of the spread is -0.7324 with a standard deviation of 0.619.

Figure 5: IOZ-VAS Cointegrating Price & Spread Series
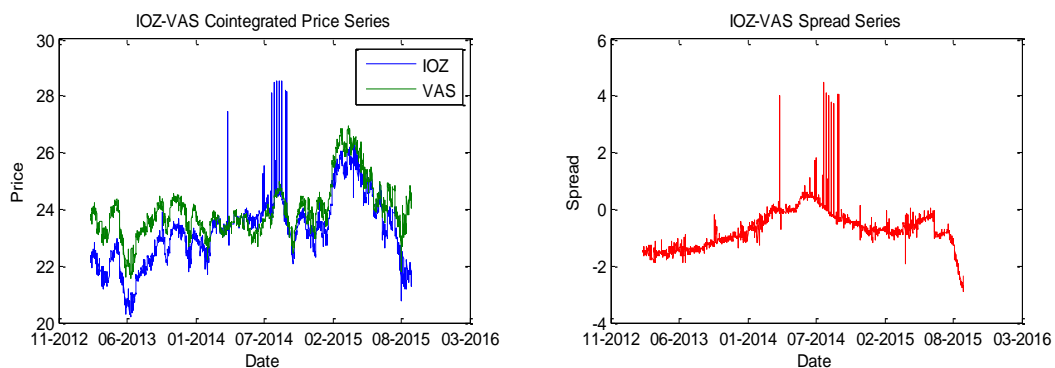
Similarly, the spread series for IOZ-STW has a mean of -0.4994 and a standard deviation of 1.0943. The series ranges from a minimum of -3.6453 to a maximum of 5.441.
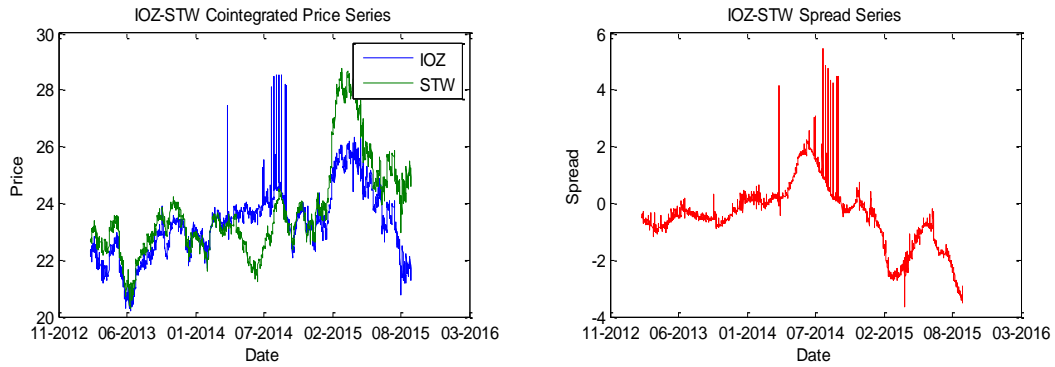
The spread series for STW-VAS ranges from a minimum of -4.0247 to a maximum of 4.148. The mean of the spread is -0.4045 with a standard deviation of 1.7926.

Figure 7: STW-VAS Cointegrating Price & Spread Series
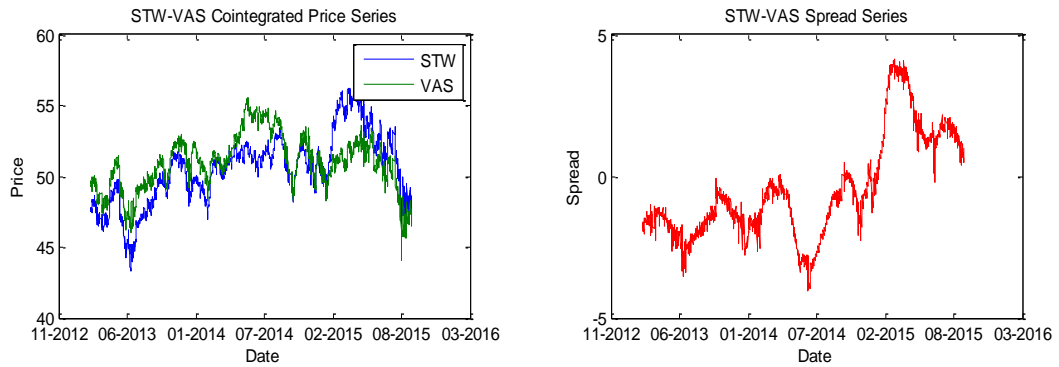
And finally, the spread series for STW-SFY ranges from a minimum of -6.9865 to a maximum of 7.2103. The mean of the spread is 0.9720 with a standard deviation of 3.4249.

Figure 8: STW-SFY Cointegrating Price & Spread Series
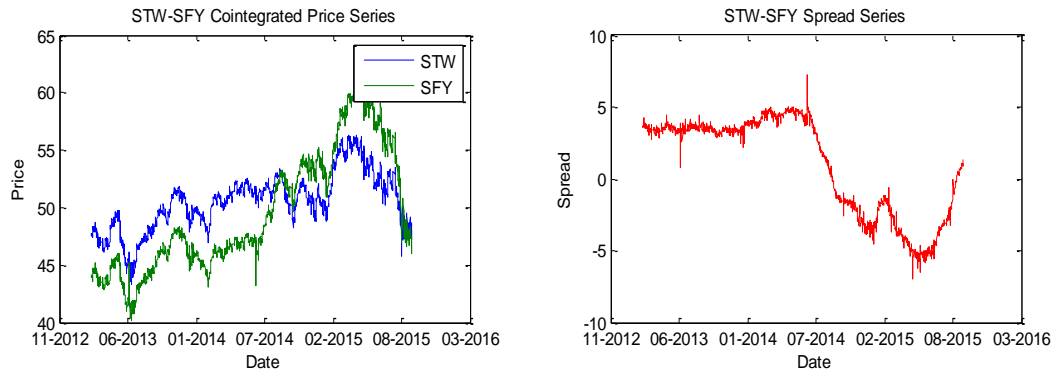
Table 6: Spread Summary Statistics

	Min	Max	Mean	Std. Dev	Skewness	Kurtosis
ISO-SSO	-0.4786	0.2943	-0.0523	0.073	1.5564	5.1126
IOZ-VAS	-2.8846	4.4884	-0.7324	0.619	-0.1071	3.404
IOZ-STW	-3.6453	5.441	-0.4994	1.0943	-0.1799	3.3056
STW-VAS	-4.0247	4.148	-0.4045	1.7926	0.7748	2.8381
STW-SFY	-6.9865	7.2103	0.9720	3.4249	-0.5318	1.6668

7. Real Time Trading System

7.1. Trading System Design

The trading system was developed using the Java programing language. The system features both back testing and live-paper trading capability. The trading system uses Kdb+ in memory database[4] for storage of real time quotes and historical data. Kdb+ is a high-performance database with built-in query and programming language that supports real-time analysis of billions of records and fast access to terabytes of historical data.

A diagram of the various components of the trading system is shown in Figure 9.

Figure 9: Trading System Components

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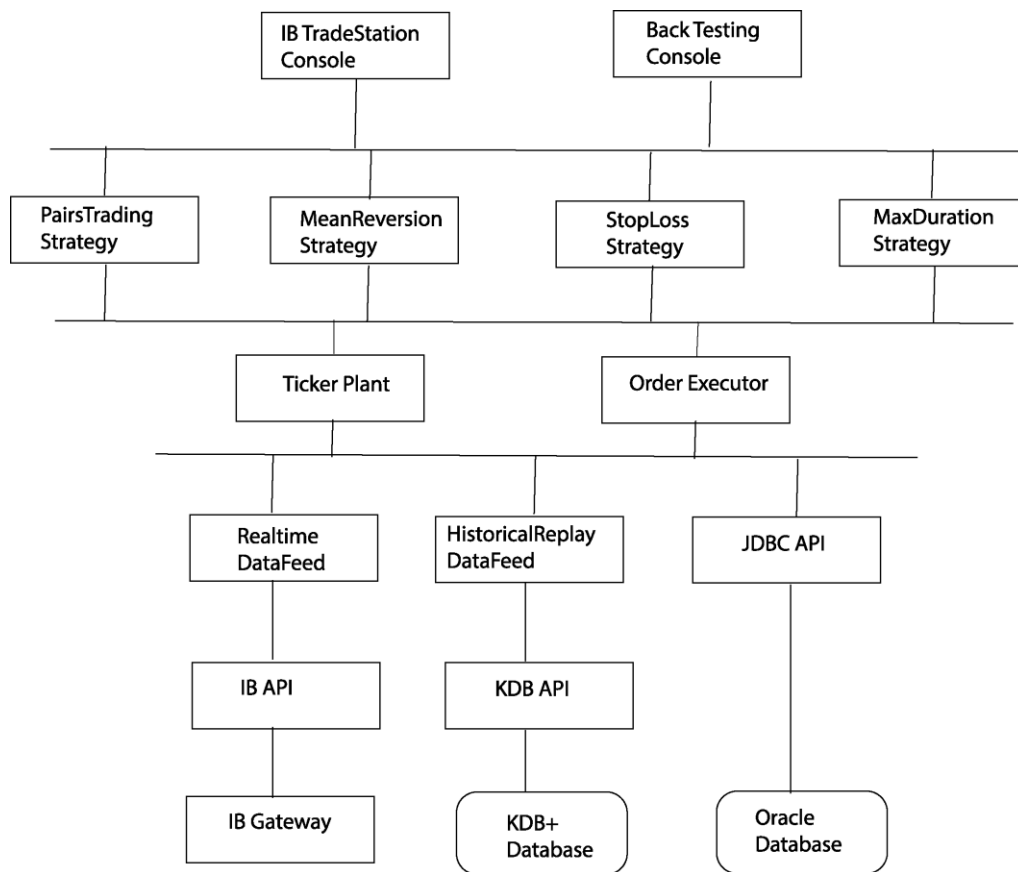
[4] Refer to www.kx.com for details

- The PairsTrading component implements the pairs trading rules outlined in Section 7.2 (1). The MeanReversion component implements the mean-reversal rules outlined in Section 7.2 (8-9) and the StopLoss component implements the real-time risk management rules outlined in Section 7.2 (10). The MaxDuration component implements the maximum duration rules outlined in Section 7.2 (11).

- The TickerPlant provides the strategies with both real-time and historical data feed via the Realtime DataFeed and the HistoricalReplay DataFeed components respectively.

- The OrderExecutor component is responsible for interfacing with external trading platform such as IB Gateway for order execution.

- The BackTesting Console provides an order management console for back testing strategies and the IB TradeStation provides real-time order management functionality.

- The Java Database Connectivity API (JDBC) provides database connectivity to the Oracle database, which stores the ETF descriptive statistics and summary information.

7.2. Trading System in Action

Screenshots of the trading system are shown below. Figure 10 shows the BackTesting Console and Figure 11 shows the Output Console for the pairs trading strategies

Figure 10: Back Testing Management Console

Figure 11: Pairs Trading Console

The trading system is launched from a command prompt by executing a separate process[5] for each ETF pairs using the configuration settings listed below:

- For back testing, the trading period commences from January 1, 2013 to September 30, 2015

- Trading frequency is 100 milliseconds

- Trading dates excludes Australian public and bank holidays

- Trading commences at 10:00am and closes at 4:00pm

- Daily mark to market (MTM) is executed at 4:00pm

- Transaction cost is 0.08% of trade value or a minimum of $6.00 per trade

- The average daily interest rate paid on short selling positions is approximately 0.07%

- Total transaction cost is approximately 0.15%.

- Trade size is 1000 shares

- Stop loss threshold is -10%

- Maximum trade duration is 50 days

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[5] In computing, a process is an instance of a computer program that is being executed. It contains the program code and its current activity. Depending on the operating system (OS), a process may be made up of multiple threads of execution that execute instructions concurrently.

8. Performance Evaluation

8.1. Performance Criteria (Individual Trades)

The following is a list of criteria used in evaluating the performance of each trade generated by the pairs trading strategies:

8.1.1. Transaction Cost

Trading of ETFs incur transaction costs and these transaction cost may impact the performance of the trading strategies. This is especially true for high frequency trading strategies, which involve many trades. Bowen et al. (2014) show more than 50% reduction in excess returns of his high frequency pairs trading strategy after a 0.15% transaction fee. Similarly Do and Faff (2012) reported that their pairs trading strategy became unprofitable after accounting for transaction costs.

Therefore to account for transaction cost, we incorporate real-time trading cost using the commission schedule provided by Interactive Brokers. The total transaction cost includes IB brokerage fees, exchange fees, regulatory fees and short selling fees. The real-time transaction costs are calculated based on the order size and the prevailing ETF quotes.

8.1.2. Quoted Spread

The simplest measure of implicit transaction cost is the quoted spread, which is defined as the difference between the bid and ask prices. The quoted spread measures the cost of completing a round trip (buy and sell) if trades are executed at the quoted prices. The quoted spread for the pairs trading is defined as:

$$Quoted\ Spread\ (QS_t) = \frac{Bid_t^A - Ask_t^A}{2} + \frac{Bid_t^B - Ask_t^B}{2} \tag{25}$$

where Bid_t^A and Ask_t^A are the posted bid and ask quotes for ETF A, Bid_t^B and Ask_t^B are the posted bid and ask quotes for ETF B at time t.

8.1.3. Potential Profit

Following Gundersen (2014), we calculate the potential profit prior to position entry using the following equation:

$$Potential\ Profit\ (PT_t) = \text{Abs}[\ P_t^A\ + \beta * P_t^B\ ] - QS_t - 4 * C_t \tag{26}$$

Where QS_t is the quoted bid-ask spread, β is cointegrating coefficient, P_t^A is the mid-quote for ETF A, P_t^B is the mid-quote for ETF B and C_t is the total transaction cost at time t.

8.1.4. Profit & Loss (P&L)

The trading profit & loss is calculated as the continuous compounding return (RD), which is defined as follows:

$$RD_t = I * [\ \ln\left(\frac{P_t^A}{P_{t-1}^A}\right) - \beta * \ln\left(\frac{P_t^B}{P_{t-1}^B}\right)\ ] + 2 * \ln\left(\frac{1-C_t}{1+C_{t-1}}\right) \tag{27}$$

where β is the cointegrating coefficient and I is an indicator variable, which is equal to +1 for a BUY-SELL trade and equal to -1 for a SELL-BUY trade. P_{t-1}^A and P_{t-1}^B are the trade entry prices at time t-1, P_t^A and P_t^B are the trade exit prices at time t, C_{t-1} is the real-time transaction cost associated with the trade entry at time t-1 and C_t is the transaction cost associated with the trade exit at time t.

8.1.5. Maximum Draw Down

The maximum drawdown is regarded as a measure of downside risk, and is calculated as the largest percentage drop in returns over a specified trading period.

8.2. Performance Criteria (Overall Strategy)

We estimate the following measures to evaluate the overall performance of the trading strategies.

8.2.1. Average & Annualized Daily Returns

The average daily returns and annualized returns are calculated as:

$$\text{Average Daily Returns } (\mu) = \frac{1}{T} \sum_{t=1}^{t=T}(RD_t) \tag{28}$$

$$\text{Annualized Returns } (A\mu) = \text{Average Daily Returns} * 252 \tag{29}$$

where RD_t is the continuous compounding returns at time t, T is the trading period and the number of trading days in a year is 252.

8.2.2. Cumulative Returns

The cumulative returns over the trading period T is calculated as:

$$\text{Cumulative Returns} = \sum_{t=1}^{t=T}(RD_t) \tag{30}$$

8.2.3. Standard Deviation

The standard deviation of returns and the annualized standard deviation are calculated as:

$$\text{StdDev } (\sigma) = SQRT[\frac{1}{T-1}\sum_{t=1}^{t=T}(RD_t - \mu)^2] \tag{31}$$

$$\text{Annualized StdDev } (A\sigma) = \text{StdDev} * SQRT (252) \tag{32}$$

8.2.4. Sharpe Ratio

The Sharpe ratio is a risk-adjusted measure of returns, which is used to determine the return per unit of risk. The Sharpe ratio is calculated as follows:

$$\text{Sharpe ratio (SR)} = \frac{A\mu - r_f}{A\sigma} \tag{33}$$

where $A\mu$ is the annualized returns, $A\sigma$ is the annualized standard deviation of returns, and r_f is the annualized risk free rate.

9. *Strategy Results*

9.1. *Back Testing Result*

The pairs trading strategies was back tested between January 1, 2013 and September 30, 2015 using a trading frequency of 100 milliseconds. The results of the strategies are presented in Table 7.

Table 7: Back Testing Result

ETF Pairs	ISO-SSO	IOZ-VAS	IOZ-STW	STW-VAS	STW-SFY
Total Trades	12	9	21	30	23
Profitable Trades	11	8	18	30	21
Losing Trades	1	1	3	0	2
Average Duration (Days)	30	42	27	13	23
Average Daily Return (%)	0.0022%	0.0013%	0.0025%	0.0055%	0.0054%
Cumulative Return (%)	10.08%	4.41%	19.70%	62.27%	46.60%
Average Daily Quoted Spread	0.09	0.15	0.08	0.20	-0.08
Standard Dev. of Returns	0.02	0.01	0.02	0.03	0.03
Sharpe Ratio	2.21	1.00	9.29	15.12	11.17
Max Draw Downs (%)	-11.76%	-32.47%	-29.65%	-4.83%	-11.68%

The risk free rate used in calculating the Sharpe ratio is 1.99%. This is the average yield to maturity of the Australian 2 Year Treasury Bond.

For the ISO-SSO pairs, the strategy generated 12 trades with a maximum draw down of -11.76% and a Sharpe ratio of 2.21. The average duration is 30 days. Figure 12 shows the cumulative returns and the profit-loss ratio chart for ISO-SSO pairs trading strategy. The chart shows that the strategy yield a cumulative return of 10.08% over the trading period with 92% profitable trades compared to 8% losing trades.

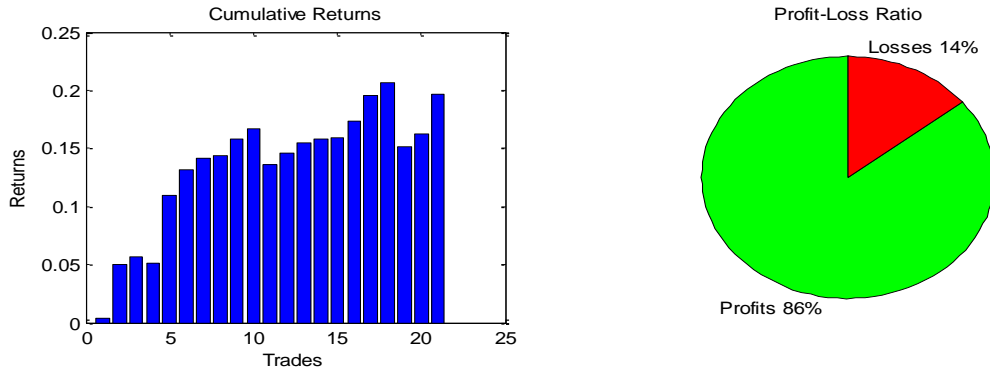**Figure 12: ISO-SSO Cumulative Returns & Profit-Loss Ratio**
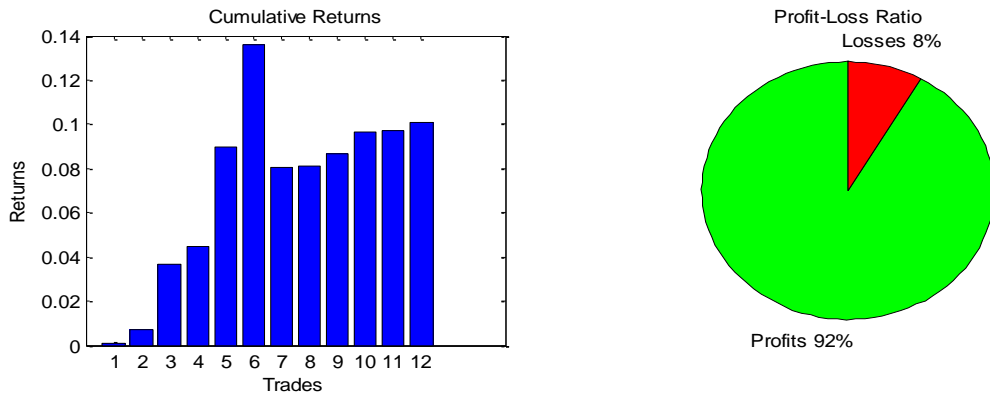
The IOZ-VAS pairs generated 9 trades with a maximum draw down of **-32.47%** and a Sharpe ratio of 1. The average duration is 42 days. Figure 13 show that the strategy yield a cumulative returns of 4.41% over the trading period, with 89% profitable trades and 11% losing trades.

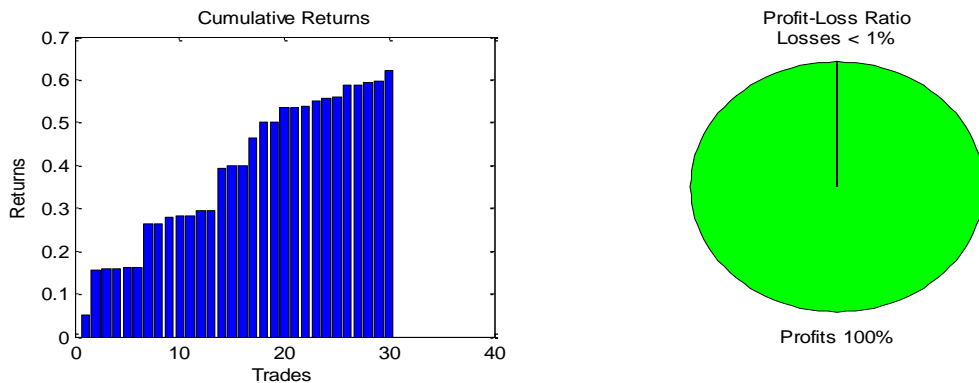**Figure 13: IOZ-VAS Cumulative Returns & Profit-Loss Ratio**
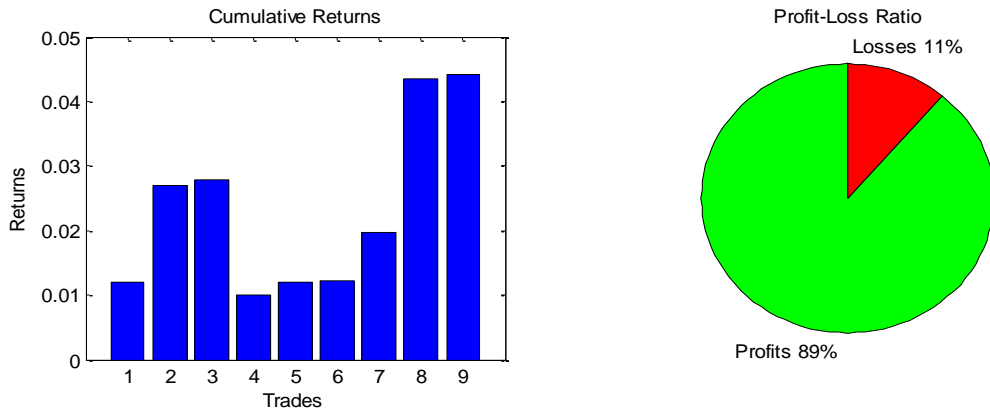
The IOZ-STW pairs generated 21 trades with a maximum draw down of -29.65% and a Sharpe ratio of 9.29. The average duration is 27 days. Figure 14 show that the strategy yield a cumulative returns of 19.70% over the trading period with 86% profitable trades and 14% losing trades.

**Figure 14: IOZ-STW Cumulative Returns & Profit-Loss Ratio**

The STW-VAS pairs generated 30 trades with a maximum draw down of -4.86% and a Sharpe ratio of 15.12. The average duration is 13 days. Figure 15 show that the strategy yield a cumulative returns of 62.27% over the trading period with 100% profitable trades and no losing trades.

Figure 15: STW-VAS Cumulative Returns & Profit-Loss Ratio

And finally The STW-SFY pairs generated 23 trades with a maximum draw down of -11.68% and a Sharpe ratio of 11.17. The average duration is 23 days. Figure 16 show that the strategy yield a cumulative returns of 46.60% over the trading period with 91% profitable trades and 9% losing trades.

Figure 16: STW-SFY Cumulative Returns & Profit-Loss Ratio
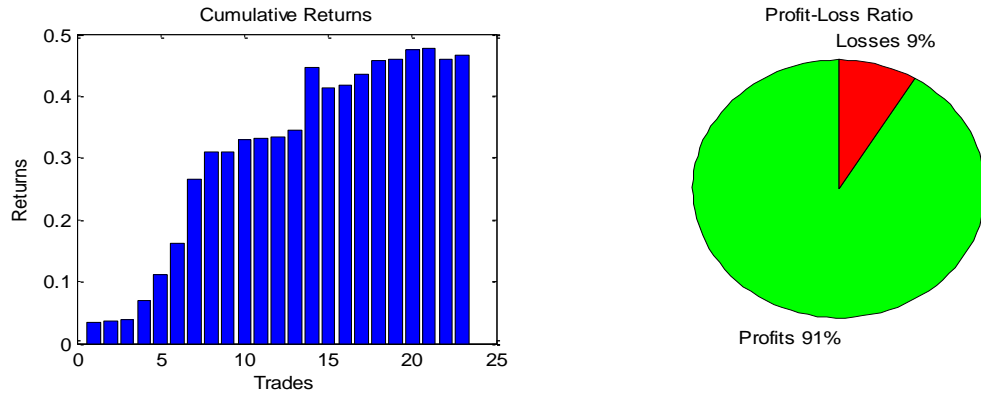
10. Conclusion

10.1. Findings

This study evaluates the profitability of dynamic pairs trading strategies using a proposed 3-step pairs selection approach. We extend the pairs trading methodology employed by Miao (2014) to the broad-based exchange traded funds (ETFs) listed on the Australian Securities Exchange (ASX).

The 3-step approach incorporates the correlation, cointegration and error correction coefficient as the pre-selection criteria during the formation period. In the subsequent trading period, we employ a daily re-calibration of the parameters using a 252-day rolling window from January 1, 2013 to September 30, 2015.

The trade entry rules are based on the standardize spreads (z-score) from the cointegrating equation, the bid-ask spread, transaction cost and profit potential. Similarly the trade exit rules are based on the z-score, bid-ask spread, transaction cost, profit threshold, stop-loss threshold and the maximum duration threshold.

We developed a real-time trading system using the Java programming language and KDB+ database and back test the strategies using tick-by-tick historical quotes during the trading period.

The back testing of the top five ETF pairs: ISO-SSO, IOZ-VAS, IOZ-STW, STW-VAS and STW-SFY yield cumulative returns of 10.08%, 4.41%, 19.70%, 62.27%, 46.60% and Sharpe ratios of 2.21, 1.00, 9.29, 15.12, 11.17 respectively. The maximum draw down is -32.47% over the trading period.

The results of the pairs trading strategies highlight the potential for profitable statistical arbitrage trading opportunities within the Australian ETF market.

10.2. Limitations of results

The results of this study are limited to the assumptions used in the design and implementation of the pairs trading strategies. The assumptions include the choice of the

formation period for the estimation of cointegration parameters, the trading period, the choice of stop loss and maximum duration threshold, and the upper and lower z-score threshold used for signal generation. Different assumptions could lead to different results and hence different conclusions.

Furthermore, the study did not incorporate the effect of dividends in our parameter estimation and trading strategies. When a stock/ETF pays dividend, this typically leads to a decrease of the stock price (Stander, 2011) and the dividend payment may affect the performance of the trading strategies.

10.3. Suggestions for future research

Further research into ETFs in the Australian market is crucial given the limited number of research on ETFs in Australia. A natural extension of this study is to examine the profitability of pairs trading strategies using international ETFs listed on the ASX within a high frequency trading environment. The research can also be extended to include commodity ETFs, currency ETFs and Fixed Income ETFs listed on the ASX.

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