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An Analysis of Feasibility for Implementing Pairs Trading Strategy in Dhaka Stock Exchange using Vector Error Correction Model

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Abstract

The objective of this study is to develop a financially profitable Pairs trading model for trading in Dhaka Stock Exchange. Pairs Trade is a statistical arbitrage investment strategy. The scope of this research is the primary stock market of Bangladesh – Dhaka Stock exchange. The study uses daily stock prices of a sample of 20 stocks listed in Dhaka Stock Exchange. The research first identifies a pair of stocks whose prices have a long-run equilibrium using Johansen's test for Co-integration. The co-integrated stock pair is then modeled using a Vector Error Correction Model. The residual obtained from the estimated model serves as the guide to implementing Pairs Trade Strategy. The research finally identifies three pairs of stocks which have general long-run equilibriums. The residual series obtained from the Vector Error Correction Model for all three pairs are statistically significant. Based on this, the study implemented the pairs trade strategy using the residual series for a period of one to two months using real time data but doing hypothetical trading. It generated more than 100% (annual) rate of return for all three stock pairs. Finally, the study also compares the return using the Pairs Trade strategy with returns using the conventional financial analysis and found that pairs trading generated a much higher annualized returns compared to investment strategies using conventional financial analysis.

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CHAPTER 1 INTRODUCTION

1. Introduction

Pairs Trading strategy is an investment trading strategy pioneered by Gerry Bamberger and quantitative analyst Nunzio Tartaglia of global investment bank, Morgan Stanley in the 1980s according to Puspaningrum (2012). They teamed up with a set of physicists, computer scientists and mathematicians in order to develop statistical rules to find ways to implement arbitrage trades and take the "skill" out of trading as identified by Evan Gatev (2006).

Pairs trade is a market neutral trading strategy that gives traders opportunity to profit from any market condition: be it an uptrend, downtrend or sideways movement of the general market index. Vidyamurthy (2004) thus defined Pairs-trade as a statistical arbitrage hedge fund strategy. It works by taking the arbitrage opportunity of temporary irregularities between prices of related assets which generally have a long-run equilibrium. When such an event occurs, one asset will be overvalued compared to the other asset. A trader can then create a two-asset portfolio or a "Pair" where a short position is taken in the overvalued asset and a long position is taken on the under-valued one. This trade is completed by taking an exit strategy in each of the assets when the two have returned to their original or long run equilibrium path – essentially this strategy utilizes the concept of "mean reversion" as stated by Hillebrand (2003). The profit is thus captured from the short-term or temporary anomaly that arises in a pair of asset prices. Vidyamurthy (2004) states that because this movement to and away from the long-run equilibrium relationship between a pair of financial assets does not depend on the movement of the overall market, pairs trading strategy is known as a market-neutral investment strategy.

Pairs trade has several advantages. It creates an automatic hedge by matching a long position with a short position. It gives the investor a profit regardless of market movement since profitability of the strategy does not depend on market direction; rather it counts on the relationship between the two assets. It also removes directional risk, which is the risk against exposure to adverse direction of price movement – as profit depends on differences in price changes of the two instruments as defined by Investopedia (2013).

The objective of this research is to develop a financially profitable Pairs trading model with pairs of stocks. The study first identifies pairs of stocks for pairs trading using the Johansen Test for co-integration. The pair of stocks is then modeled using a Vector Error Correction Model (VECM), which is a natural extension of the Vector Auto-regression (VAR) model with error component incorporated in it as identified by Schmidt (2008). The estimated VECM model will then give a residual series which will act as the primary guide for implementing a Pairs Trade.

The scope of this study is the primary stock market of Bangladesh – Dhaka Stock Exchange. While this strategy has been used extensively in developed capital markets, Investment Banks in Bangladesh have never introduced this concept to the local stock exchange. Primary reason for this is the lack of professional statisticians and mathematicians among the investment teams of the few investment banks that operate in Bangladesh. However, given that Bangladesh stock market is frequently subjected to mispricing due to political turmoil, fraudulent activity, speculation and mixed economic performance, introduction of a market-neutral or market-condition independent investment strategy is of utmost importance in terms of balance between risk mitigation and maximized return. The pairs trading strategy will thus be of immense value to investors and to general development of the Bangladesh stock market.

This research is divided into eight chapters. Chapter one gives the introduction while the second chapter discusses the literature review on Pairs trading including the significance of long, short strategies and co-integration. The third chapter provides a review of estimation methods on Pairs trading strategy in several financial markets like the American, Brazilian and European stock markets. Chapter four deals with the sources of data and data management techniques used in the research. Chapter five discusses the overall methodology of identifying a pairs trading portfolio and deriving the correct time-series model to estimate the required timing to carry out the strategy for Dhaka Stock Exchange. It also discusses the theoretical and practical aspects of estimation like Stationarity, Co-Integration, Vector Error Correction Models and the steps in implementing these mathematical tools correctly. The sixth chapter shows results obtained from this research. It also evaluates the profitability of the models with the chosen stock pairs to validate the model. The final chapter draws relevant conclusions.

CHAPTER 2 LITERATURE REVIEW

2. Literature Review

2.1 Introduction to Pairs trading

Pairs trading is a trading strategy that matches the long position in one instrument with a short position in another instrument which is co-integrated with the former as defined by Investopedia (2013).The instruments can be stocks, bonds, exchange-traded funds, commodities, currencies or options. Pairs trading begin with pairs traders waiting for weakness in the relationship between two assets. They take long positions on the under-performer while simultaneously take short position on the over-performer, and ends their positions as the relationship returns to its statistical equilibrium. The profit is then derived from the difference in price change between the two instruments, and not from the change in value of only one instrument. Therefore, profit can be realized if the long position goes up more than the short, or the short position goes down more than the long. Ideally, the stock with the long position will rise in value and the stock with short position will fall in value.

A long position in an asset, is an investment concept of a person owning a security, such as a stock or a bond, to make profit if the price of the asset appreciates. Schmidt (2008) identified that "going long" has been the traditional investment strategy of both retail and institutional investors all around the globe and is contrasted with the unconventional "going short" strategy.

Going short implies selling financial securities that are not owned, with the goal of eventually re-purchasing them at a lower price in future. The short seller will make profit in the event of price depreciation since he will be able to buy back the same number of units of the security at lower price. The difference between initial price and declined price is the profit for the short seller. Conversely, the seller will incur a loss if price of the asset rises since he has to repurchase the same number of units at a high price. In the securities markets, the short seller must borrow the securities from an agent in order to bring about the delivery as outlined by Schmidt (2008). A short seller borrows through a broker, who is holding securities for another investor (who actually owns the securities); the broker rarely purchases securities to lend to the short seller. The lender does not lose the right to sell the securities when securities are lent. The broker usually holds a large pool of such securities for a number of investors which, as such securities are fungible, can instead be transferred to any buyer. In most market conditions there is a ready supply of securities that can be borrowed and are often held by pension funds, mutual funds and other investors according to Investopedia (2013).

Schmidt (2008) points out that Pairs trading is an investment strategy which has historically been linked with hedge funds. However, in the last 5 years, the concept has gained popularity among traditional asset managers like mutual funds because of the simplicity of its concept. This concept is oriented around purchasing long and selling short in the hope that the former would increase and the latter would decrease in value. A Pairs trade strategy seeks to minimize market exposure, while profiting from capital gains in the long positions and in the short positions. Although this may not always be the case, the strategy would be profitable on a net basis as long as the long positions generate more profit than the short positions, or the other way around. To further illustrate this consider the following scenario. A retail investor buys X units of stock A in the hope that it's price will appreciate in the near future. Simultaneously, he borrows Y units of stock B from a broker and sells these stocks in the open exchange. His expectation is that price of stock B will decline. In the event that both of his expectations are met, price of Stock A rises and the capital gain is his profit from his long position. And, as price of stock B falls, the investor buys back Y units from the open exchange at the reduced price. The difference between his selling price of stock B and the new lower price is his "spread" or profit as he only needs to return the Y units of stock B to the lender. It can also be the case that because the pair of stocks are expected to behave in a patter, the investor may make a loss from one of the long/short strategies, but generally the net effect is positive.

Hsieh (1999) notes that this strategy is based on fundamental analysis of individual companies in which investments are made. Careful analysis of the stocks gives an investor the idea of whether it will appreciate or depreciate in value. Long/short covers a variety of sectors. Fund managers focus on specific sectors or regions or specialize in a certain category – large cap stocks[1], mid cap stocks or small cap stocks. However, the most significant priority for fund managers when carrying out long and short strategies is liquidity. This is especially true for short selling. When price is expected to depreciate and the seller wants to take advantage (of the spread of initial

[1] Large cap stocks are those that have a market capitalization of more than 1.0% of the total stock market capitalization. Mid cap stocks range between 1.0% and 0.1% of total market capitalization while stocks lower than 0.1% of total market cap are termed as small cap stocks.

price and new price), if the stock is illiquid[2] then buying the desired amount at a specific price may not be possible. Therefore as Hsieh (1999) points out, fund managers and investors will need to prioritize a list of highly liquid tradable stocks before deciding on Pairs trading strategies.

According to Investopedia (2013) the biggest advantage of this strategy is versatility. There is no standard investment allocation among pairs trading investment managers: An investor can usually diversify and change investments based on diverging trends in sectors overall market conditions. If an investor actively manages a pair trading strategy, meaning he will regularly monitor the market and invest using this strategy whenever the opportunity arises, it generally results in higher returns. Long/short equity funds typically experience higher "alpha[3]" returns compared to other investment strategies: alpha refers to returns above the market (or beta) returns on a risk adjusted basis attributed to a manager's skill in picking investments.

2.2 Significance of market neutrality, mean reversion and co-integration in Pairs Trading

As outlined before, Pairs trading is a market-neutral trading strategy that matches a long position with a short position of a pair of highly co-integrated financial assets like stocks, bonds, commodities, currencies etc. When the co-integration is temporarily weak, Pairs trader goes long on the under-performing stock and asset on the over-performing asset with assumption that the co-integration will return to its equilibrium, giving the trader an opportunity to gain according to Schmidt (2008).

The concept of market-neutrality is critical to extract benefits of pairs-trading. Joseph G. Nicholas, (2000) states that these strategies seek to neutralize certain market risks by taking offsetting long and short positions in instruments which have an actual relationship. This means

[2] Illiquid stocks are those which generally have a daily average trading volume of less than 100,000 shares in the stock market.
[3] Alpha is a risk-adjusted measure of the active return on an investment. It is the return in excess of the compensation for the risk borne, and thus commonly used to assess active managers' performances. Often, the return of a benchmark is subtracted in order to consider relative performance, which yields Jensen's alpha according to Feibel (2003).

that these approaches actually limit exposure to systematic risk[4] in asset prices due to fundamental drivers – macroeconomic changes, industry-specific shifts, investor sentiment etc.

How is market neutrality involved in pairs trading?

Because one position is taken considering another position to reduce directional risk exposure, these strategies hedge against market risk. In other words, exposure to market is replaced by exposure to association between the long and short calls. One must be clear about the fact that this does not mean that pairs trading is a risk-free investment. There are several risks associated with it also. However, Hsieh (1999) determined that such risks are different than traditional risks that are associated with only long investing.

Pairs trading reduce the directional risk by going long on one stock and short on another. The value of both investments must be equal and generally the assets chosen must be from the same sector (Eg: Two stocks from the Pharmaceuticals sector). Since, it does not matter whether the market goes on a bear[5] or a bull run[6], directional risk is reduced. Profits ultimately depend on the difference in price changes between the two stocks, regardless of market movement.

Significance of Mean reversion and Co-integration

Having covered the concepts of long, short and market neutrality in pairs trading, the relevance of mean reversion in this research will now be explored. According to Schmidt (2008), mean reversion is the assumption that a stock's highs and lows are temporary and a stock's price will tend to move to an average price over long-run. Application of mean reversion concept in stock price analysis involves both identifying a trading range of a stock, and computing its average price taking into consideration earnings of the company. When the current price is less than its average price, the stock is considered attractive for buying (giving rise to long investing) and when the current price is above its average, it is considered ripe for selling (giving rise to short investing). In other words, a deviation from the average is expected to be temporary and the asset will eventually revert to its mean.

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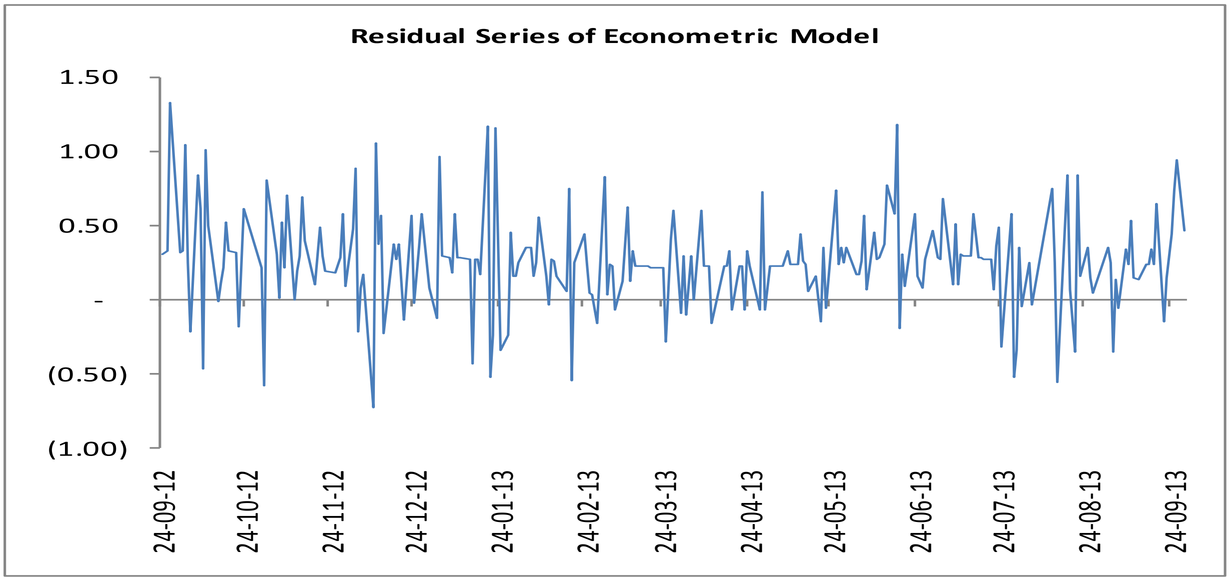
[4] Risk that is inherent in an entire market.

[5] Bear run is a market condition in which the prices of securities are falling, and widespread pessimism causes the negative sentiment to be self-sustaining.

[6] Bull run is a financial market of a group of securities in which prices are rising or are expected to rise.

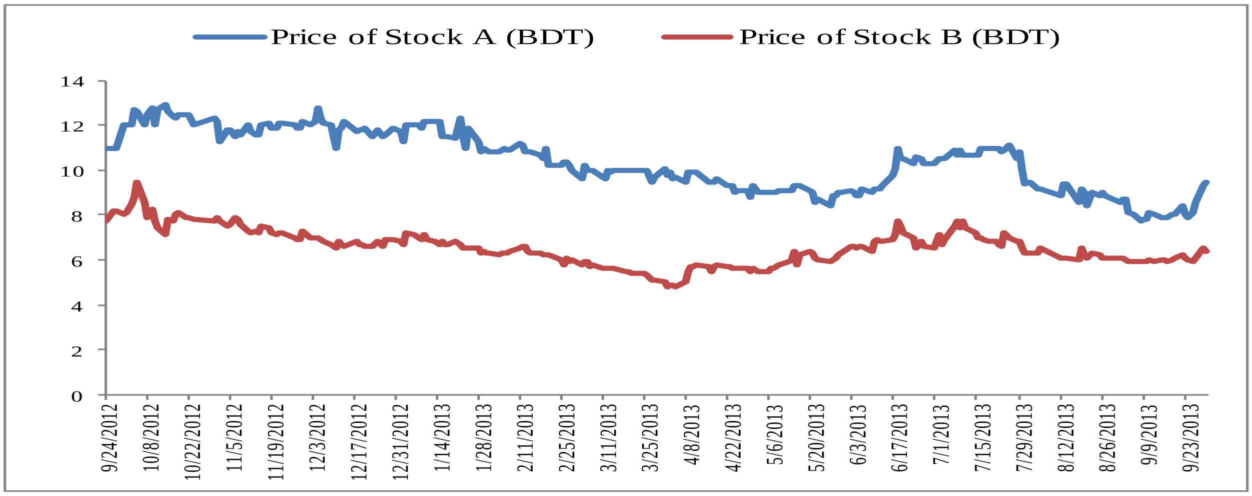
Figure 1 Mean reversion occurs when residual value returns to 0



Mean reversion is a key characteristic of co-integrated variables. According to Engle and Granger (1987), when two or more time-series variables are individually integrated, but a linear combination of these variables has a lower order of integration, then these variables are said to be co-integrated. For example, a stock market index and the price of its associated futures contract, whilst both following a random walk[7] will be in a long-run equilibrium and deviations from this equilibrium will be stationary. These deviations are the opportunities for Pairs traders since the relationship between the two variables will eventually revert to their means. Co-integration is discussed in details in Section 5.1.2.

[7] A random walk is a mathematical formalization of a path that consists of a succession of random steps. For example, the path traced by a molecule as it travels in a liquid or a gas, the search path of a foraging animal, the price of a fluctuating stock and the financial status of a gambler can all be modeled as random walks, although they may not be truly random in reality according to Pearson (1905).

Figure 2 Co-Integrated Stocks generally have similar price movements



A pairs trader carries our long/short investments on a co-integrated pair of stocks with the assumption that the two will ultimately move towards their mean price levels. Thus, the temporary anomaly that arises is a potential for long and short investments and so there is potential profit when they revert to their means.

2.3 Risks and disadvantages of Pairs trading

Investopedia (2013) states that a pair trading primarily consists of two major risks - model risks and execution risk.

Model Risk: Pairs trading is exposed to model risk – meaning the model used to create the strategy does not perform as expected. This can be due to various factors. Like incorrect logic, inaccurate research or miscalculation. When this happens, one of various results can materialize. For instance, the two assets may not revert to a co-integrated mean. Or, a loss in long position is in net effect greater than the profit in the short position.

Execution risk: This type of risk can reduce the potential return from a pairs trade. It occurs when the strategy is not expected as planned. For instance, an investor might face slippage in price or could receive a partial fill on an order, which reduces the profit potential. Slippage occurs when the price an investor receives for an order is less favorable than the expected one. Since pairs trading depends on timing, any delay in capturing the most favorable time for executing the trade will results in either lower gains or losses.

Behavioral risk: This is the risk that a market index can fall significantly if, through a bandwagon effect, many sellers execute pairs trading strategy simultaneously and take exit at the same time. However, given the diversity and quantity of financial assets in a capital market, probability of many sellers using the same stock pair is relatively low.

Apart from the risks involved in this strategy, Pairs trading also has several disadvantages of which any investor should be aware of. First the investor has to pay the commission twice. This is because the strategy involves two separate investment initiatives – a long and short call. Therefore, the investor engaged in pairs trading has to take this into his calculation of net profit which can pile up quickly depending on the number and frequency of pairs trade execution.

Second disadvantage is that many such strategies are based on very small movements. Therefore, the only way to make returns substantially worthwhile for an investment is by taking very large positions in these stocks according to Investopedia (2013). Investor must be financially capable of making large investment calls to actually make a worthwhile return from investment. Such monetary capacity is usually available for institutional investors or asset management companies, who have necessary capacity to invest sizeable amount of money into a pairs trading strategy.

CHAPTER 3

LITERATURE ON ESTIMATION METHOD

3. Literature on Estimation Method

In this chapter, three estimation methods for implementing pairs trading strategy are discussed. These three methods are the stochastic[8] spread method, stochastic residual method and the co-integration method.

3.1 The stochastic residual spread method

Do, Faff and Hanmza (2006) put forward a pairs trading strategy which was completely different from the general ones used traditionally (stochastic spread method). It models mispricing or "returns" level and not "prices" level. The model incorporates a theoretical foundation for the relationship between stock prices to eliminate ad hoc routines that previous researches and models uses to identify a stock pair for pairs trading.

This theoretical foundation is based on the assumption that there always exists an equilibrium in relative valuations of two stocks measured by some spread. According to Do, Faff and Hamza (2006), mispricing is thus interpreted as a state of disequilibrium which is quantified by this function called "residual spread" $G(R_t^A, R_t^B, U_t)$ where U is an exogenous vector present in bringing about the eventual equilibrium. The "residual spread" referred to in this model talks about any excess over a long-term spread and may-take non-zero values depending on the formulation of the spread. The model assumes that market forces are the main drivers of the spread returning to its long run equilibrium position. Therefore a trading position is opened once the disequilibrium is sufficiently large and correction time is adequately short. Schmidt (2008) stated that this model adopts the same estimation framework as the one by Elliot et al (2005) where the residual spread is a function that captures any excess over the long term spread and can take non-zero values depending on the formulation of the model. To illustrate, let x be the residual spread with respect to a given equilibrium whose dynamics are modeled by the Vasicek process introduced by Vasicek (1977) is:

$$\partial x_t = k(\theta - x_t)\partial t + \sigma \partial B_t \quad (3.1)$$

where ∂x_t = rate of change of residual spread

k = speed of reversion

[8] In probability theory, a purely stochastic system is one whose state is non-deterministic so that the subsequent state of the system is determined probabilistically as defined by Logan (1976).

θ = Long term mean level

σ = volatility

∂B_t = Wiener Process[9]

The mispricing is:

$$Y_t = x_t + \omega_t \quad (3.2)$$

Where Y_t is the mispricing between the two assets, x_t is the residual spread and ω_t is a Gaussian noise[10].

These equations represent a state space model of relative mispricing with respect to an equilibrium position between the two assets. The equilibrium relationship, G, comes from the Asset Pricing Theory introduced by Ross (1976). The APT model asserts that the return on a risky asset, over and above a risk free rate, should be the sum of risk premiums multiplied by their exposure.

Do et al (2006) built a continuous time model of mean reversion in the relative pricing of two assets. This relative pricing model has been adopted from the APT [11] (Arbitrage Pricing Theory) model of single asset pricing. To estimate the model, an econometric model was used. However Schmidt (2008) notes that this model does not make any assumptions regarding the validity of the APT model. Rather, it adapts the factor structure of the APT to derive a relative pricing framework without requiring the validity of the APT to the fullest sense. Therefore, whereas a strict application of the APT may mean the long-run level of mispricing, or θ, should be close to zero, a non-zero estimate does not serve to invalidate the APT or the pairs trading model as a whole. Rather it may imply that there is a firm specific premium commanded by one company relative to another, which could reflect such things such as managerial superiority. This could

[9] In mathematics, the Wiener process is a continuous-time stochastic process named in honor of Norbert Wiener. It is often called standard Brownian motion according to Steven E (2008).

[10] Gaussian noise represents statistical noise having probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution as defined by Tudor (2013).

[11] In finance, arbitrage pricing theory (APT) is a general theory of asset pricing that holds that the expected return of a financial asset can be modeled as a linear function of various macro-economic factors or theoretical market indices, where sensitivity to changes in each factor is represented by a factor-specific beta coefficient as defined by Ross (1976).

easily be incorporated into the model by simply adding or subtracting a constant term in the equilibrium function, Gt.

3.2 Stochastic spread approach

Mean reverting behavior of spread in Pairs trade can also be modeled in a continuous time setting. The spread is the difference in means of two stock prices. This was covered by Elliot et al (2005) who proposed that the spread is driven by a latent variable x, which follows a Vasicek process as shown in Equation 3.3:

$$\partial x_t = k(\theta - x_t)\partial t + \sigma \partial B_t \tag{3.3}$$

where ∂x_t = rate of change of residual spread

k = speed of reversion

θ = Long term mean level

σ = volatility

∂B_t = Wiener Process

where ∂B_t is a standard Brownian motion (Wiener process) in some defined probability space. The state variable is known to revert to its mean θ at the rate k. By making the spread equal to the state variable plus a Gaussian noise, or:

$$Y_t = x_t + H\omega_t \tag{3.4}$$

where Y_t = spread between two stock prices

x_t = latent state variable

ωt = Gaussian noise

H= constant

Trader asserts that the observed spread is driven mainly by a mean reverting process, plus some measurement error where ωt~N(0,1).

According to Eliot (2005), this process has three advantages. Firstly, it empirically captures mean reversion which is the underlying pivot of pairs trading. Secondly it is a continuous time model, and thus is best suited for researchers looking to forecast out of sample ranges. This is of utmost importance since an investor or a trader can then forecast how much time it will take for the spread to converge or return to its general equilibrium. In doing so, an investor will be able to determine the expected holding period (i.e. keeping the trade position open) and the expected return. The final advantage of the stochastic spread approach is that the model is quite tractable, and its parameters can be easily estimated in the state space setting.

The estimator used in this case is a Maximum Likelihood Estimator (MLE). Despite several advantages, Do et al. (2006) believed that this approach does have a fundamental limitation in that it restricts long-run relationship between two stocks to one of return parity.

Schmidt (2008) stated, in the long-run, stock pairs chosen must provide the same return such that any departure from it expected to be corrected in the future. This severely limits this model's generality as in practice it is rare to find two stocks with identical return series. While risk-return models such as Arbitrage Pricing Theory (APT) and Capital Asset Pricing Model (CAPM)[12] could suggest that two stocks with similar risk factors should exhibit identical expected returns, in reality it is not necessarily the case because each stock is subject to firm-specific risks which differentiate the return series of two firms. It is also important to note that the Markovian concept of diversification does not apply here since a pairs trading portfolio is not sufficiently diversified.

Given this fundamental limitation, in what circumstances can this approach be applicable? One possibility is a case where companies adopt a dual-listed company[13] (DLC) structure; a merger between two companies domiciled in two different countries with separate shareholder registries and identities.

Globally, there are only a small number of dual listed companies, with notable examples including Unilever NV/PLC, Royal Dutch Petroleum/Shell, BHP Billiton Ltd/PLC and Rio Tinto Ltd/PLC. In a DLC structure both groups of shareholders are entitled to same cash flows,

[12] In finance, the capital asset pricing model (CAPM) is used to determine a theoretically appropriate required rate of return of an asset, if that asset is to be added to an already well-diversified portfolio, given that asset's non-diversifiable risk as defined by Fama (2004).

[13] A dual-listed company or DLC is a corporate structure in which two corporations function as a single operating business through a legal equalization agreement, but retain separate legal identities and stock exchange listings. Virtually all DLCs are cross-border, and have tax advantages for the corporations and their stockholders according to Bedi (2013).

although shares are traded on two separate exchanges and often attract different valuations. The fact that shares cannot be exchanged for each other precludes riskless arbitrage although there is a clear opportunity for pairs trading. Another candidate for pairs trading assuming returns parity is companies that follow cross listing. A cross listing occurs when an individual company is listed in multiple exchanges, the most prominent form being via American Depository Receipts (ADRs).

3.3 The co-integration approach

After Markowitz (1959), Sharpe (1964) and Lintner (1965), the most widespread statistical tool for portfolio optimization was correlation analysis of asset returns. Most optimization models focus on minimizing variance, for any given return, with additional constraints such as certain investment allowances, costs of rebalancing the portfolio etc.

However, in the last one decade, concept of co-integration has been used widely in estimation methods in financial econometrics, time-series analysis and macro economics. Over time, it has emerged as a powerful statistical tool as it allows application of simple estimation methods like OLS[14] and MLE[15], to non-stationary variables. Even then, application of co-integration for investment analysis has been quite limited because traditional practice of using correlation analysis for portfolio and risk management is still standing strong. However, Alexander and Dimitriu (2002) pointed out that correlation is only possible for stationary variables. This gave rise to a significant problem of modeling portfolio optimization techniques when variables are non-stationary. It does have a simple solution. Taking first differences in log prices can ensure stationarity, but this solution has one major flaw. It loses valuable information and de-trending variables can eliminate the possibility of tracking any common trends in prices. Alexander et al. (2001) outlined that the aim of co-integration analysis is to detect any stochastic trend in the price data and use these potential trends for dynamic analysis of correlation in returns.

Puspaningram (2012) believed that the main advantage of co-integration approach as compared to classical correlation approach is that it allows user to utilize the full information set comprised

[14] Ordinary Least Squared is a method for estimating unknown parameters in a linear regression model as defined by Gujarati (1996)

[15] In statistics, maximum-likelihood estimation (MLE) is a method of estimating the parameters of a statistical model. It is generally used for non-linear regression models as defined by Pfanzagl (1994).

in the levels of financial variables. Also, a co-integrated relationship is able to determine long-run general equilibrium relationship or association between two time-series variables, whereas its counterpart the correlation test is mostly concerned with short-term measurements. Co-integration adds further benefits to the investors. These include reductions in the amount of rebalances of trade in a hedging strategy and consequently associated transaction costs.

Furthermore, in its application in pairs trading, Error-Correction models combine stock price series which are integrated in order 1, to produce a stationary time series. This is a critical property of co-integration because regression of non-stationary variables results in "spurious regression".

Co-integration incorporates mean reversion into a pairs trading framework which is the most important statistical relationship required for success. If the value of a portfolio is known to move around its mean, than the deviations from this equilibrium can be capitalized upon. Co-integrated time-series variables can be modeled in a Vector Error Correction Model according to the Granger Representation Theory as introduced by Granger (1987). The dynamics of one time series is modeled as a function of its own lag, lagged values of its pair, and an error correction component which rectifies the deviation from the equilibrium.

To test for co-integration, Vidyamurthy (2004) adopts the Engle and Granger's (1987) 2-step approach in which the log price of stock A is first regressed against log price of stock B in what we refer to as the co-integrating equation:

$$Log(p_t^A) - aLog(p_t^B) = \mu + \varepsilon_t \tag{3.5}$$

Where Log (p_t^A) = Log of price of stock A

Log (p_t^B) = Log of price of stock B

α= co-integrating coefficient

μ= Premium[16] between two stock prices

ε_t = Value of deviation from long-run equilibrium

In the above equation, α is the co-integrating coefficient and the constant μ captures the premium between stock A and stock B**.** The equation says that a portfolio comprising long 1 unit of stock

[16] Premium is the difference in net change between two instruments.

A and short γ units of stock B has a long-run equilibrium value of μ and any deviations from this value are merely temporary fluctuations given by ε_t. The portfolio will always revert to its long-run equilibrium value since ε_t is known to be an I(0) process. Vidyamurthy (2004) develops trading strategies based on the assumed dynamics of the portfolio. The fundamental trading idea is to open a long position in the portfolio when it is sufficiently below its long-run equilibrium (μ-Δ) and similarly, short the portfolio when it is sufficiently above its long-run value (μ+Δ). Once the portfolio mean reverts to its long-run equilibrium value the position is closed and profit is earned equal to \$$\Delta$ per trade**.**

Schmidt (2008) carried out one such research where he used co-integration tests to identify pairs of stocks and then modeled the residual as a Vector Error Correction Model. However, Schmidt did not aim to produce a profitable portfolio of a pairs stock, instead focused on a theoretically sound model which can be applied to the practical scenario. Unlike Vidyamurthy (2004), Schmidt (2008) uses a different test for identifying co-integrated stocks. This is because Schmidt (2008) identified that apart from being rather ad hoc, Vidyamurthy's approach may be exposed to errors arising from the econometric techniques employed. Firstly, the 2-step co-integration procedure renders results sensitive to the ordering of variables, therefore the residuals may have different sets of statistical properties. Secondly, if the bivariate series is not co-integrated, the end result may turn out to be a set of spurious regressions.

Consequently, Schmidt (2008) uses the Johansen's Test for Co-integration which is based on a vector error correction model. The research goes on to find several pairs of co-integrated stocks and develops a Granger causality model to find causal relationship between stocks for their deviations from the mean.

CHAPTER 4 DATA

4. Data

4.1 Source of data

Data used in this study was from Dhaka Stock Exchange. It comprises of daily prices of 20 stocks listed in Dhaka Stock Exchange. A total of 500 days of observations were divided into two groups - one for estimating the model, the other half were for post-estimation and back-testing. The sample used for estimating the model is for a year's time period starting from 24/9/2012 to 30/9/2013. The weekends and public holidays are omitted as the stock market was closed. Thus a sample size of 243 days of observation were used for estimation of co-integration relationship and modeling the subsequent Vector Error Correction Model,

A statistical software EViews and data analysis spreadsheet Microsoft Excel were used for entire modeling procedure.

4.2 Data Classification

Two major considerations were taken into account when organizing the dataset. First, the research was restricted to only 20 most actively traded stocks in the market. The research searched and identified the most liquid[17] stocks and used them for this study. This was done by taking the daily volume[18] of all stocks listed in DSE, and then sorting according to highest average volume for the period concerned. This is because Pairs trading depends on perfect market timing for buy-sell decisions. However, many stocks in the market are illiquid, meaning their shares are much tougher to obtain at the desired quantity. If such shares are included in such trading, additional risk arises because one may not be able to buy (or sell) desired number of stocks at a particular price or when indicated by the trade signal.

The second step in data classification made in this research is organization of stocks according to the same sector or industry[19]. By restricting trading pairs to stocks from within the same industry it is assumed that these stocks will have similar exposures to systematic risk, or beta. Thus the resulting portfolio should have a beta close to zero. But as Schmidt (2008) identified, ideally one

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[17] Liquid stocks are defined as those with daily average volume of 100,000 shares traded in Dhaka Stock Exchange. Liquidity of all twenty stocks in the sample is shown in Appendix C.

[18] This is the number of stocks of particular company in a day. The information is available in the website of Dhaka Stock exchange.

[19] Sector/Industry: Companies listed in the same sector in Dhaka Stock exchange

would choose stocks with the same betas so that combined portfolio had a beta of exactly zero, but because this research is working with a limited sample the current constraint will suffice.

Another reason for classification only within the same industry is that the researcher will be able to back the econometric observations with some theoretical reasoning. For a Pairs trader, it is very important to understand the fundamental drivers of a stock pair according to Schmidt (2008). It is likely that stocks from same industry will move up or down due to same fundamental factors than two stocks from differing sectors. For example, consider two stocks from textile and RMG (Ready-made Garments) industry. They are generally both vulnerable to the same factors. For instance, consider the news that the European Union removed Generalized System of Preferences for Bangladesh RMG products. This fundamental news will reverberate all across the sector and generally affect all the companies separately. Similarly, if the national budget reduced taxes for listed RMG manufacturers, prices of all listed companies would rise on this same fundamental factor. Therefore, using a co-integrating relationship backed by sound theoretical or economic reasoning is more robust than one without proper justification.

Pairs trading is especially effective in bear markets, when the market is characterized by volatility and uncertainty. Schmidt (2008) points out that no one would want to remain market neutral in a bull market since over-weighting[20] their portfolio would be the more prudent thing to do. For instance, consider the state of the Bangladesh capital market in pre-election year in 2013. The market is undergoing a lot of uncertainty and prolonged bear run due to domestic political violence. Consequently, such a time is perfect for pairs trading since one needs to be free of the market risks which are prevalent due to fundamental factors in Bangladesh during such times. Thus the final summary of the 20 stocks selected for Pairs Trade selection is summarized in Table 1:

[20] Over-weighting refers owning an asset class as a percentage of total assets at a proportion greater than its percentage share in the capital market.

Table 1 - Stock Names according to Dhaka Stock Exchange ticker

TEXTILES & RMG	**PHARMACEUTICALS**	**BANKS**	**FUEL & POWER**
ENVOYTEX	ACTIVEFINE	EBL	TITASGAS
RNSPIN	KEYACOSMET	CITYBANK	KPCL
SQUARETEXT	SQURPHARMA	ISLAMIBANK	BDWELDING
MALEKSPIN	PHARMAID	EXIMBANK	MPETROLEUM
SAIHAMCOT		NBL	GBBPOWER
ARGONDENIM			

CHAPTER 5 METHODOLOGY

5. Methodology

Methodology used in this study is divided into two parts. First part involves the process of selecting a Pairs Trade. This chapter gives a detailed discussion on concepts of Stationarity and Co-integration. The chapter also discusses different tests used to identify co-integrated pair of time-series variables and gives rationality of the test ultimately chosen for co-integration testing.

The second section of this chapter introduces concepts of Vector Auto-regression and Vector Error Correction model (VECM) and illustrates why a VECM is necessary to model co-integrated pairs of stocks. Once the VECM model is applied, the study goes on to obtain a series of residuals from the VECM and use that as the necessary "trade signal", to be discussed in section 5.2.4, to carry out Pairs trade. The section concludes by briefly discussing the final model for post estimation.

5.1 Rationality and process of selecting a trading pair

5.1.1 The concept of stationarity

Stationarity is a common assumption in many time-series techniques. Many time series variables observed in practice are non-stationary and estimation with such variables gives rise to what is commonly termed as "spurious regression"[21] according to Green (2003) – a phenomenon which econometricians aim to avoid. If two variables are non-stationary, they need to be transformed to some stationary time-series and then be used for analysis. According to Priestley (1988), stationarity is a stochastic process whose joint probability distribution does not change when shifted in time or space. Furthermore, Schmidt (2008) states that a time series, y_t, is a stationary series if its mean, variance and autocorrelations are well approximated by sufficiently long time averages based on a single set of realizations. As a result, the mean (Equation 5.1), variance (Equation 5.2) and auto-covariance (Equation 5.3) structure of the time-series does not change over time, meaning they do not follow trends.

$$E(X_t) = \mu \; for \; all \; t \tag{5.1}$$

$$E\,(X_T^2) = \sigma^2 \; for \; all \; t \tag{5.2}$$

$$Cov\,(X_t X_k) = Cov\,(X_{t+s} X_{t+s}) \; for \; all \; t, k, s \tag{5.3}$$

[21] This refers to a regression with significant results due to the presence of a unit root in both variables.

Most business and economic time series are far from stationary when expressed in their original units of measurement, and even after deflation or seasonal adjustment they will typically still exhibit trends, cycles, random-walking, and other non-stationary behavior. If the series has a stable long-run trend and tends to revert to the trend line following a disturbance, it may be possible to stationarize it by de-trending (e.g., by fitting a trend line and subtracting it out prior to fitting a model, or else by including the time index as an independent variable in a regression or ARIMA[22] model), perhaps in conjunction with logging or deflating. Such a series is said to be trend-stationary. However, sometimes even de-trending is not sufficient to make the series stationary, in which case it may be necessary to transform it into a series of period-to-period and/or season-to-season differences. If the mean, variance, and autocorrelations of the original series are not constant in time, even after de-trending, perhaps the statistics of the changes in the series between periods or between seasons will be constant. Such a series is said to be difference-stationary as mentioned by Green (2003).

The first difference of a time-series is a series of absolute value changes of a variable from one period the next one. For instance if X_t denotes the value of variable X at period t, then the first difference of X at period t would be given by the following equation:

$$X_t - X_{t-1} = Diff(X) \tag{5.4}$$

If the first difference is stationary and also completely random, then X can be described as a random walk model as well – meaning each value is a random step away from the previous value. First difference is generally one of the most commonly used techniques to remove the problem of non-stationarity.

5.1.2 The concept of co-integration

Most studies in empirical economic research almost always have unwanted characteristic of non-stationary variables. Trending variables like consumption, money demand, price levels, exchange rate, and stock prices are a common phenomenon in econometric analysis. Thus, the best solution for these problems is the one described above – first differencing and then analyzing the resulting series as a VAR or a VECM whichever is appropriate depending on the objective. But

[22] In statistics and econometrics, and in particular in time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting) as described by Mills (1991).

recent research has come up with a new way of analyzing trending variables. Here the concept of Co-integration is introduced.

According to Green (2003), in the fully specified regression model like $y_t = \beta x_t + \varepsilon_t$ there is a presumption that the disturbances (εt) are a stationary, white noise series. But this presumption is unlikely to be true if y_t and xt are integrated series. Generally, if two series are integrated to different orders, then linear combinations of them will be integrated to the higher of the two orders. Thus, if y_t and xt are I (1)[23]—that is, if both are trending variables—then we would normally expect $y_t - \beta x_t$ to be I (1) regardless of the value of β, not I (0) (i.e., not stationary). If y_t and x_t are each drifting upward with their own trend, then unless there is some relationship between those trends, the difference between them should also be growing, with yet another trend. There must be some kind of inconsistency in the model. On the other hand, if the two series are both I (1), then there may be a β such that

$$\varepsilon_t = y_t - \beta x_t \tag{5.5}$$

is I (0). Intuitively, if the two series are both I (1), then this partial difference between them might be stable around a fixed mean. The implication would be that the series are drifting together at roughly the same rate. Two series that satisfy this requirement are said to be Co-integrated and the vector [1,− β] (or any multiple of it) is a co-integrating vector. In such a case, one can distinguish between a long-run relationship between y_t and x_t that is, the manner in which the two variables drift upward together, and the short-run dynamics, that is, the relationship between deviations of y_t from its long-run trend and deviations of x_t from its long-run trend. If this is the case, then differencing of the data would be counter-productive, since it would obscure the long-run relationship between y_t and x_t. Studies of co-integration and a related technique, error correction, are concerned with methods of estimation that preserve the information about both forms of co-variation.

5.1.3 Testing for co-integration: Engle-Granger vs. Johansen test approach

According to Granger (1981) there is a simple procedure of determining whether two variables are co-integrated by order CI (1,1). If two time-series are co-integrated, then a linear combination of them must be stationary. For instance:

[23] Integrated to the order of one

$$Y_t - \beta x_t = U_t \text{ ,} where\ U_t\ is\ stationary \quad (5.6)$$

If one could derive U_t then it could be tested for stationarity using common tests such as Dickey-Fuller Test[24]. Since one does not knowβ, one would need to estimate this first using Ordinary Least Squared method. Then estimate U_t and test for stationarity. Engle-granger is thus a simple two-step procedure. But this model has two disadvantages.

According to Schmidt (2008), the Engle-Granger methodology has two specific drawbacks which can give inaccurate results.

- The test for co-integration uses residuals from either of the two "equilibrium" equations. If the sample size increases indefinitely, then the test for a unit root is $E_{it} = E_{2t}$. However, this is not applicable to smaller samples which may be the case for many researches.
- The process relies on a two-step estimator and as such this gives rise to a major problem. The process first generates the residual series from one of the equilibrium equation, then it uses the generated errors to estimate a regression model. The problem here is that the coefficient obtained is done by regressing the residuals on another regression on lagged difference of itself. Thus any error introduced in the first step is then going to be carried to the second step making this model subject to twice the estimation error.

An alternative to Engle-Granger test is Johansen's Co-integration test named after Danish econometrician Soren Johansen (1988). This test estimates the VECM using maximum likelihood under several assumptions about the trend or intercepts, parameters, and the number of co-integrating vectors, denoted by r, and then conducts likelihood ratio tests. Johansen proposes two types of tests for the vector r:

According to Johansen (1991) the two types of test statistic are:

The Eigen-value test

This test is based on the log-likelihood ratio ln[Lmax(r)/Lmax(r+1)], and is conducted sequentially for r = 0,1,..,k-1. The name comes from the fact that the test statistic involved is a maximum generalized Eigen value. This test, tests the null hypothesis that the co-integration rank is equal to r against the alternative that the co-integration rank is equal to r+1.

[24] In statistics, the Dickey–Fuller test tests whether a unit root is present in an autoregressive model according to Dickey (1979).

The trace-statistic test

This test is based on the log-likelihood ratio ln[Lmax(r)/Lmax(k)], and is conducted sequentially for r = k-1,...,1,0. The name comes from the fact that the test statistic involved is the trace (= the sum of the diagonal elements) of a diagonal matrix of generalized eigen-values. This test investigates the null hypothesis that the co-integration rank is equal to r against the alternative that the co-integration rank is k. The latter implies that Xt is trend stationary.

Both tests have non-standard asymptotic null distributions. Moreover, given co-integration rank r, Johansen also derives likelihood ratio tests of co-integrating restrictions on the intercept or trend parameters.

This study thus uses Johansen's test (1988) to identifying co-integrated stocks from Dhaka Stock Exchange. The test uses MLE for estimation and in this way manages to avoid the problems that arose during the Engle-Granger methodology. Schmidt (2008) said the test relies heavy on the relationship between the rank of a matrix and its characteristic roots. He also suggests that the Johansen procedure is nothing more than a multivariate generalization of the Dickey-Fuller test.

5.2 The model derivation

5.2.1 The concept of Vector Auto-Regression Model and Vector Error Correction Model

Model derivation now moves to the second stage where co-integrated pair of stocks is modeled as a time-series regression model. The most prevalent time-series model used today for capturing linear interdependencies among multiple time-series variables is the Vector Auto-regression (VAR) model introduced by Christopher Sims (1980).

A VAR model contains a series of m variables each of which is a function of its own lagged values plus m-1 other endogenous variables and an error term. Using the concept of a VAR for two stock prices let us denote each stock prices as x and y. In the pairs trading strategy for this study, we can let the time path of Δyt be a function of lagged differences of yt, combined with current and past realizations of the Δxt sequence. The dynamics of the Δxt sequence is simply a mirror image of that described for the Δyt sequence. Thus the system of equations for the VAR model is shown in Equations 5.7a and 5.7b, where the lags are set at unity for simplicity:

$$\Delta y_t = \beta_{10} + \beta_{12}\Delta x_t + \mu_{11}\Delta y_{t-1} + \mu_{12}\Delta x_{t-1} + \varepsilon_{yt} \quad (5.7a)$$

$$\Delta x_t = \beta_{20} + \beta_{21}\Delta y_t + \mu_{21}\Delta y_{t-1} + \mu_{22}\Delta x_{t-1} + \varepsilon_{xt} \quad (5.7b)$$

The equations 5.7a and 5.7b represent a first-order VAR (in differences as shown by Δ) since the lag lengths are set to unity. According to Schmidt (2008), it is important to note that the structure of the system incorporates feedback since Δy_t and Δx_t are allowed to affect each other. For example, b_{12} is the contemporaneous effect of a unit change in Δx_t on Δy_t and μ_{21} the effect of a unit change in Δy_{t-1} on Δx_t. The error terms ε_{yt} and ε_{xt} are pure innovations (or shocks) in the Δy_t and Δx_t sequences, respectively. Furthermore, it is evident that when b_{21} is significantly different from zero, εy_t has an indirect contemporaneous effect on Δx_t, and if b_{12} is significantly different from zero then εz_t also has an indirect contemporaneous effect on Δy_t.

It is to be noted that this model uses first differences of each of the stock prices time-series values. This is to avoid the problem of spurious regressions as stated above, and taking first differences of the series removes the problem of non-stationarity allowing one thus to model variables as one desires. The VAR model shown above assumes that errors are white noises and uncorrelated with each other as identified by Schmidt (2008).

The model actually used for estimation in this research for preparing a stock trading pair is a Vector Error Correction Model (VECM). The reason for this is that the VECM, while in most ways similar to the general VAR model, also includes an error-correction component which considers the present of a co-integrated relationship between two time-series variables.

The error terms in the model reflect that part of y and x that are unrelated to its lagged values. This is the unpredictability in each variable. These “unpredictability” is generally correlated with each other due to perhaps a causal relationship according to Davidson (1978).

Now if x_t and y_t are co-integrated, the VAR model shown above becomes the Vector Error Correction Model. To illustrate the dynamics of the VECM model as explained by Granger Representation Theorem (1987):

Consider,

$$\Delta x_t = \alpha_2(\beta_1 x_{t-1} + \beta_2 y_{t-1}) + c_{21}\Delta x_{t-1} + c_{22}\Delta y_{t-1} + \varepsilon_t + v_t \tag{5.8a}$$

$$\Delta y_t = \alpha_1(\beta_1 x_{t-1} + \beta_2 y_{t-1}) + c_{11}\Delta y_{t-1} + c_{12}\Delta x_{t-1} + u_t + v_t \tag{5.8b}$$

Where x_t = Price of stock x

y_t = Price of stock y

α = speed of adjustment to equilibrium

β = co-integrating co-efficient

This is the vector error correction model. The error correction comes from the co-integrating relationship. The betas contain the co-integrating equation and the alphas the speeds of adjustment. If y and x are far from their equilibrium relationship, either y or x or both must change in order to restore the equilibrium relationship between the two variables.

One significant aspect of understanding and implementing VARs and VECMs is between the "unpredictability" terms v in VAR and underlying exogenous, orthogonal shocks to each variable, which we shall call ε and u respectively for each variable. The "unpredictability" in y_t is that part of the variable which cannot be predicted by lag values of y or x. A portion of this unpredictability in y_t may be caused due to ε_{ty} , an exogenous shock to y_t that is completely unrelated or independent of any behavior exhibited by variables x, y or in fact any other variable if it were to be included in the system. However, if x has a simultaneous effect on y, then some part of v_{ty} will be due to the indirect effect of the current shock to x, ε_{tx} , which enters the y_t equation in the model through the error term because current xt is not allowed to be on the right-hand side of this model.

In conclusion, the primary reason for using VECM is to estimate the speed with which the variables return to long-run equilibrium after a short term deviation. For the context of this research, this is very important as the trader will need to identify how long Pairs trade position should be kept open.

The VECM also gives the residual series, which will be used to understand when to go long and when to go short in a pairs trading strategy; finally it will tell us when to close the trade position and book the profit from the investment. Due to these reason the VECM is used for building the model.

5.2.2 The process of obtaining the residual series from the VECM

Now that the dynamics of the time-series model used for this test has been established, the procedure for estimation of the residual series will be discussed. As stated before, this model runs Johansen's Co-integration test to obtain co-integrated pairs of stocks from the same sectors of listed companies in Dhaka Stock exchange. The model obtains co-integrated stocks using trace statistic. Then once the co-integrated pairs are identified the VECM is used to model the stock pairs. The pairs are modeled in first difference form to ensure stationarity. Once the parameters of the model are estimated, the p-values are used to test for significance of the parameter. The research conforms to the rule that if the p-value is less than 5% than a parameter is statistically significant and if the value is more than 5% it is statistically insignificant. Using this thumb-rule the estimated VECM is finalized with only statistically significant parameters.

Next, all the significant parameters are re-arranged to the right-hand side of the equation. The left-hand side gives the residual series and can be illustrated as:

$$\mathbf{E_t = zY_t - \beta X_t - \alpha} \tag{5.9}$$

Where Y_t = Price of stock A

X_t = Price of stock

z = statistically significant coefficient

β = statistically significant coefficient

α = statistically significant intercept

E_t= Residual

It must be pointed out that the variables in question do not necessarily have to be prices of different stocks. Given the statistical significance, the residual series may also be a function of simple one stock and its lagged values. Note that the goal here is to monitor the movement and value of the residual which will then be used as a "trade signal" to open short, long positions and eventually close the trade.

5.2.3 Problem of lag-length selection: applying AIC and BIC criterion

When determining optimal lag-length for models of Johansen's Co-integration test and the Vector Error Correction Model, the study applied Akaike Information Criterion and Bayesian Information Criterion (also known as Schwarz criterion). These provide the information criterion for competing models. According to Akaike (1977) and Schwarz (1978), when selecting the optimized model, the goal is to maximize the goodness-of-fit or the value of R^2. This is generally done by minimizing the Residual Sum of Squares (RSS). The AIC and BIC impose a penalty for including unnecessary variables in the model. By unnecessary one to those variables that do not significantly increase the explanatory power of the overall model or R^2. For instance, the AIC aims to obtain the minimum value for the following statistic:

$$\mathbf{AIC = (e^{2k/n})(RSS/n)}$$

k = number of repressors including intercept

n = number of observations

RSS = Residual Sum of Squares

5.2.4 The final model – Using residual values as Trade Signal

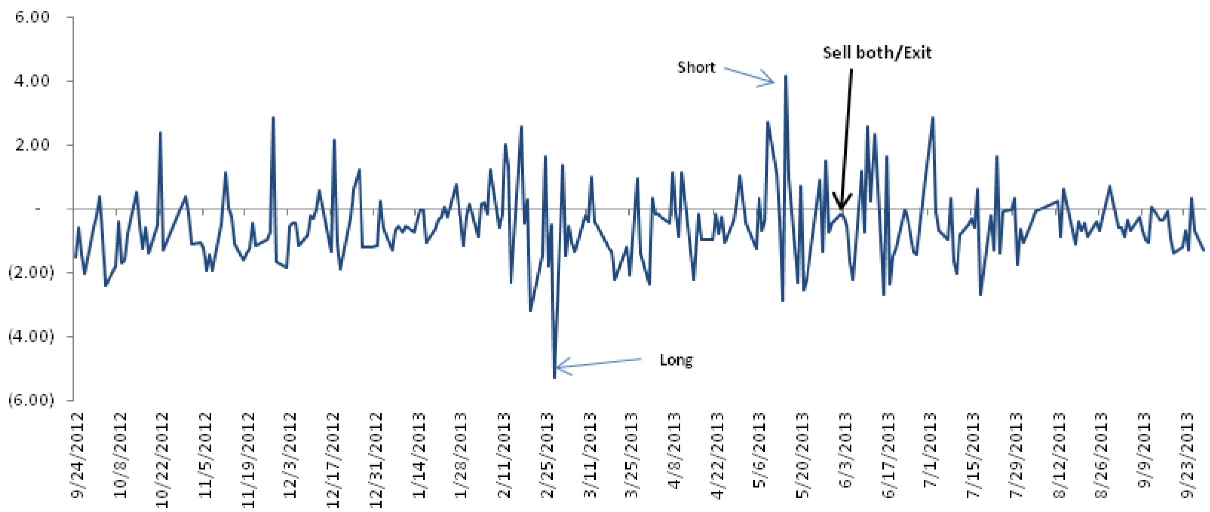
Before going into the final step of the methodology, let us recap the major steps taken for producing the pairs trade model.

1. Filter stocks according to liquidity and sectoral distribution in Dhaka Stock Exchange.
2. Obtain co-integrated stocks using Johansen's test.
3. Run Vector Error Correction Model on the identified co-integrated stocks using first difference form.
4. Estimate the parameters and test for significance.
5. Obtain the residual series as a function of only the significant parameters.

Once these are established, the study aims to develop the actual trading rule so that this strategy can be successfully carried out in the stock market. First it identifies which stock to long, and which one to short. The study uses the statistic from the Johansen's co-integration test termed "Normalized Co-integrated Coefficients". From here, it longs the stock with the higher value, and shorts the one with the lower value because these coefficients are telling a Pairs Trader how price levels will change in the long run. If for instance, one stock as a normalized coefficient of +2, while the other has one of -2, it means the one with higher value will increase in long run while the one with lower value will decrease in long run to restore equilibrium.

Let us now develop the thumb-rule for a **"Trade Signal"**. A trade signal will be an indication from the residual series when to go long and when to go short for Pairs trade. The trader will observe the historical pattern of the residual series. When the residual series is at or close to zero one can infer that the two stocks are moving in their general long-run equilibrium. When the value of the residual series is furthest from 0, relative to its historical pattern, the pairs trader opens the pairs trade position. If the value is for instance, -4 (for a stock pair which had a residual historically between 2 and -2 and hovering around 0 most of the time) then a trader goes for a long strategy because of the assumption that price will appreciate as the residual returns to 0. Right after that, he looks for a trade signal showing that the value is significantly positive, like, +4. This is where he goes short since he assumes that as the stocks return to their equilibrium, price of the shorted stock will fall. Puspaningrum (2012) mentions that the monetary value invested in long and short positions have to be equal in order to divide equally the probability of profiting from this strategy.

Figure 3 Illustration of Pairs Trade



There are several further considerations an investor must remember during implementation of this strategy.

- Firstly, an investor is unlikely to gain from both long and short strategy. The likely scenario is that gain from one strategy will be more than the loss from the other, brining a profit in net position in the trade strategy.
- Secondly, an investor must actively monitor his profit position by incorporating daily price levels into the residual series model. In the event that he sees the residual has returned to 0 and he is in a net loss position, then the investor has an option of waiting for another disequilibrium and subsequent mean reversion in order to allow the strategy to reach a net profit.
- The investor also must remember that it is not impossible to make a loss from one single pairs trade strategy. However, the rationale for undertaking this strategy is that, an investor is likely to find himself in a net profit position if he carries out this strategy several times during the course of a year.

5.2.5 Impulse Response Functions

In this final section of model derivation, the concept of Impulse Response Functions will be introduced. Rossi (2013) states that in applied work it is often of interest to know response of one variable to an impulse in another variable in a system that involves a number of further variables as well. Impulse response functions trace the effect of an exogenous shock or innovation in one of the variables on some or all of the other variables. Impulse response functions are important in analyzing the inter-relationships between the price time-series variable represented in a VAR model according to Schmidt (2008). The function is analogous to a vector moving average representation of the VAR (shown in equation 5.10) since variables in this function are expressed in terms of current and past values of two types of shocks.

$$z_t = \mu + \sum_{i=0}^{\infty} A_1^i e_{t-i} \tag{5.10}$$

Where, z_t = Impulse response function

A_1^i = i-th coefficient matrix of the moving-average representation of a VAR(1) process

e_{t-i}= Exogenous shock

$\mu = [\bar{y}\bar{z}]'$

$\bar{y} = \frac{[a_{10}(1-a_{22})+a_{12}a_{20}]}{\Delta}$, $\bar{x} = \frac{[a_{20}(1-a_{11})+a_{21}a_{10}]}{\Delta}$

$\Delta = (1-a_{11})(1-a_{22}) - a_{12}a_{21}$

This representation allows one to trace out the time path of the several shocks to the variables in the VAR system. Schmidt (2008) points out that this is critical from a pairs trading point of view since it is intriguing to know how shocks to one of the variables are filtered through each of the individual price series and how long it would take for equilibrium to be restored within the system.

Thus this research plots the impulse response function in order to visually represent behavior of one of the variables in response to a one-standard deviation shock to that or another variable in the system. This is carried out after the final model is derived as part of model evaluation process.

CHAPTER 6 RESULTS

6. Results

6.1 Identifying trading pairs

This section presents empirical findings from the model. The first part of this chapter deals with the identification of a Pairs trade. This part presents the findings from Co-Integration test output, and identifies stock pairs which have a co-integrating relationship according to Johansen Test for Co-Integration. Second part of this chapter evaluates profitability of Pairs Trade Strategy using the residual series from the VECM. Using the concept of "Trade Signal", the strategy is implemented to arrive in net profit positions. The study uses actual price levels of in-sample and out-of sample values to test for profitability. The last part of this study shows how Pairs trading is more profitable over investments using financial analysis only. This is presented by using conventional financial ratios and other major fundamental indicators to illustrate how the investor would have made his stock buy-sell decisions had he used theories of finance *only* rather than mathematical modeling.

6.1.1 Co- integration test output

The first step in this study was to test each potential pair in the sample of 20 stocks listed in DSE for presence of Co-integration relationship. The Johansen test was implemented using daily data of stock price with an acceptable occurrence of type-1[25] errors set at 5%. The critical characteristic of a successful pairs trading strategy is the presence of a mean-reverting equilibrium relationship between the pairs as stated by Schmidt (2008). Co-integration provides a pairs trader with this necessary condition, and, because of this, the model sets α=5% so that one can be sure that any detected co-integrating relationship is robust.

Trace statistic was used to identify presence of Co-integration between stock pairs. A trace statistic greater than the 5% critical value indicates a co-integrating relationship between the two variables. Trading pairs were retained if their p-values were less than 5%. Thus it can be inferred that the likelihood of rejecting the null hypothesis of "no co-integrating relationship" when in fact it is true will be less than 5 out of every 100.

[25] A type I error (or error of the first kind) is the incorrect rejection of a true null hypothesis. It is a false positive. Usually a type I error leads one to conclude that a supposed effect or relationship exists when in fact it doesn't as defined by Sheskin (2004).

It must be mentioned that Co-integration test also gives a potential pairs trader information for which stocks out of a pair to long and which one to short. This is given by the "normalized co-integrating co-efficient". The higher value among the co-integrated variables indicates that a stock will rise in value over the long run, making it suitable for long investing. The lower value of the two stocks indicates that its price will fall (relative to the other) over the long run meaning it is conducive for short selling[26].

Co-integrated test was carried out on stocks from the same sector. Implementing Johansen's test on the stocks chosen for this research, yields three co-integrated pairs. The full results are shown in Appendix A. Tabulated below are the primary indicators looked at from the Co-integration test results.

Table 2 Co-Integration result for ACTIVEFINE and PHARMAID

	ACTIVEFINE	PHARMAID
Trace Statistic		18.15406
5% Critical Value		15.49471
p-value		0.0194
Normalized Co-integrating Coefficients	1.000000	-0.519327

ACTIVEFINE and PHARMAID have a trace statistic higher than 5% critical value in the Johansen's test – they have one co-integrating equation. The pair has a p-value of 1.94%, thus ensuring statistical significance. Value of the normalized co-integrating coefficient indicates that for the purpose of Pairs Trade, ACTIVEFINE will be suitable for long position, and PHARMAID for short position.

Table 3 Co-Integration result for GBBPOWER and KPCL

	GBBPOWER	KPCL
Trace Statistic		15.53677
5% Critical Value		15.49471
p-value		0.0493
Normalized Co-integrating Coefficients	1.000000	2.192939

[26] If both coefficients are positive it means both will rise in the long run. In such a case the one with higher value will be chosen for long position and the other stock for short position. This is because the long position is expected to generate higher profit than a possible loss from the short position.

The next pair found to have one co-integrating equation is GBBPOWER and KPCL. The p-value at 4.93% passes the significance test at the 5% level. Normalized co-integrating coefficients show that KPCL is conducive for long investment, and GBBPOWER for short positions.

Table 4 Co-Integration result for TITASGAS and BDWELDING

	TITASGAS	BDWELDING
Trace Statistic		15.95171
5% Critical Value		15.49471
p-value		0.0427
Normalized Co-integrating Coefficients	1.000000	10.64156

The last pair which was found to have a co-integrating relationship from the sample chosen for this research is TITASGAS and BDWELDING. The pair is statistically significant and BDWELDING was found to be the stock for long investment and TITASGAS for short selling.

Now that the co-integration test has been implemented on the sample chosen, three stock pairs have been found to be co-integrated. All three have statistical significance. Below is a tabulation of the three pairs which will be estimated through Vector Error Correction Model.

Table 5 Summary of Final trading pairs

	Long	**Short**	**Sector**
PAIR 1	ACTIVEFINE	PHARMAID	Pharmaceutical
PAIR 2	KPCL	GBBPOWER	Fuel & Power
PAIR 3	BDWELDING	TITASGAS	Fuel & Power

6.1.2 Estimation of Vector Error Correction Model

In this section, estimation output from the VECM is presented. The objective is to obtain the residual from this model. This is done by estimating the VECM and retaining only the statistically significant variables. Then the residual is derived by using algebraic manipulation of re-arranging all statistically significant variables on one side of the equation leaving the other side as the residual.

The VECM estimated for ACTIVEFINE and PHARMAID is shown in Equation 6.1a.

$$D\ (ACTIVEFINE) =$$
$$C(1) * (\ ACTIVEFINE(-1)\ -\ 0.479960438913 * PHARMAID(-1)\ +\ 2.5423410255)\ +$$
$$C(2) * D(ACTIVEFINE(-1))\ +\ C(3) * D(ACTIVEFINE(-2))\ +\ C(4) *$$
$$D(PHARMAID(-1))\ +\ C(5) * D(PHARMAID(-2))\ +\ C(6) \qquad (6.1a)$$

Analysis of p-values of this model (APPENDIX B) shows that the only statistically significant variable is ACTIVEFINE(-1) with a p-value of less than 1%. The model itself does not explain much of the variation in ACTIVEFINE. As can be seen from Appendix-B, the Adjusted R-Squared is only 1.6%. However, the goodness of fit R^2 is not of concern here because the objective is not to find the relationship of variation of ACTIVEFINE due to variation of PHARMAID. Since the research is dealing with a system of equations, it is more concerned with the sign of the coefficients and statistical significance of coefficients. The goal is to keep statistically significant coefficients from VECM when calculating the residual series. Thus, the final model becomes:

$$D(ACTIVEFINE)\ =\ C(1) * (\ ACTIVEFINE(-1) \qquad (6.1b)$$

where C(1) = -0.033926

Thus the residual series, R_{AC}, (Residual for ACTIVEFINE and PHARMAID) is given by:

$$\boldsymbol{R_{AC}\ =\ D(ACTIVEFINE) - (-0.033926 * (\ ACTIVEFINE(-1))} \qquad \textbf{(6.1c)}$$

Using similar methodology the VECM estimated for GBBPOWER and KPCL is:

$$D(KPCL) =$$
$$C(7) * (\ GBBPOWER(-1) +\ 3.05040807582 * KPCL(-1) -\ 186.008031019\ ) +\ C(8) *$$
$$D\big(GBBPOWER(-1)\big) +\ C(9) * D\big(GBBPOWER(-2)\big) +\ C(10) * D\big(KPCL(-1)\big) +\ C(11) *$$
$$D\big(KPCL(-2)\big) +\ C(12) \qquad (6.2a)$$

Analysis of the p-values (APPENDIX B) shows that the only statistically significant variable is GBBPOWER(-1), meaning the first lag value of GBBPOWER. It is interesting to note that in the previous model, the only statistically significant variable for the dependant variable was its own lagged value. However, in this case, the explanatory variable is the other stock in the pair – meaning first differences in KPCL is being explained by lagged variables of GBBPOWER.

However, with the ultimate goal being to derive a statistically significant residual series, identity of the explanatory variables is not significant to this research's objective. Thus, the final model for this pair's residual series is given by Equation 6.2b.

$$D(KPCL) = C(7) * (GBBPOWER(-1) \tag{6.2b}$$

where C(7) = -0.014164

The residual series, $R_{KG,}$ (Residual for KPCL and GBBPOWER) is shown by Equation 6.2c.

$$\boldsymbol{R_{KG} = D(KPCL) - (-0.014164 * (GBBPOWER(-1))} \tag{6.2c}$$

The last pair that will be presented is TITASGAS and BDWELDING. The VECM for this pair of stocks is shown by Equation 6.3a.

$$D(TITASGAS) = C(1) * (TITASGAS(-1) + 10.5335364118 * BDWELDING(-1) - 313.426704686) + C(2) * D(TITASGAS(-1)) + C(3) * D(TITASGAS(-2)) + C(4) * D(BDWELDING(-1)) + C(5) * D(BDWELDING(-2)) + C(6) \tag{6.3a}$$

Using p-values from this model, the statistically significant variable is first lag variable of TITASGAS, represented in the model by TITASGAS(-1). Therefore, final model for this pair is shown below:

$$D(TITASGAS) = C(1) * (TITASGAS(-1) \tag{6.3b}$$

where C(1)= -0.007158

With the resulting residual series, R_{TB}, (Residual for TITASGAS and BDWELDING) is given by:

$$\boldsymbol{R_{TB} = D(TITASGAS) - (-0.007158 * (TITASGAS(-1))} \tag{6.3c}$$

Using the methodology described in section 5.2.5, the residual series will be used as the guide for carrying out pairs trade strategy.

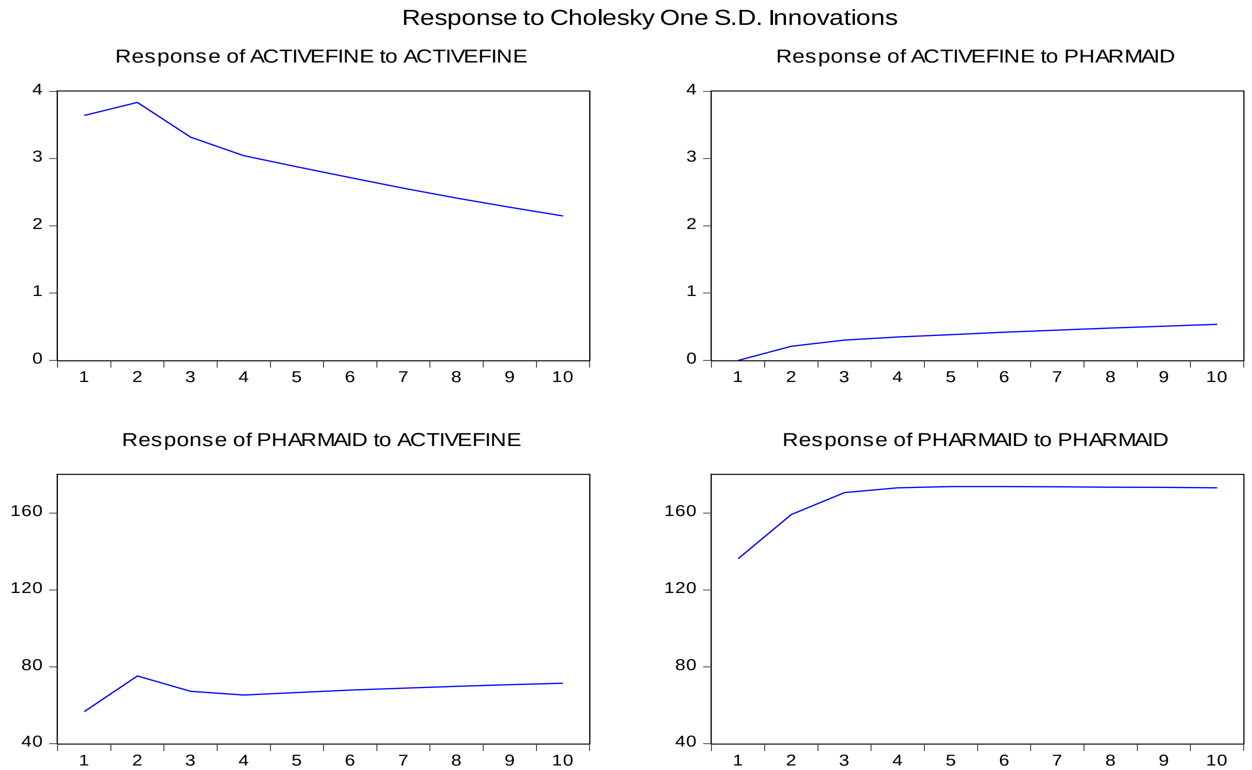
Detailed VECM outputs for the three pairs are reported in Appendix B.

6.2 Evaluation of Vector Error Correction Model

6.2.1 Results of Impulse Response Functions

The previous section showed estimation output of the VECM model which provided the long-run behavior of the co-integrated pairs of stocks. However, a Pairs trader may also be interested in understanding short-term dynamics of a pair used for investment. Impulse response functions show short-term reaction of the variables in response to a shock to the system. These shocks are applied individually, and its impact is then studied against time. The shock to a variable can be given by the variable itself or other variables in a system. Below are findings of Impulse response functions of each of the three pairs this research has used for Pairs trading.

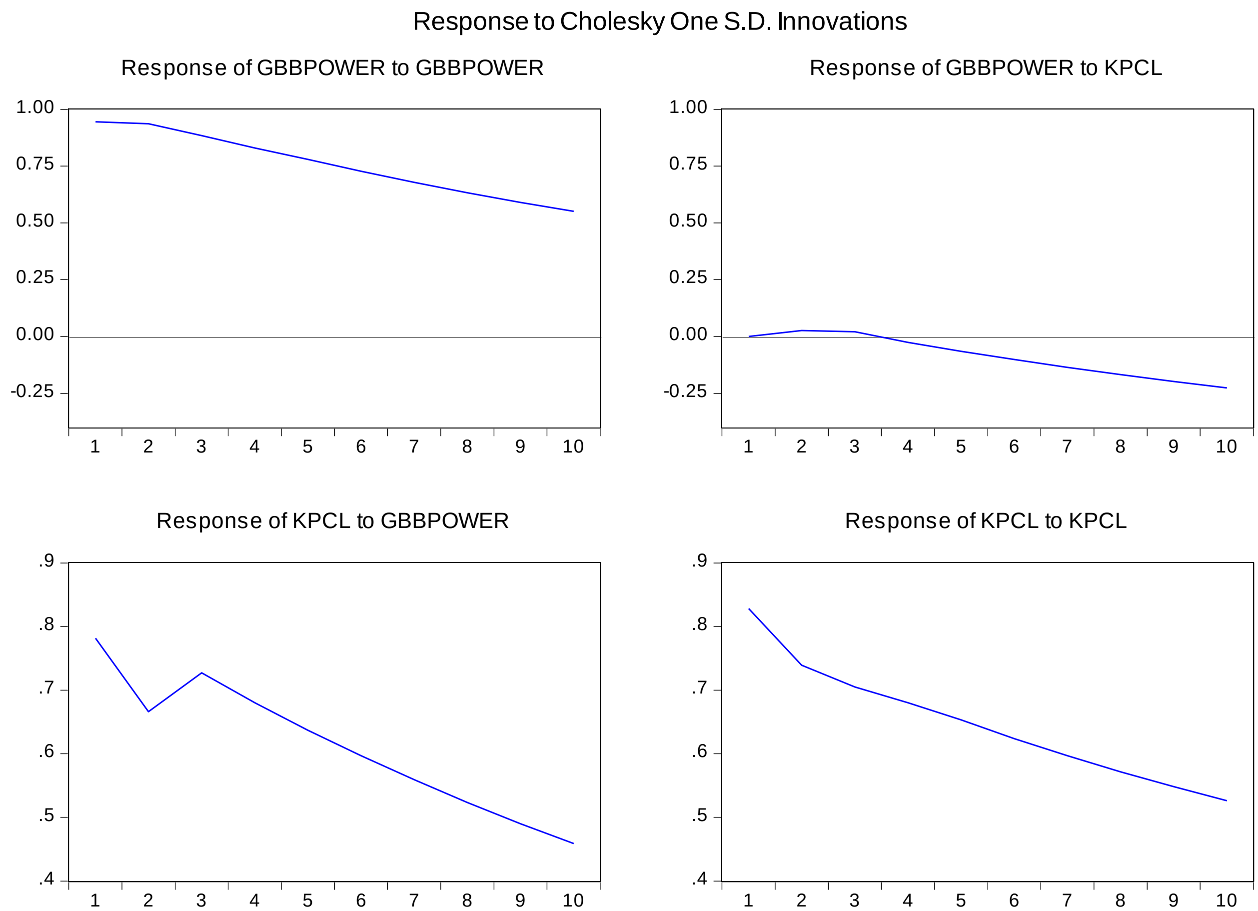
Figure 4 Impulse Response Function for ACTIVEFINE & PHARMAID



The top left box plots response of ACTIVEFINE to itself; the bottom right box plots response of PHARMAID to itself, while the other two plots response of one variable to the other when a one standard deviation shock is applied to the system.

For instance, the top-left box shows that ACTIVEFINE first increases from first period to second, and then linearly decreases till the tenth period following a one-standard deviation shock to ACTIVEFINE. Similarly, ACTIVEFINE increases by 0.2 units from first to second period following a shock to PHARMAID, and then increases marginally till the 10th period. Conversely, when a shock is applied to ACTIVEFINE, PHARMAID responds by increasing about 20 units from first to second period, then decreasing in third period, after which the change is negligible till the 10th period. Lastly, following a shock to PHARMAID, PHARMAID itself increases by about 40 units from the 1st to 3rd period and then the change becomes quite negligible.

Figure 5 Impulse Response Function for GBBPOWER and KPCL

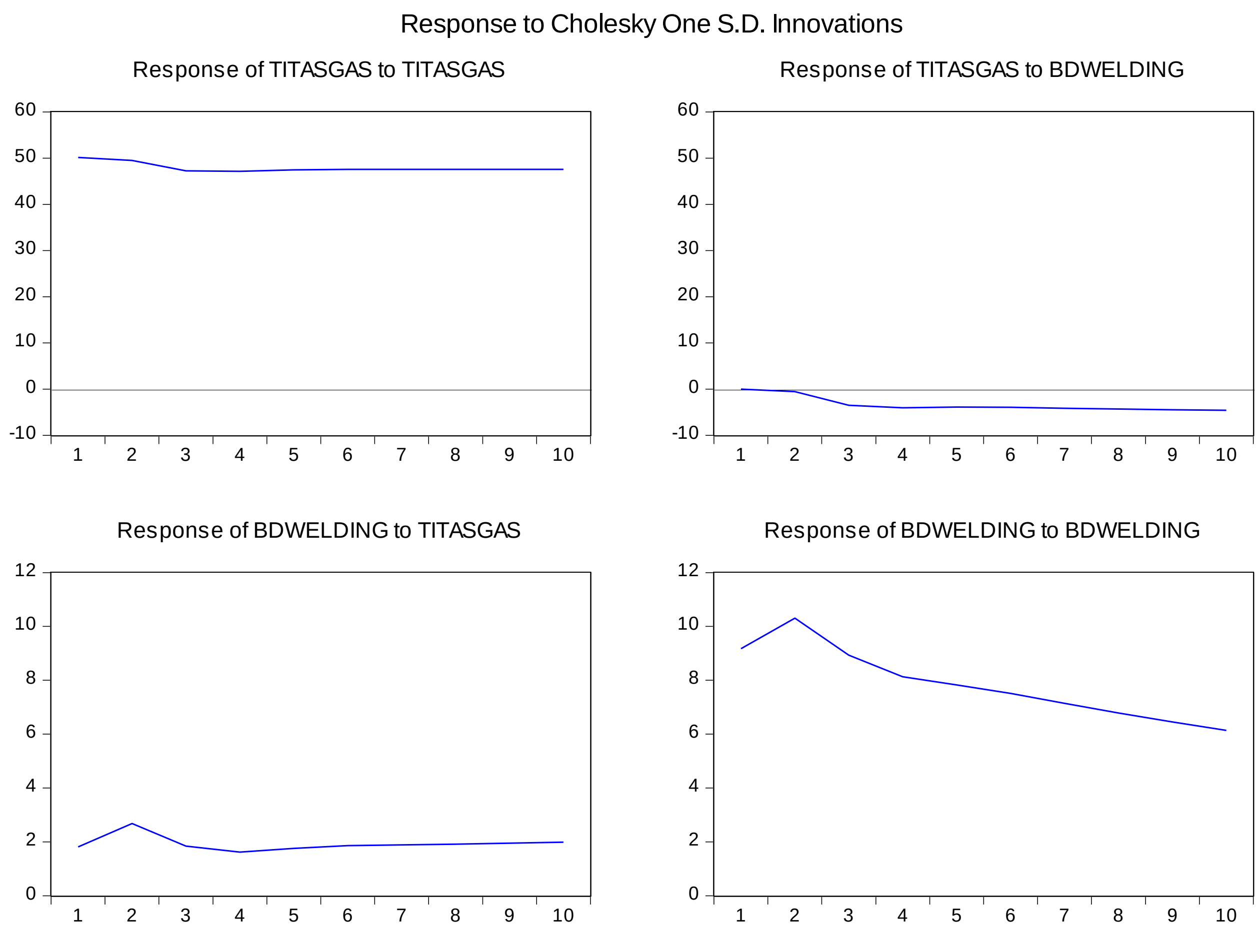


In response to a one-standard deviation shock to GBBPOWER by itself, GBBPOWER increases by 0.9 units in the first period and then gradually falls to 0.6 units in the 10^{th} period following a linear trend. The response of GBBPOWER to KPCL varies significantly. Following a shock by KPCL, GBBPOWER does not move in any statistically significant manner in the first three periods and then starts decreasing in 4th period linearly till the 10th period to create a change of -0.25 units.

When GBBPOWER gives a shock to KPCL, KPCL increases by 0.78 units, then falls to 0.66 units in the second period. Intriguingly, it rises to 0.73 units again in the third period after which it gradually decreases to below 0.50 units by the 10th period implying that after the third period, GBBPOWER's shock has decreasing impact on KPCL in the short-term.

Finally, KPCL's response to its own shock is broadly a linear fall after the second period. While a shock by itself increases it by 0.8 units in the first period, it falls to around 0.74 units in the second period and then decreases continuously till the 10th period to 0.55 units.

Figure 6 Impulse Response Function for TITASGAS and BDWELDING



As Figure 6 shows, TITASGAS does not exhibit any significant movement when a shock is applied to it by itself. When a shock is applied to it by BDWELDING, it decreases by about 5 units from the 2^{nd} to the 3^{rd} period and then does not exhibit any significant movement till the 10^{th} period. When a shock is applied to BDWELDING by TITASGAS, BDWEDLING increases by about 0.8 units from the 1^{st} to the 2^{nd} period, then falls back to the original level in the third period after which it does not show too much movement to a one-standard deviation shock. BDWELDING, when given a shock by itself, rises by 1.2 units in the 2^{nd} period and then decreases till the 10^{th} period.

It is interesting to note that for all three pairs, a one standard deviation shock to the system has a very temporary change. Anomalies in movements can be seen for the first three periods generally after which the impact of the shock decreases linearly. Thus it can be said that for all three pairs shown above, a shock to the system creates a change in price movements of the variables for 3 months after which the shock's effect decreases steadily.

6.2.2 Results of profitability using Pairs trade

This section presents analysis profitability using Pairs Trading. In implementing the strategy, the thumb-rules discussed in Section 5.2.5 were followed. By studying historical pattern of the residual series a trader chooses a pair of extreme values above and below which he will short (when the value is abnormally higher than 0) and long (when the value is abnormally lower than 0) respectively. The extreme values of residual series is the “trade signal” discussed earlier, which acts as the guiding principal in carrying out this strategy. These extreme values will differ for different stock pairs.

Adhering strictly to the thumb-rule of shorting at relative extreme maximum and minimum values and selling when the residual returns to or close to 0, Pairs trading was implemented. As discussed in section 5.2.5, it was assumed that not every Pairs trade will yield a profit; however the incentive for the trader is that implementing this strategy several times over a period will bring him to a net profit position.

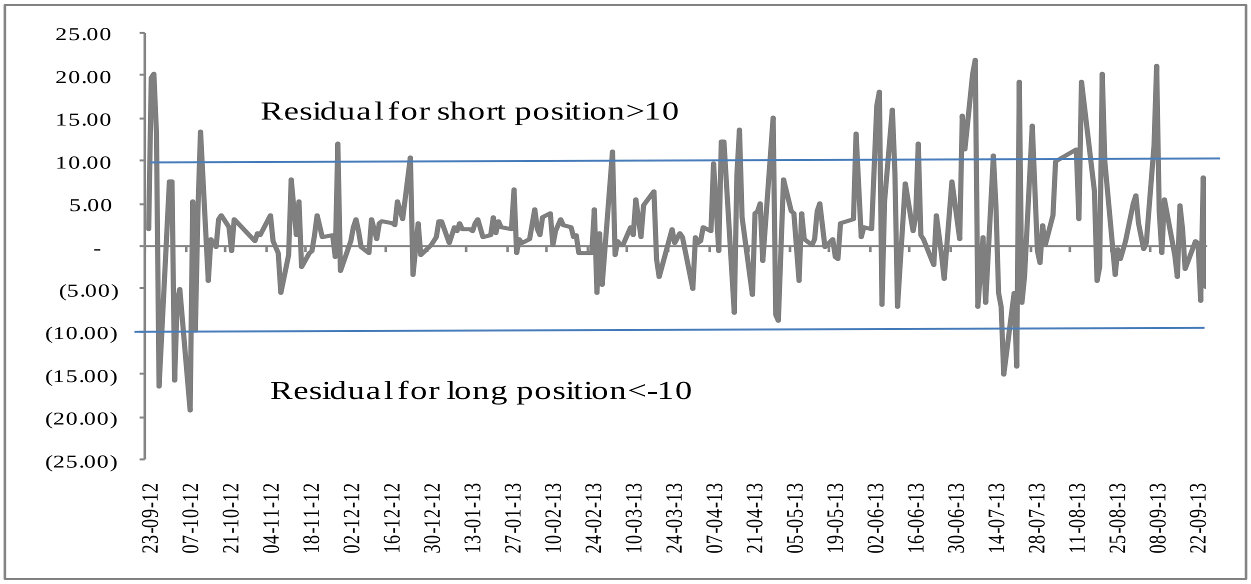
To illustrate the monetary profitability of this strategy, the study used real-time data and assigned a hypothetical monetary investment of BDT 100,000 invested equally between long and short positions. Furthermore, return from this investment is annualized using a common mathematical formula used in investments called Compounded Annual Growth Rate, or CAGR as defined by Fabozzi (2011), which is calculated as follows:

$$CAGR = \left(\frac{Enging\ Value\ of\ Investment}{Beginning\ Value\ of\ Investment}\right)^{\left(\frac{1}{Number\ of\ Year}\right)} - 1$$

The research illustrates findings from one pairs trade carried out for each of the three stock pairs estimated from Vector Error Correction Model. The trade is carried out from the actual prices in the sample used for estimation. A Pairs trade for each stock pairs from time periods outside of the sample is tabulated in Appendix D. This has been carried out to validate the model and confirm that the model works outside the sample used for estimation.

The pair-wise thumb-rules for long and short investing and resulting profitability for a pairs trade is given below.

Figure 7 Residual time-series for ACTIVEFINE & PHARMAID



Given the thumb-rule shown in the diagram above, a Pairs trade carried for ACTIVEFINE and PHARMAID generates a return of 9.32% in 22 days. The compounded annual growth rate for this trade is 339%. The cost and gain from the investment are tabulated below:

Table 6 Pairs Trade initiated on 25/9/12 for 22 days

Stock Name	PHARMAID	ACTIVEFINE
Monetary Amount (BDT)	50,000	50,000
Trading Price (According to trade rules)	205.0	74.0
No of Shares at Trading price[27]	244	676
Selling price (According to trade rules)	164.00	75.00
Gain (BDT)[28]	10,000	(676)
Net Gain from Pairs Trade (BDT)[29]		9,324.3
Return (%)[30]		9.32%
Duration (Days)		22
CAGR (%)		339%

[27] No of Shares = Monetary Amount/Trading price
[28] For short investing: (Trading price – Selling price); For long investing: (Selling price – Trading price).
[29] Gain/Loss from short investing + Gain/Loss from long investing
[30] Net Gain from Pairs trade/Total Initial investment

As mentioned before, a pair trader does not gain from both the long and the short position. The net profit comes from a greater profit from one position (in this case the short position) than the loss from the other position (in this case the long position).

The next pair trade is carried out for KPCL and GBBPOWER using the same methodology.

Figure 8 Residual time-series for KPCL and GBBPOWER

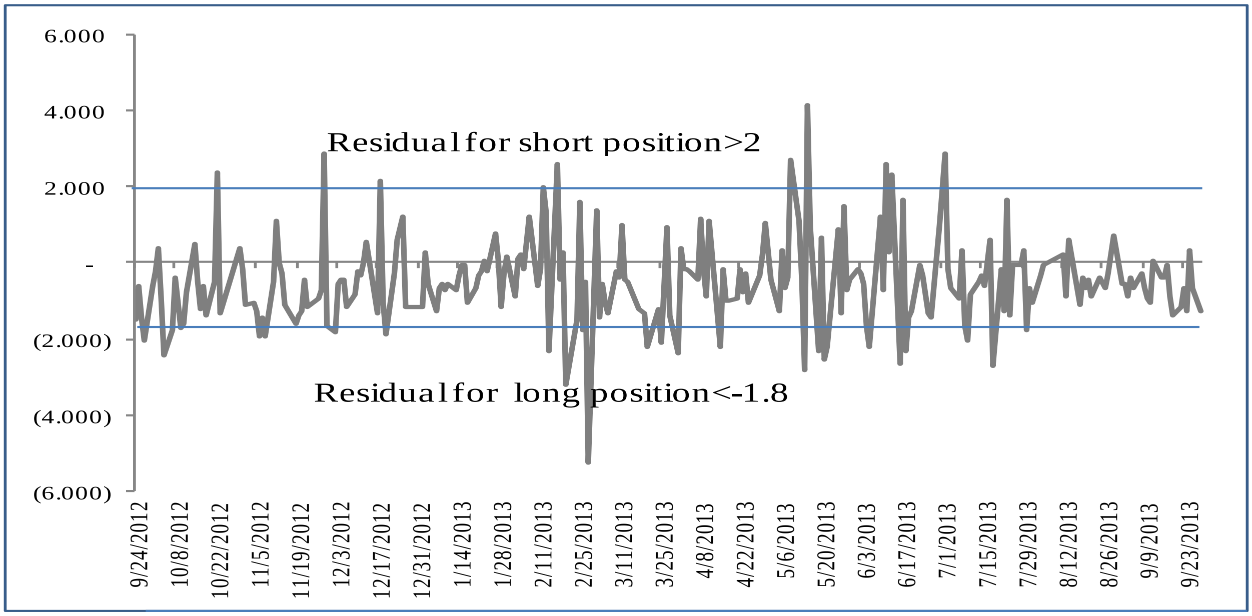


Table 7 Pairs Trade initiated on 23/10/12 for 22 days

Stock Name	**KPCL**	**GBBPOWER**
Monetary Amount (BDT)	50,000	50,000
Trading Price (According to trade rules)	52.0	43.0
No of Shares at Trading price	1020	1163
Selling price (According to trade rules)	51.00	34.0
Gain (BDT)	(962)	10,465 .1
Net Gain from Pairs Trade		9,503.6
Return (%)		9.50%
Duration (Days)		22
CAGR		351%

As before, only one of the two simultaneous investing strategies (long/short) generates a profit. KPCL and GBBPOWER generate a return of 9.50% which has a CAGR of 351%.

In a similar manner, the residual thumb-rule and profitability results are shown below:

Figure 9 Residual time-series for TITASGAS and BDWELDING

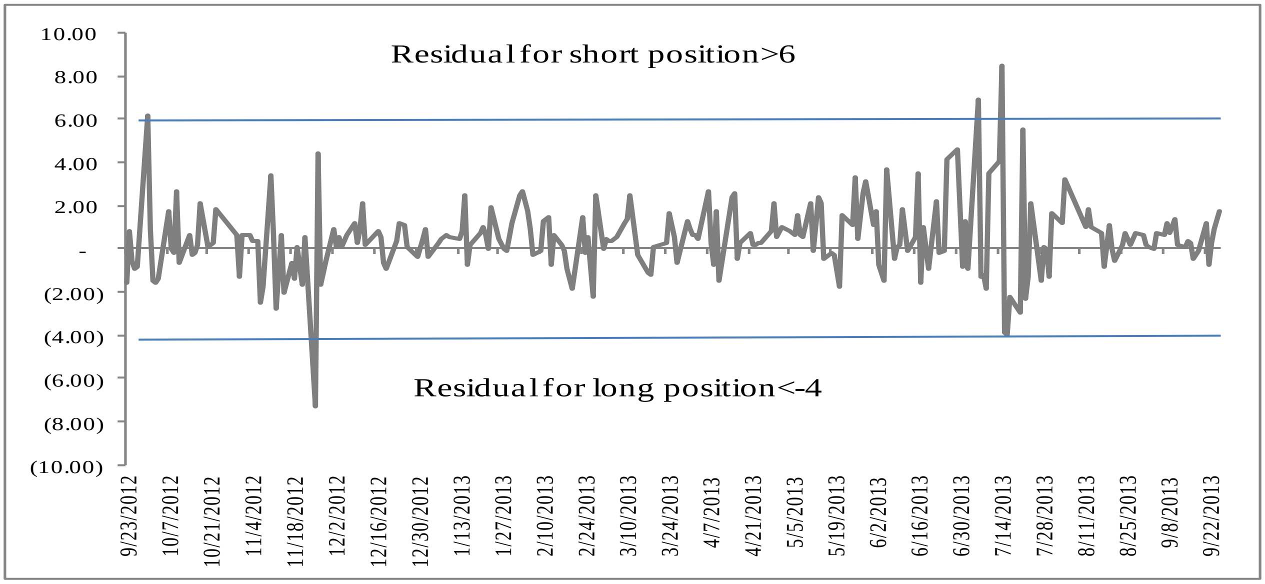


Table 8 Pairs Trade initiated on 02/10/12 for 64 days

Stock Name	TITASGAS	BDWELDING
Monetary Amount (BDT)	50,000	50,000
Trading Price (According to trade rules)	92.7	23.8
No of Shares at Trading price	539	2101
Selling price (According to trade rules)	63.80	23.70
Gain (BDT)	15,588	(210)
Net Gain from Pairs Trade		15,378
Return (%)		15.38%
Duration (Days)		64
CAGR		126%

It is important to note that the thumb-rule for fixing a residual limit for long and short positions has to be changed according to price movements of the stocks. By regularly observing the residual series using daily stock price levels, the trader can adjust his residual limits accordingly.

6.2.3 Comparison of profitability using financial analysis

This section aims to determine profitability of similar simultaneous long and short investment strategies using financial analysis instead of Pairs Trading. The objective is to demonstrate the value of a mathematically derived Pairs Trading strategy over financially analyzed investment strategies. The section first outlines financial ratios that are most commonly used for fundamental analysis in investments and then illustrates buy-sell investment decision based on such indicators only.

Ratios to be used for financial analysis as defined by Schweser (2010) are:

Earnings-per-Share: An EPS is total after tax profit of a company divided by the number of shares outstanding. EPS serves as a common indicator of a company's profitability.

$$Earnings\ Per\ Share = \frac{Net\ Profit\ After\ Tax}{Number\ of\ Ordinary\ Shares\ Outstanding}$$

Price-Earnings ratio: A P/E ratio gives the valuation ratio of a company's current share price to its per-share earnings. It is calculated as:

$$PE = \frac{Market\ Value\ per\ Share}{Earnings\ Per\ Share}$$

According to Schweser (2010) when a company trades at a high P/E, investors are expecting higher earnings growth in future compared to companies with a lower P/E. But, if a company does not have fundamentally[31] sustainable earnings potential, it also implies that a stock is over-valued and is likely to face a price correction in the future. Investors generally compare P/E of a company with the standard industry P/E to understand if a stock is fairly priced, over-valued or undervalued.

Fair price: This is a rational and unbiased estimate of the potential market price for a stock based on its fundamental drivers and financial performance. Fair price is one of the most critical aspects for an investor to look at when buying or selling a stock. A stock trading at a price higher than its fair value is likely to see a price correction in the future, while that which is trading

[31] Qualitative and quantitative information that contribute to the economic well-being and subsequent financial valuation of a company.

below its fair value is likely to appreciate in value in the future. An investor can use a company's EPS and its PE ratio to calculate a PE-based fair value.

$$Fair\ Value = PE * Earnings\ Per\ Share$$

Return on Equity (ROE): ROE is the amount of net income returned as a percentage of shareholders equity. Return on equity measures a corporation's profitability by revealing how much profit a company generates with the money shareholders have invested. ROE is expressed as a percentage and calculated as:

$$ROE = \frac{Net\ Profit\ After\ Tax}{Shareholder's\ Equity} * 100$$

Gross Profit Margin: This is the company's gross profit[32] divided by the company's Revenue. A company's total sales revenue minus its cost of goods sold, divided by the total sales revenue, expressed as a percentage. Gross margin represents the percent of total sales revenue that a company retains after incurring direct costs associated with producing goods and services sold by a company. The higher the percentage, the more the company retains on each dollar of sales to service its other costs and obligations as outlined by Investopedia (2013).

Investors generally compare this ratio with the industry standard to see how a company is actually doing. An absolute value without comparables does not give the investor much room to make an inference about the potential of a company.

Profit After Tax (PAT) Margin: Ratio of net profits to revenues for a company or business segment - typically expressed as a percentage – that shows how much of each dollar earned by the company is translated into profits. Net margins can generally be calculated as follows:

$$Net\ Margin = \frac{Net\ Profit}{Revenue} * 100$$

where, Net profit = Revenue – Cost of Goods Sold – Operating Expense – Financial expense – Tax

Investors are likely to compare a company's PAT margin with industry PAT margin to see if it is doing better or worse than the industry.

[32] Gross profit = Revenue – Cost of Goods Sold

Growth ratios: Investors generally focus on growth of a company as well. The most common growth ratios are revenue growth and net profit growth. This gives an investor an idea of the prospects of a company in the future.

To compare the profitability of Pair's Trade over financially derived investment strategy, the study used the above ratios to make informed buy-sell decisions. Note that no mathematical reasoning is used here and the study bases its reasoning solely through these financial indicators.

Since the time-frames will differ for the stocks to reach fair prices, the duration of trading using Pairs Trading and financial analysis will be different. Thus it is difficult to compare profitability given different time taken to generate respective returns. In order to standardize the comparison, returns are annualized.

To standardize the entire comparison the following strategies are followed:

- Using latest publicly available financial information at the time when pairs trade was started using the model from this research.
- Investment decisions using financial analysis starts at the same dates as Pairs Trade.
- Since time duration to generate targeted returns using financial analysis and Pairs Trade are different, returns are annualized using Compounded Annual Growth Rate (CAGR) as outlined in section 6.2.2.

The ratios calculated for the six stocks that we used for Pairs Trading are as tabulated below.

Table 9 Summary of Financial Ratios

	PHARMAID	**ACTIVEFINE**	**GBBPOWER**	**KPCL**	**TITASGAS**	**BDWELDING**
Price-Earnings	32.0	28.6	16.2	10.0	8.61	58.82
Sector P/E	17.5	17.5	14.3	14.3	14.3	14.3
EPS (BDT)	5.1	3.2	1.85	4.9	9.0	0.35
Fair Value	162.0	92.3	30.0	49.0	77.6	20.6
Price[33] (BDT)	205	74	43.0	54.0	92.7	23.8
ROE	19.2%	23.3%	7.0%	30.9%	25.0%	2.9%
Sector ROE	12.7%	12.7%	21.4%	21.4%	21.4%	21.4%
Sales growth	11.0%	62.8%	-0.15%	-8.0%	4%	73.0%
PAT growth	13.7%	66.9%	50.20%	99.20%	-3.0%	62.9%
GP Margin	32.8%	54.2%	64.80%	27.10%	16.0%	31.8%
Industry GP	48.0%	48.0%	30.7%	30.7%	30.7%	30.7%
PAT Margin	14.6%	30.9%	25.7%	16.0%	12.0%	6.6%
Industry PAT	10.5%	10.5%	17.3%	17.3%	17.3%	17.3%

[33] Prices reported are from those dates when Pairs Trade was initiated

Comparison with Pair 1 (PHARMAID ACTIVEFINE)

Pairs trade strategy generates a return of 9.32% in a duration of 22 days for PHARMAID and ACTIVEFINE. Using these two stocks, similar long/short strategies are derived based on fair value and profitability ratios as shown in table 9. From here, one can see that PHARMAID is over-valued and ACTIVEFINE is under-valued indicating that one can enter a short strategy with the former and a long strategy with the latter (Similar to the Pairs trade model). However, an investor basing his decisions on financial indicators will also look at other ratios listed above. First and foremost, one can see that ACTIVEFINE's PE ratio is significantly higher than industry average. This indicates that the stock is over-valued and hence refrains from long investing. However, given that it has strong Sales and PAT growth, and margins above the industry average one can enter the long strategy nonetheless.

An investor will take exit when the fair prices are reached. As can be seen from the table 10, while the actual return is greater for the investor using financial analysis, the duration required to generate that return is much longer. To standardize the time durations to generate returns using these two methodologies, Compounded Annual Growth Rate was used. The CAGR of the return generated by Pairs trade is 339% while the same generated by financial analysis is 41.60%.

Table 10 Comparison of Profitability using financial analysis and Pairs Trade

Strategy	**Financial Analysis**		**Pairs Trade**	
Stock Name	PHARMAID	ACTIVEFINE	PHARMAID	ACTIVEFINE
Monetary Amount (BDT)	50,000	50,000	50,000	50,000
No of Shares at market price	244	676	244	676
Gain (BDT)	10,488	12,365	10,004	676
Total profit (BDT)		22,853		9324.3
Return (%)		22.85%		9.32%
Duration (Days)		213		22
CAGR (%)		**41.60%**		**339.0%**

Comparison with Pair 2 (GBBPOWER KPCL)

Pairs trade strategy generates a return of 10.47% in a duration of 22 days for GBBPOWER and KPCL. Financial Analysis however gives a different decision. Fair value of GBBPOWER is BDT 30, the same price at which it was trading on the day chosen for pairs trading. Using financial analysis thus implies that an investor will not benefit from a long or a short strategy since its then current price was its intrinsic value. Furthermore, KPCL (shorted in pairs trade) was trading at a PE below its fair price, meaning its price is expected to appreciate (making it conducive for long strategies only). However, an investor will also notice that KPCL had a gross margin and PAT margin lower than the industry average which implies the company is weaker than industry average. Furthermore, its revenue growth had a negative value of -8%. A rationale investor will generally refrain from long investing in companies which have poor top-line or sales growth performance as it indicates weakness in its critical fundamental drivers. Given these ratios, a rationale investor will refrain from investing in this stock as its price is not supported by fundamental ratios. Thus, the investor will not enter into a simultaneous long and short investment strategy using financial analysis.

Comparison with Pair 3 (TITASGAS BDWELDING)

Pairs trade strategy generates a return of 15.38% in a duration of 64 days for TITASGAS and BDWELDING. Given the fair value of TITASGAS, and its then market price, the stock is conducive for short strategies (similar to Pairs trade). BDWELDING has financial ratios lower than industry average. Most notably, its ROE and PAT margin are significantly below the industry average. On top of that, its then market price was higher than its Fair value meaning it is not conducive to long-investments. A rationale investor will thus only use TITASGAS (for short strategies) when given this pair of stocks and refrain from long investments in TITASGAS.

Therefore, similar to the previous comparison, one cannot derive a pair of stocks for simultaneous long-short investment strategies.

CHAPTER 7 CONCLUSION

7. Conclusion

The purpose of this study was to develop a financially profitable Pairs trading strategy for Dhaka Stock Exchange (DSE). Pairs trading strategy uses the concepts of mean reversion for a pair of assets with a long-run general equilibrium. The strategy aims to gain from the short-term movements away from the long-run equilibrium that occur between these two assets by taking short positions in the over-valued asset and long positions in the under-valued asset.

The study uses Johansen's Co-integration test to identify stock pairs with long-run equilibrium. The research was restricted to the 20 most liquid stocks of DSE to eliminate the problems associated with moving "illiquid" stocks, such as increased transactions costs. Furthermore, by restricting the search to include only stocks from within the same industry group, it was assumed that their price movements were driven by the same fundamental drivers. Therefore, co-integration relationships that occur in-sample are also likely to occur out-of-sample. All prices were corrected for stationarity using first difference forms.

The research identified 3 trading pairs which were co-integrated using daily prices. The test for co-integration was carried out using the trace statistic. Values of this indicator greater than the 5% critical value suggested co-integrating relationships. The co-integration test also gives the critical information of which stock to take a long position and which one to take a short position. The stock with the higher "Normalized Co-integrating Coefficient" implies its price will rise in the long run (thus becoming conducive for long position) and the one with the lower "Normalized Co-integrating Coefficient" implies its price will fall in the long run (making it suitable for short positions).

Upon identification of these three pairs, a Vector Error Correction Model was used to model the stock pair. The estimated model gave the residual series which was then used as the "Trade signal" to carry out the necessary long/short investments for pairs trade. The residual series from the estimated Vector Error Correction model, uses only the statistically significant parameters.

Once the model for the residual series is determined, the study implements long/short investment strategies when the residual values move significantly away from the equilibrium value of 0. When the residual series returns to 0, an exit strategy is taken. Profitability analysis is carried out using gain/loss from a pairs trade. The study reveals that the three stock pairs all generate returns which have compounded annual growth rates (CAGR) in excess of 100%. Finally, to substantiate the value of the model over conventional investments using financial analysis, a comparative study is carried out between profitability of Pairs Trade and profitability of investing using traditional financial ratios of the same three stock pairs used in this research. The analysis finds that only one of the three pairs can be used for similar investments while the other two cannot be used since financial indicators do not provide any rationale for investing with these stocks. For the one pair that can be used for a similar long/short strategy using financial analysis, it is found that the CAGR return of profitability using financial analysis is significantly lower than that of Pairs Trade.

We can thus conclude that Pairs trading strategy has the potential of delivering greater returns with minimized risk since the strategy is market-neutral. Given the volatility of Dhaka Stock Exchange due to fundamental macroeconomic drivers, this model can be a valuable hedge for both retail as well as institutional investors. Pairs Trade can therefore increase investments in Bangladesh’s stock market and ultimately aid in developing the country’s capital market and overall financial sector in the long run.

CHAPTER 8 BIBLIOGRAPHY

8. Bibliography

Akaike, H. "On entropy maximization principle." (1977).

Bedi, Jaideep. "The Characteristics and Trading Behavior of Dual-Listed Companies." (2013).

Bierens, Herman J. "Guided tour on Johansen's cointegration analysis." n.d. *http://econ.la.psu.edu/.* October 2013. <http://econ.la.psu.edu/~hbierens/EasyRegTours/COINTJ.HTM>.

Binh Do, Robert Faff,Kais Hamza. "A New Approach to Modeling and Estimation for." (2006).

David A. Hsieh, William Fung. "A Primer on Hedge Funds." (1999). November 2013.

Davidson. "Econometric modelling of the aggregate time-series relationship between consumers' expenditure and income in the United Kingdom." *Economic Journal* (1978).

Dickey. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." (1979).

ELLIOTT, ROBERT J. "Pairs trading." (2005).

Evan Gatev, William N. Goetzmann, K. Geert Rouwenhorst. "Pairs Trading: Performance of a Relative Value Arbitrage rule." *The Review of Financial Studies* (2006).

Fabozzi, Frank J. "The handbook of traditional and alternative investment vehicles." (2011).

"Faculty of Economics and Administration, MASARYK UNIVERSITY." n.d. *MASARYK UNIVERSITY*. Nov 2013. <http://www.econ.muni.cz/~hlousek/teaching/stationarity.pdf>.

Fama. "The Capital Asset Pricing Model: Theory and Evidence." *Journal of Economic Perspectives* (2004).

Feibel, Bruce J. "Investment Performane Management ." (2003).

Granger, Clive (1981). "Some Properties of Time Series Data and Their Use in Econometric Model Specification." *Journal of Econometrics* (1981).

Granger, Engle and. "Cointegration and Error Correction: Representation, Estimation and Testing." *Econometrica* (1987).

Green, William H. *Econometric Analysis*. 5 Edition. Prentice Hall, 2003.

Gujarati. *Basic Econometrics*. McGraw Hill, 2004.

Hillebrand, Eric. "A Mean-Reversion Theory of Stock Market Crahes." (2003).

Investopedia. n.d. 02 Novermber 2013. <http://www.investopedia.com/university/guide-pairs-trading/advantages-pairs-trading.asp>.

Johansen, S. "Statistical Analysis of Co-Integrating Vectors." *Journal of Economic Dynamics and Control* (1988).

Johansen, Soren. *Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models*. Econometrica, 1991.

Lin, Y., M. McRae. "Loss Protection in Pairs Trading through Minimum Profit Bounds: A Co-integration Approach." *Journal of Applied Mathematics and Decision Sceinces* (2006).

Logan, M. Kac & J. "Fluctuation Phenomena." (1976).

Mills, Terence. "Time Series Techniques for Economists." (1991).

Moura, João F. Caldeira and Guilherme V. "Selection of a Portfolio of Pairs Based on Cointegration: The Brazilian Case." (2012).

Pearson. "The Problem of the Random Walk." (1905).

Priestley, M. B. "Non-linear and Non-stationary Time Series Analysis." (1988). 2013.

Puspaningrum, Heni. "Pairs Trading Using Co-integration Approach." (2012).

Ross. "The Arbitrage Theory of Capital Asset Pricing." (1976).

Rossi, Eduardo. "Impulse Response Functions,Universit`a di Pavia." n.d. Nov 2013. <http://economia.unipv.it/pagp/pagine_personali/erossi/dottorato_svar.pdf>.

Schmidt, Arlen David. *Pairs Trading: A Co-integrating Approach*. PhD Thesis. Sydney, 2008. August 2013.

Schwarz, Gideon E. "Estimating the dimension of a model." (1978).

Schweser. *CFA Level 1*. Kaplan, 2010.

Sheshkin, David. *Handbook of Parametric and Nonparametric Statistical Procedures*. CRC Press, 2004.

Shreve, Steven E. "Stochastic Calculus for Finance II: Continuous Time Models." (2008).

Stationarity and differencing, Duke University. n.d. 2013. <http://people.duke.edu/~rnau/411diff.htm>.

Tudor. " Variational Image Denoising Approach with Diffusion Porous Media Flow." (2013).

Vasicek, Oldrich. "An equilibrium characterisation of the Term Structure." *Journal of financial economics* (1977).

Vector Error Correction Models and Cointegration, University of Colorado Denver. n.d. 2013. <econ.ucdenver.edu/.../Intro%20to%20VAR%20and%20VEC-%20PPP%2...>.

Vidyamurthy, Ganapathy. *Pairs Trading: Quantitative Methods and Analysis*. John Wiley & Sons, 2004.

CHAPTER 9 APPENDIX

9. Appendix

Appendix A – Results of Johansen's Co-integration tests

Co-Integration Output for ACTIVEFINE & PHARMAID

Date: 10/12/13 Time: 11:41
Sample (adjusted): 9/30/2012 9/30/2013
Included observations: 239 after adjustments
Trend assumption: Linear deterministic trend
Series: ACTIVEFINE PHARMAID
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.064703	18.15406	15.49471	0.0194
At most 1	0.009026	2.167001	3.841466	0.1410

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

ACTIVEFINE	PHARMAID
-0.090079	0.046780
0.095309	-0.005258

Unrestricted Adjustment Coefficients (alpha):

D(ACTIVEFINE)	0.317000	-0.158988
D(PHARMAID)	-0.801394	-0.502901

1 Cointegrating Equation(s): Log likelihood -1261.530

Normalized cointegrating coefficients (standard error in parentheses)

ACTIVEFINE	PHARMAID
1.000000	-0.519327
	(0.08439)

Adjustment coefficients (standard error in parentheses)

D(ACTIVEFINE)	-0.028555
	(0.01222)
D(PHARMAID)	0.072189
	(0.03620)

Co-Integration Output for GBBPOWER & KPCL

Sample (adjusted): 9/30/2012 9/30/2013
Included observations: 239 after adjustments
Trend assumption: Linear deterministic trend
Series: GBBPOWER KPCL
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.050478	15.53677	15.49471	0.0493
At most 1	0.013124	3.157298	3.841466	0.0756

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

GBBPOWER	KPCL
-0.100600	-0.220610
0.208018	-0.297305

Unrestricted Adjustment Coefficients (alpha):

D(GBBPOWER)	0.212782	0.013332
D(KPCL)	0.153206	0.104120

1 Cointegrating Equation(s): Log likelihood -613.1163

Normalized cointegrating coefficients (standard error in parentheses)

GBBPOWER	KPCL
1.000000	2.192939
	(0.93052)

Adjustment coefficients (standard error in parentheses)

D(GBBPOWER)	-0.021406
	(0.00616)
D(KPCL)	-0.015413
	(0.00745)

Co-Integration Output for TITASGAS & BDWELDING

Date: 10/12/13 Time: 21:28
Sample (adjusted): 9/30/2012 9/30/2013
Included observations: 239 after adjustments
Trend assumption: Linear deterministic trend
Series: TITASGAS BDWELDING
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.060563	15.95171	15.49471	0.0427
At most 1	0.004260	1.020348	3.841466	0.3124

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

TITASGAS	BDWELDING
0.026527	0.282283
0.105431	-0.103864

Unrestricted Adjustment Coefficients (alpha):

D(TITASGAS)	-0.286578	-0.077027
D(BDWELDING)	-0.172932	0.024910

1 Cointegrating Equation(s): Log likelihood -728.6107

Normalized cointegrating coefficients (standard error in parentheses)

TITASGAS	BDWELDING
1.000000	10.64156
	(2.92181)

Adjustment coefficients (standard error in parentheses)

D(TITASGAS)	-0.007602
	(0.00285)
D(BDWELDING)	-0.004587
	(0.00136)

Appendix B – Results of Vector Error Correction Model estimation

VECM output for ACTIVEFINE & PHARMAID

Vector Error Correction Estimates
Date: 10/12/13 Time: 11:42
Sample (adjusted): 9/27/2012 9/30/2013
Included observations: 240 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
ACTIVEFINE(-1)	1.000000	
PHARMAID(-1)	-0.479960	
	(0.08628)	
	[-5.56262]	
C	2.542341	
Error Correction:	**D(ACTIVEFINE)**	**D(PHARMAID)**
CointEq1	-0.033926	0.046910
	(0.01289)	(0.03889)
	[-2.63120]	[1.20627]
D(ACTIVEFINE(-1))	0.038310	-0.261771
	(0.06969)	(0.21020)
	[0.54970]	[-1.24534]
D(ACTIVEFINE(-2))	0.013942	0.158982
	(0.06956)	(0.20979)
	[0.20044]	[0.75783]
D(PHARMAID(-1))	0.009267	0.128606
	(0.02330)	(0.07028)
	[0.39767]	[1.82983]
D(PHARMAID(-2))	-0.030545	-0.043363
	(0.02300)	(0.06936)
	[-1.32820]	[-0.62517]
C	0.070446	-0.127033
	(0.13508)	(0.40741)
	[0.52152]	[-0.31181]
R-squared	0.036883	0.022252
Adj. R-squared	0.016304	0.001360
Sum sq. resids	1021.735	9294.495
S.E. equation	2.089590	6.302386
F-statistic	1.792242	1.065117
Log likelihood	-514.3795	-779.3299
Akaike AIC	4.336495	6.544416
Schwarz SC	4.423511	6.631432
Mean dependent	0.072083	-0.142917
S.D. dependent	2.106836	6.306677
Determinant resid covariance (dof adj.)		144.5345
Determinant resid covariance		137.3981
Log likelihood		-1271.836
Akaike information criterion		10.71530

Dependent Variable: D(ACTIVEFINE)
Method: Least Squares
Date: 10/12/13 Time: 11:42
Sample (adjusted): 9/27/2012 9/30/2013
Included observations: 240 after adjustments
D(ACTIVEFINE) = C(1)*(ACTIVEFINE(-1) - 0.479960438913*PHARMAID(-1)
+ 2.5423410255) + C(2)*D(ACTIVEFINE(-1)) + C(3)*D(ACTIVEFINE(
-2)) + C(4)*D(PHARMAID(-1)) + C(5)*D(PHARMAID(-2)) + C(6)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.033926	0.012894	-2.631201	0.0091
C(2)	0.038310	0.069693	0.549699	0.5831
C(3)	0.013942	0.069555	0.200440	0.8413
C(4)	0.009267	0.023303	0.397671	0.6912
C(5)	-0.030545	0.022997	-1.328196	0.1854
C(6)	0.070446	0.135079	0.521517	0.6025

R-squared	0.036883	Mean dependent var	0.072083
Adjusted R-squared	0.016304	S.D. dependent var	2.106836
S.E. of regression	2.089590	Akaike info criterion	4.336495
Sum squared resid	1021.735	Schwarz criterion	4.423511
Log likelihood	-514.3795	Hannan-Quinn criter.	4.371557
F-statistic	1.792242	Durbin-Watson stat	1.986967

VECM output for KPCL and GBBPOWER

Vector Error Correction Estimates
Date: 10/11/13 Time: 16:43
Sample (adjusted): 9/27/2012 9/30/2013
Included observations: 240 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
GBBPOWER(-1)	1.000000	
KPCL(-1)	3.050408 (1.08820) [2.80317]	
C	-186.0080	
Error Correction:	D(GBBPOWER)	D(KPCL)
CointEq1	-0.017852 (0.00479) [-3.73080]	-0.014164 (0.00577) [-2.45619]
D(GBBPOWER(-1))	-0.017887 (0.08448) [-0.21173]	-0.019181 (0.10181) [-0.18840]
D(GBBPOWER(-2))	-0.031951 (0.08349) [-0.38269]	0.107924 (0.10062) [1.07261]
D(KPCL(-1))	0.086072 (0.07353) [1.17055]	-0.064485 (0.08861) [-0.72770]
D(KPCL(-2))	0.052752 (0.07267) [0.72588]	-0.008241 (0.08758) [-0.09409]
C	-0.081545 (0.06131) [-1.33009]	-0.043633 (0.07388) [-0.59057]
R-squared	0.058802	0.042260
Adj. R-squared	0.038691	0.021795
Sum sq. resids	209.0023	303.5437
S.E. equation	0.945078	1.138945
F-statistic	2.923867	2.065022
Log likelihood	-323.9500	-368.7316
Akaike AIC	2.749583	3.122764
Schwarz SC	2.836599	3.209780
Mean dependent	-0.084167	-0.046667
S.D. dependent	0.963909	1.151563
Determinant resid covariance (dof adj.)		0.612751
Determinant resid covariance		0.582497
Log likelihood		-616.2387
Akaike information criterion		5.251989

Dependent Variable: D(KPCL)
Method: Least Squares
Date: 10/11/13 Time: 16:45
Sample (adjusted): 9/27/2012 9/30/2013
Included observations: 240 after adjustments
D(KPCL) = C(7)*(GBBPOWER(-1) + 3.05040807582*KPCL(-1) -
186.008031019) + C(8)*D(GBBPOWER(-1)) + C(9)*D(GBBPOWER(
-2)) + C(10)*D(KPCL(-1)) + C(11)*D(KPCL(-2)) + C(12)

	Coefficient	Std. Error	t-Statistic	Prob.
C(7)	-0.014164	0.005767	-2.456187	0.0004
C(8)	-0.019181	0.101811	-0.188398	NA
C(9)	0.107924	0.100618	1.072615	0.2845
C(10)	-0.064485	0.088615	-0.727696	0.4675
C(11)	-0.008241	0.087581	-0.094090	0.9251
C(12)	-0.043633	0.073884	-0.590566	0.5554

S.E. of regression	1.138945	Akaike info criterion	3.122764
Sum squared resid	303.5437	Schwarz criterion	3.209780
Log likelihood	-368.7316	Hannan-Quinn criter.	3.157825
Durbin-Watson stat	1.996477		

VECM output for TITASGAS & BDWELDING

Vector Error Correction Estimates
Date: 10/12/13 Time: 21:28
Sample (adjusted): 9/27/2012 9/30/2013
Included observations: 240 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
TITASGAS(-1)	1.000000	
BDWELDING(-1)	10.53354	
	(3.05779)	
	[3.44482]	
C	-313.4267	

Error Correction:	D(TITASGAS)	D(BDWELDING)
CointEq1	-0.007158	-0.004240
	(0.00281)	(0.00134)
	[-2.54285]	[-3.16432]
D(TITASGAS(-1))	-0.084750	-0.016046
	(0.06727)	(0.03202)
	[-1.25987]	[-0.50112]
D(TITASGAS(-2))	-0.014946	0.006008
	(0.06704)	(0.03191)
	[-0.22294]	[0.18829]
D(BDWELDING(-1))	0.180603	-0.021224
	(0.13883)	(0.06609)
	[1.30085]	[-0.32116]
D(BDWELDING(-2))	-0.079583	-0.034189
	(0.14089)	(0.06706)
	[-0.56487]	[-0.50980]
C	-0.037374	-0.053904
	(0.10812)	(0.05146)
	[-0.34567]	[-1.04741]
R-squared	0.037808	0.045846
Adj. R-squared	0.017249	0.025458
Sum sq. resids	653.4844	148.0650
S.E. equation	1.671128	0.795460
F-statistic	1.838965	2.248676
Log likelihood	-460.7468	-282.5868
Akaike AIC	3.889557	2.404890
Schwarz SC	3.976573	2.491906
Mean dependent	-0.037500	-0.051667
S.D. dependent	1.685730	0.805783

Determinant resid covariance (dof adj.)	1.665045
Determinant resid covariance	1.582833
Log likelihood	-736.1965

Dependent Variable: D(TITASGAS)
Method: Least Squares
Date: 10/12/13 Time: 21:29
Sample (adjusted): 9/27/2012 9/30/2013
Included observations: 240 after adjustments
D(TITASGAS) = C(1)*(TITASGAS(-1) + 10.5335364118*BDWELDING(-1) - 313.426704686) + C(2)*D(TITASGAS(-1)) + C(3)*D(TITASGAS(-2)) + C(4)*D(BDWELDING(-1)) + C(5)*D(BDWELDING(-2)) + C(6)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.007158	0.002815	-2.542852	0.0004
C(2)	-0.084750	0.067269	-1.259873	0.6598
C(3)	-0.014946	0.067039	-0.222937	0.8238
C(4)	0.180603	0.138835	1.300849	0.1946
C(5)	-0.079583	0.140888	-0.564868	0.5727
C(6)	-0.037374	0.108118	-0.345674	0.7299

S.E. of regression	1.671128	Akaike info criterion	3.889557
Sum squared resid	653.4844	Schwarz criterion	3.976573
Log likelihood	-460.7468	Hannan-Quinn criter.	3.924618
Durbin-Watson stat	1.993417		

Appendix C – Daily Average Volume of the sample of twenty stocks used in the study (1/1/2012-9/30/2013)

Ticker	Sector	Daily Average Volume
ENVOYTEX	Textile	982,667
RNSPIN	Textile	2,459,300
SQUARETEXT	Textile	137,049
MALEKSPIN	Textile	1,101,980
SAIHAMCOT	Textile	1,209,684
ARGONDENIM	Textile	1,184,346
ACTIVEFINE	Pharmaceuticals	636,624
KEYACOSMET	Pharmaceuticals	1,296,103
SQURPHARMA	Pharmaceuticals	333,054
PHARMAID	Pharmaceuticals	147,250
EBL	Bank	290,516
CITYBANK	Bank	769,379
ISLAMIBANK	Bank	573,877
EXIMBANK	Bank	1,023,417
NBL	Bank	2,207,772
TITASGAS	Fuel & Power	1,427,706
KPCL	Fuel & Power	571,336
BDWELDING	Fuel & Power	282,928
MPETROLEUM	Fuel & Power	471,460
GBBPOWER	Fuel & Power	673,598

Appendix D – Pairs Trading Illustration

Pairs trade for ACTIVEFINE & PHARMAID at respective prices per share (In-sample and out-of-sample)

DATE	PHARMAID	ACTIVEFINE	
	Short	Long	
9/25/2012	205		
9/30/2012		74	
10/17/2012	**164**	**75**	**Exit**
Gain	41	1	42
1/11/2011	3,990		
1/18/2011		92	
2/2/2011	**2,684**	**88**	**Exit**
Profit	1,306	(4)	1,302

Return calculations for out-of sample trade between 1/11/2011-2/2/2011

	PHARMAID	ACTIVEFINE
Monetary Amount (BDT)	50,000	50,000
Trading Price (According to trade rules)	3990.0	92.0
No of Shares at Trading price	13	543
Selling price (According to trade rules)	2,684.00	88.00
Gain (BDT)	16,366	(2,174)
Net Gain from Pairs Trade		14192
Return (%)		14.19%
Duration (Days)		22
CAGR		804%

Pairs trade for GBBPOWER & KPCL at respective prices per share (In-sample and out-of-sample)

Date	GBBPOWER	KPCL	
	Short	Long	
10/23/2012	43		
11/11/2012		52	
11/14/2012	34	49	Exit
Profit	9	(3)	6
6/28/2012		54	
7/17/2012	27		
7/22/2012	27	55	Exit
Profit	-	1.00	1.00

Return calculations for out-of-sample trade between 6/28/2012 – 7/22/2012

	KPCL	GBBPOWER
Monetary Amount (BDT)	50,000	50,000
Trading Price (According to trade rules)	54.0	27.0
No of Shares at Trading price	926	1852
Selling price (According to trade rules)	55.00	27.00
Gain (BDT)	926	-
Net Gain from Pairs Trade		926
Return (%)		0.93%
Duration (Days)		24
CAGR		15%

Pairs trade for TITASGAS & BDWELDING at respective prices per share (In-sample and out-of-sample)

	TITASGAS	BDWELDING	
	Short	Long	
10/2/2012	92.7		
11/28/2012		23.8	
12/5/2012	**63.80**	**23.70**	**Exit**
Profit	28.90	(0.10)	28.80
1/9/2011	890	218	
1/11/2011	979	216	
2/2/2011	**917**	**228**	**Exit**
Profit	63	10	72.8

Return calculations for out-of-sample trade between 6/28/2012 – 7/22/2012

Stock Name	TITASGAS	BDWELDING
Monetary Amount (BDT)	50,000	50,000
Trading Price (According to trade rules)	979.0	218.0
No of Shares at Trading price	51	229
Selling price (According to trade rules)	917.00	228.00
Gain (BDT)	3,166	2,294
Net Gain from Pairs Trade		5460
Return (%)		5.46%
Duration (Days)		24
CAGR		124%