The volatility spillover effect of a dual-listed stock for international markets

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DEDICATION

I would like to dedicate this dissertation to my best friend, master and Lord, Jesus Christ.

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Luke 12:29-31 "And do not seek what you are to eat and what you are to drink, nor be worried. For all the nations of the world seek after these things, and your Father knows that you need them. Instead, seek His kingdom, and these things will be added to you."

Abstract

The 2008 financial crisis caused a great increase in volatility in world stock markets, creating the need to develop alternative diversification strategies to minimise decreasing portfolio value. This study proposes a possible diversification instrument, which utilises the dual-listed stock price volatility in the London Securities Exchange (LSE) to determine Johannesburg Securities Exchange (JSE) stock price movements. This implies that the ability to determine possible buy opportunities on the JSE can be identified by examining volatility movements on the LSE. By using the price differences in the Anglo American Plc. dual-listed stock prices on the LSE to measure the volatility spillover impact on the JSE, evidence of both co-movement and volatility spillover effects between the two markets was found. The evidence indicates that the LSE does have an influential effect on the JSE, which justifies the use of LSE dual-listed stock price movements as a partial indicator for determining JSE dual-listed stock price movements. This study illustrates the possibility of exploiting the volatility spillover effects between international markets to enhance international portfolio diversification in times of great market fluctuations.

Keywords: *Co-movement; dual-listed stocks; Exponential General Autoregressive Conditional Heteroskedastic model; Johansen cointegration; stock price differential; Vector Error Correction model*; *volatility spillover effect*

Uittreksel

Die 2008-finansiële krisis het ’n groot toename in volatiliteit in aandelemarkte regoor die wêreld veroorsaak. Dit het aanleiding gegee tot die behoefte om alternatiewe diversifikasie-strategieë te ontwikkel om sodoende afnemende portefeuljewaardes te beperk. Hierdie studie bied ’n potensële diversifikasie-instrument wat die volatiliteit van dubbelgenoteerde aandele op die LSE (London Securities Exchange) gebruik om die aandele op die JSE (Johannesburg Securities Exchange) se prysbewegings te voorspel. Dit behels ’n indikator wat deur middel van volatiliteitbewegings op die LSE ’n koopsein kan bied vir aandele op die JSE. Deur die prysbewegings in die Anglo American Plc. dubbelgenoteerde aandeel op die LSE te gebruik om die impak van ’n volatiliteit-oordrag op die JSE te meet, is bewyse gevind van beide medebeweging en ’n volatiliteits oorspoeleffek tussen die twee markte. Die bewyse dui daarop dat die LSE ’n invloedryke impak op die JSE het, wat die gebruik van dubbelgenoteerde aandele op die LSE se prysbewegings as ’n gedeeltelike indikator om die dubbelgenoteerde aandele se prysbewegings op die JSE te bepaal, ondersteun. Hierdie studie illustreer die moontlikheid om die volatiliteits oorspoeleffek tussen internasionale markte te gebruik om internasionale portefeulje diversifikasie in tye van groot aandeelmar kfluktuasies te bevorder.

Sleutelwoorde: *Mede-beweging; dubbelgenoteerde aandele; Eksponensiële Algemene Outoregressiewe Voorwaardelike Heteroskedastiese model; Johansen koïntegrasie; aandele prysverskil; Vektor-foutaanpassings model; volatiliteit oorspoel effek.*

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CHAPTER 1

Introduction

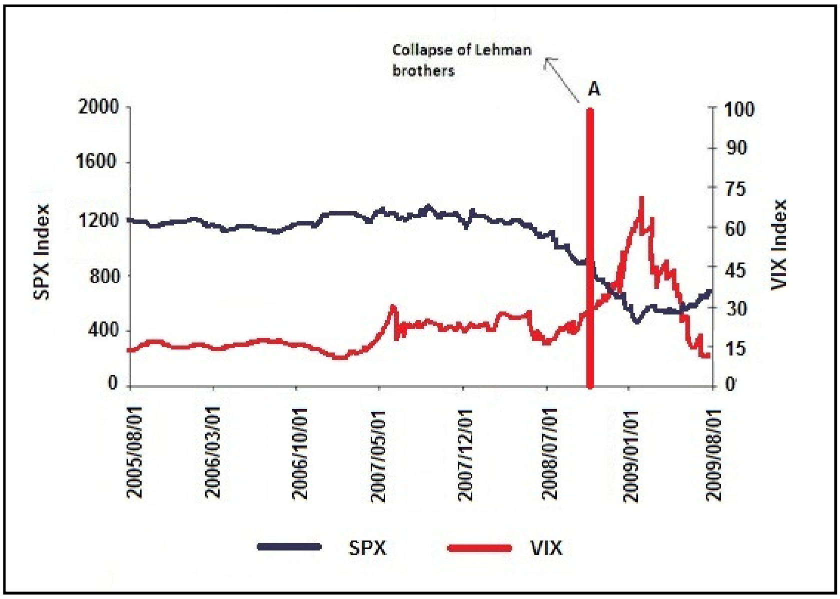
"In our seeking for economic and political progress, we all go up – or else we all go down."

— Franklin D Roosevelt

1.1 INTRODUCTION

From 2004 to early 2007, the major financial markets had been very calm in terms of market volatility, as measured by the S&P 500[1] volatility and the VIX index[2], which were below long-term averages (Manda, 2010:2). This changed, however, with the 2008 financial crisis, when volatility increased substantially after the Lehman brothers announced their bankruptcy on 15 September 2008, as illustrated by point A in Figure 1.1. During this time, the S&P 500 lost approximately 56% of its value from the October 2007 peak to the March 2009 trough, whereas the VIX Index lost more than triple its value (Manda, 2010:2).

Figure 1.1: Historical values of the S&P 500 and the VIX index



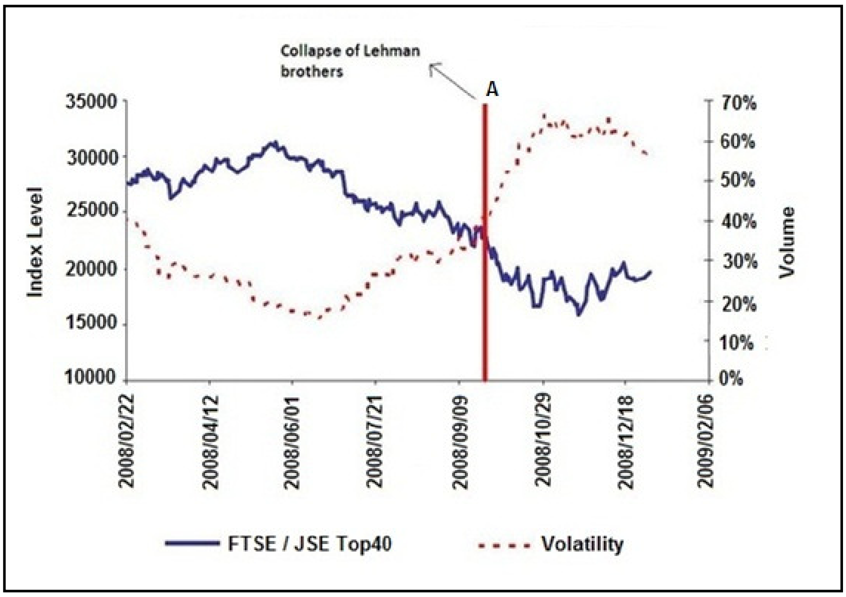
Source: Manda (2010:2)

1 The S&P 500 is a free-float capitalisation-weighted index of 500 large-cap common stocks that are actively traded in the United States (Investopedia, 2011:1).

2 VIX is the ticker symbol for the Chicago Board Options Exchange Market Volatility Index, a popular measure of the implied volatility of S&P 500 index options (Manda, 2010:2).

The South African Volatility Index (SAVI), which is an index designed to measure the JSE's[3] volatility (Figure 1.2), emphasised the presence of high volatility levels in the South African market (JSE, 2011:1).

Figure 1.2: Values of the JSE Top40 and the SAVI (Volatility)



Source: JSE (2011:1)

This increase in volatility was accompanied by a loss in stock prices on the JSE Top40[4], with a profound loss in value of 27% in 2008, coupled with a 4,3% loss for the first month of 2009 (JSE, 2011:1). Furthermore, the high volatility levels in the European markets led to a sell-off in European stocks, after experiencing a period of 26 month where stocks on the European markets closed at below-average prices (CIPS, 20011:1). The increased stock market volatility during the post-financial crisis has also been significant, causing the JSE to reach a record of 751,381 trades in one week[5] in 2011. This topped the previous record of 535,883 trades, which was set in October 2008 in the middle of the 2008 financial crisis (Bloomberg, 2011:1).

The record trading volumes and the fall in stock prices, which is directly correlated with the rise in market volatility (Parsons, 2011:13), pose a threat to portfolio managers, because increased volatility can affect the returns of the overall stock portfolio due to a larger fluctuation in stock prices (Burhan, 2007:13). In order to minimise the negative effect of increased volatility,

3 JSE denotes the Johannesburg Securities Exchange.
4 The JSE Top40 is an indicator made up of the forty leading shares found on the JSE.
5 The week started on 3 May 2011 and ended on 7 May 2011 (Bloomberg, 2011:1).

portfolio managers can make use of a strategy called diversification (Yueshen, 2009:1). Diversification is the inclusion of assets from different sectors in the economy and/or different asset classes, in order to spread the total risk of a collective investment (Marx *et al.*, 2008:5). This diversification strategy can be extended to international diversification by including international stocks in the portfolios. The advantages of diversifying portfolios internationally include reduced exposure to single currency risk, reduced exposure to domestic policies, and a more effective spread of systematic risk exposure (Driesen *et al.,* 2007:1693). International portfolio diversification can be advanced by investing in dual-listed stocks, as these stocks are exposed to the volatility of more than one country's market (Yueshen, 2009:1), which can be exploited as a portfolio diversification strategy.

1.2. RESEARCH QUESTION

By investigating the ,relationship between the Johannesburg Securities Exchange (JSE) and the London Securities Exchange (LSE), the following research question is posed: *Can LSE dual-listed stock price volatility be utilised as an indicator for determining expected JSE dual-listed stocks price movements?*

1.3 MOTIVATION

Evidence indicates that the volatility spillover effect is negatively correlated to stock price changes (Chen *et al.,* 1986:300). This is supported by the study of Xiaoqing and Hung-Gay (2002:563), who found that the volatility spillover effect causes price differences in dual-listed stocks, which have several implications for investors, hedgers, speculators or arbitrageurs (Burger & Smit, 1997:5). The volatility spillovers in dual-listed stocks influence hedge-fund portfolio managers, because they are driven, *inter alia,* by a desire to reduce the volatility exposure of portfolios in order to achieve an absolute return on their portfolios. Therefore, the presence of volatility spillovers between dual-listed stocks can force hedge-fund managers to exclude dual-listed stocks as hedging instruments from their portfolios (Burger & Smit, 1997:5). This is confirmed by the results found by Snell (1990:5), who indicated that the volatility spillover effect between dual-listed stocks affects daily returns on a hedged portfolio. However, if the volatility spillover effect can be effectively exploited and implemented as an instrument for international portfolio diversification, portfolio and hedge-fund managers may reconsider the effectiveness of investing in dual-listed stocks to diversify their portfolios.

1.4 RESEARCH METHOD

This study will commence with a literature study on factors influencing the price composition of dual-listed stocks (Section 2.2). Once the price composition is examined, the literature study will redirect the focus to volatility spillovers as a result of the price differences in dual-listed stocks (Section 3.3). The literature study will conclude by examining historical studies regarding different approaches for measuring co-movement (Section 3.3.5) and the volatility spillover effect (Section 3.3.6), in order to determine the most appropriate models to use in the empirical study. The second part of this study entails an empirical study, where the co-movement and the effect of the volatility spillover effect between the JSE and LSE will be examined. The Anglo American Plc. dual-listed stock prices will be used in the empirical study. The reason why this stock was chosen is because it is viewed as highly liquid and it forms part of the resources index of the JSE, which is the most influential sector in the market (CIPS, 2011:1). The data was collected from the Reuters database and is in intra-day, hourly format.

The empirical study will be divided into an initial analysis on co-movement, which will be followed by analysing the volatility spillover effect between the JSE and LSE. The first step in examining the presence for co-movement will entail estimating the Johansen (1991) cointegration test (Section 4.4.1) and a Vector Error Correction (VEC) model (Section 4.4.2). The results from the cointegration analysis will elaborate on the existence of a long-run cointegration relationship between the JSE and LSE to establish the presence of co-movement. The results from the VEC model, on the other hand, will evaluate the long-run relationship by means of a speed of adjustment estimate and a long-run coefficient. The second measure of co-movement includes the Sims (1972) and Granger (1969) causality tests (Section 4.5). These causality tests will provide results on the direction of causality and will determine in which market the volatility spillover effect originates.

After the presence of co-movement is established, the next step will be to initiate a further investigation on examining the volatility spillover effect between the JSE and LSE. The first measure of the volatility spillover effect is the Variance Decomposition (VDC) model (Section 4.6), which will decompose the long-run coefficient of the VEC model (Section 4.4.2). The Exponential GARCH (EGARCH) model (Section 4.7) will then be estimated as the final step in the volatility spillover analysis. Results from the EGARCH model will evaluate the existence of a volatility spillover effect and will also provide information on the shock persistence and the asymmetric effect of the volatility spillover effect.

1.5 CHAPTER LAYOUT

1.5.1 Chapter 2: Asset pricing and arbitrage

This chapter will initiate the literature study by investigating the concept of dual-listed stocks (Section 2.2) and the price composition of a dual-listed stock (Section 2.2.3). The factors influencing the price composition of dual-listed stocks that are examined, include index exposure, where the performance of stocks on different indices influence the prices of the stocks in different ways (Section 2.2.3.1); geographical risk, where the events in the geographical location where the dual-listed stocks are listed can influence either of the stock prices (Section 2.2.3.2); local markets, where local market performance will influence the price of one dual-listed stock more than the other (Section 2.2.3.3); regional legislation, where the legislation of one stock market influences the way dual-listed stocks are priced (Section 2.2.3.4); arbitrage effects which influences dual-listed stock prices when price differences occur between the two stocks (Section 2.2.3.5); and regional broker expectations which influence the stock prices on through the purchasing behaviour of investors (Section 2.2.3.6). Other factors that are also investigated are the information flow and the efficient market hypothesis (Section 2.3), and the risks related to a stock (Section 2.4). Risk exposure implies compensation for the investor, which will be examined in various asset pricing models. These models include the Capital Asset Pricing Model (CAPM; Section 2.5.1), the Arbitrage Pricing Theory (APT; Section

2.5.2), and the International Capital Asset Pricing Model (ICAPM; Section 2.5.3). The final part of the chapter will examine the arbitrage possibilities due to the price differences of dual-listed stocks (Section 2.6). Thus, by examining the literature behind asset pricing this chapter covers the basic principles of dual-listed stock price composition, which need to be understood before the volatility spillover effect can be explained in Chapter 3.

1.5.2 Chapter 3: The volatility spillover effect and methodology

This chapter redirects the focus to stock price differences due to volatility spillovers. This chapter will start by discussing the concept of volatility (Section 3.2), which will be followed by an investigation regarding the relationship between two international stock markets. This investigation will be divided into a study on co-movement (Section 3.3) and the volatility spillover effect (Section 3.3.6). Historical studies on co-movement and the volatility spillover effect were also examined in order to determine the most appropriate models for measuring the presence of co-movement and a volatility spillover effect between the JSE and LSE, which will be discussed in Section 3.4. This chapter contributes to the study as a whole, because it examines the essence of the study topic, namely the volatility spillover effect and also explains the methodology to be used in order to draw a conclusion regarding the research question.

1.5.3 Chapter 4: Empirical results

This chapter is divided into two sections, with the first section establishing co-movement between the JSE and LSE, followed by an examination of the presence of a volatility spillover effect. The first measure of co-movement will be the Johansen (1991) cointegration test, which indicated that there is a long-run cointegration relationship present between the JSE and LSE (Section 4.5). The Johansen (1991) cointegration analysis was accompanied by the Vector Error Correction (VEC) model, which further confirmed the presence of co-movement, by indicating that it will take approximately two days to eliminate disequilibrium between the JSE and LSE. To further examine co-movement, the Sims (1972) and Granger (1969) causality tests were used to establish in which market the co-movement originates. Further evidence was found of co-movement between the JSE and LSE, illustrating that volatility spillovers will originate in the LSE and will spill over into the JSE (Section 4.4).

The second section of the chapter – examining the extent of the volatility spillover effect – commenced with the Variance Decomposition (VDC) model (Section 4.6), which expanded on the results from the VEC model. The VDC model reported that the JSE is mainly responsible for its "own innovation" of volatility. Furthermore, the Exponential GARCH (EGARCH) model (Section 4.7) verified the presence of a volatility spillover effect between the JSE and LSE and also indicated that there is a high degree of volatility persistence in the JSE.

1.5.4 Chapter 5: Conclusion

This chapter will conclude this dissertation by reconciling the problem statement and the final results to form a logical conclusion to this study. The chapter will summarise the results of the extent that the volatility spillovers from the LSE will influence the secondary market (JSE). Recommendations for future studies will also be identified.

CHAPTER 2

Asset pricing and arbitrage

"The market can stay irrational longer than you can stay solvent."

— John Maynard Keynes

2.1 INTRODUCTION

This chapter will start by investigating the essence of a stock price and the general methods used to determine the price of a stock. Only after the composition of a stock price is understood, will the stock price be used as a decision-making tool for investing in equity. The concept of the decision-making tool will be based on the price differences of dual-listed stocks,[6,7] which may be an unconsidered tool for determining possible arbitrage opportunities. **The goal of this study is to examine whether LSE dual-listed stock price volatility can be utilised as an indicator for determining expected JSE dual-listed stocks price movements.** Price differences of dual-listed stocks include both an expectation component and a time difference (lag) component, due to the different trading hours of the Johannesburg Securities Exchange (JSE) and the London Securities Exchange (LSE). Shocks from the JSE may spill over into the LSE, or *vice versa*, influencing the performance of the market and the stock. Incorporating the expectation and lag component into one explanatory tool may enhance the ability of portfolio maximisation by means of exploiting the possible arbitrage opportunity that exists in the price difference of dual-listed stocks.

This study's point of departure is to examine the valuation of dual-listed stocks and the purpose of dual-listed stocks (Section 2.2), since it is the main concern on which the study focuses. This will be followed by a discussion on the composition of a dual-listed stock price and the factors

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[6] Dual-listed stocks are stocks that are listed on more than one stock exchange. It is therefore possible to buy the stock of a company on one exchange and sell it on another exchange (Marx *et al.*, 2006:25).

[7] In this study, the term "stocks" will be used, although in South Africa the term "shares" is more commonly used.

influencing the dual-listed stock price (Section 2.2.3). As a portfolio manager, the valuation of dual-listed stocks is necessary in order to determine which stocks would maximise the value of the portfolio. Investors want to maximise profits from the stocks they own by selling them at a higher price than their original purchasing price. Various techniques can be employed to determine which stocks might yield future growth, where one of these techniques includes the Gordon growth model (Marx *et al.*, 2006:142). This study will focus only on the Gordon growth model, because it provides a justification for using dual-listed stock, as will be discussed below.

The Gordon growth model (Dividend growth model) is based on the following price equation (Pages, 1999:2):

$$P_0 = \frac{D_1}{k-g} \tag{2.1}$$

Where:

- P_0 is the current price (value);
- D_1 is the future value of the stock's dividend;
- k is the required rate of return; and
- g is the constant rate of dividend growth.

The important part of Equation 2.1 is the growth rate g, because both dual-listed stocks in separate markets (JSE and LSE) should grow at the same rate, which is also explained by the single market hypothesis (Ip & Brooks, 1996:53). However, dual-listed stocks from the different international markets do not grow at the same rate, which will lead to arbitrage opportunities. This justifies the approach of using dual-listed stocks to measure interaction between the JSE and LSE. This financial interaction between the JSE and LSE will be discussed in Chapter 3, which focuses on the volatility spillover effect.

This discussion on the composition of a dual-listed stock will start with the Efficient Market Hypothesis (EMH) and information flow (Section 2.3). The basic formulation of a stock price starts with the trade-off between the risk involved in buying the stock and the expected return that will be anticipated by the investor (Marx *et al.*, 2006:142). Therefore, a discussion on the various risks inherent in the pricing theories, namely systematic and unsystematic risks, will follow in Section 2.4. This will be followed by a discussion of the Markowitz efficient frontier in Section 2.5. The general asset pricing models, namely the Capital Asset Pricing Model CAPM (Section 2.5.1), the Arbitrage Pricing Theory (APT; Section 2.5.2) and the International Capital Asset Pricing Model (ICAPM; Section 2.5.3) will then be discussed.

This chapter will, therefore, serve as a preamble to Chapter 3, which will extend to modelling the volatility spillover effect, by using the price differences of dual-listed stocks in Chapter 4. This volatility spillover effect will illustrate the international financial interaction between the JSE and LSE, which can provide insight into the possible arbitrage opportunity within the price differences of dual-listed stocks.

2.2 DUAL-LISTED STOCKS

2.2.1 Introduction

Globalisation has increased at a great pace in the last two decades, which has led to a much broader base for expanding companies internationally. As a result, many companies started listing their stock internationally, leading to approximately 4700 dual-listed companies in the 1990s (Karolyi, 2004:2). However, dual-listings started to decline because of many political and various global macroeconomic factors, including strict regulating laws, making it much harder for companies to list their stock on more than one exchange. Even though the number of companies following a dual-listing approach has decreased, there are still a number of advantages for companies choosing to follow this strategy. The following section will explain the advantages of dual-listing.

2.2.2 Advantages of dual-listing stocks

A company may gain various advantages when opting to dual-list a stock (Benos & Weisbach, 2004:217). Firstly, increased liquidity is provided by multiple listings, as the total number of potential buyers increase when a stock is dual-listed. The ability to attract domestic investors in multiple markets is, therefore, beneficial to the company (Lynch, 2002:4). Secondly, the taxation of a dual-listed company may be advantageous. The taxation laws differ from one country to the next, thereby allowing a company to exploit this in such a way that may lead to an overall reduction in payable taxes. Furthermore, dual-listing often leads to less tax being paid on the capital gains of a company. Securing tax efficiency may therefore be a great incentive for potential buyers (Lynch, 2002:4). Thirdly, the level of shareholder approval required in order to complete business ventures is greatly reduced when a company is dual-listed. Most public deals require a level of shareholder approval, and the choice of the stock exchange listing structure may have some bearing on the level required. Consider the following example: If Company A wishes to take over Company B, the majority vote of shareholders may be required. However, if a company is dual-listed, it generally leads to a situation where shareholder votes tend to be more unbiased, which leads to greater overall company efficiency (Benos & Weisbach, 2004:217).

The fourth advantage of a dual-listed company is that regulatory consents may potentially be easier to acquire under a dual-listed company structure. However, mergers by means of a dual-listed company structure are currently exempt from the United Kingdom (UK) takeover code[8]. The basic premise has been that dual-listed company transactions are not subject to the takeover code, as they do not involve a change in the relevant company's ownership. Although there is a concern that violating this code will lead to business deals being lost, there is, however, still a significant incentive to create a dual-listed company (Lynch, 2002:4). The fifth advantage is the increased efficiency in corporate governance by means of a dual-listed company structure. With cross-border deals, it is very likely that culture differences will exist between the two companies, as well as differing views on how to manage the combined business. Maintaining both national identities allows these cultures to remain, while establishing the same long-term goals (Roosenboom & Van Dijk, 2009:1898). The sixth advantage is that

[8] The United Kingdom takeover code is a set of regulations which must be upheld when a company takes ownership of another company. This rule specifically applies when companies undergo a change of ownership (Lynch, 2002:4).

flowback[9] is partly eliminated. In a traditional merger situation, the target stock will be de-listed from its indices upon completion of the transaction. Flowback will be less in a new post-merger company, which will lead to selling pressure. A takeover by a foreign firm could see a target firm lose its domestic investor base, which is obviously not ideal, and therefore a dual-listed structure would be ideal as it will see these effects being avoided (Lynch, 2002:4). The final advantage is that liquidity is greatly increased when a company dual-lists its stock, where these dual-listed stocks have lower bid-ask spreads[10] (Karolyi, 2004:6).

To summarise; from the above mentioned advantages it would seem advantageous for companies to dual-list their stocks. This would provide increased liquidity, favourable taxation advantages, a decreased level of shareholder approval required for taking decisions, a reduction in regulatory consents required, increased efficiency in corporate governance, and ultimately leading to flowback being reduced. However, investors should also consider the factors influencing the price of a dual-listed stock before opting to purchase these stocks, which will be discussed in the following section.

2.2.3 Factors influencing the price of a dual-listed stock

This section will discuss the following factors that influence the price of dual-listed stocks. These factors include index exposure (Section 2.2.3.1), geographical risk (Section 2.2.3.2), local markets (Section 2.2.3.3), regional legislation (Section 2.2.3.4), arbitrage effects (Section 2.2.3.5), and regional broker expectations (Section 2.2.3.6).

2.2.3.1 Index exposure

Whenever the stock of a company is dual-listed, it invariably occupies different weightings in different indices on the various markets where the stock is listed on. This factor makes the relative weight of money, benchmarked to each index, an important influence when considering the relative performance of dual-listed stocks (Lynch, 2002:8). The risk it holds for an investor

9 Flowback is when foreign investors perform a massive sell-off of a company's dual-listed shares back to the country of issuance as a result of an impending cross-border merger (Investopedia, 2011a:1).

10 Bid-ask spreads are the differences in price between the highest price that a buyer is willing to pay for an asset and the lowest price for which a seller is willing to sell it for (Investopedia, 2011b:1).

includes the possibility for the value of a dual-listed stock to fall in one market if the index it is linked to falls, as this influences investors' perception pertaining to the stocks underlying the index. This will, therefore, cause the price of the dual-listed stock listed on the secondary market to follow this downward trend, because of the presence of arbitrage. The opposite is also true for a situation where one index appreciates in value (Lynch, 2002:8).

2.2.3.2 Geographical risk

If a stock is listed on various markets, existing in different countries, the geographical difference may influence the pricing of the various stocks (Lynch, 2002:4). Markets existing in different countries around the world are different, as different buyers and sellers buy stocks in each market. This is the core reason for the existence of geographical risk. The London-Sydney pairs provide the best examples of this phenomenon (Roosenboom & Van Dijk, 2009:1898). Some of these differences include the timing difference between two markets. Sydney is open at a different time horizon to London, and London tends to follow any market movements in New York closely (Roosenboom & Van Dijk, 2009:1898).

2.2.3.3 Local markets

The London and Sydney dual-listed stocks are again a good way of illustrating the effect of local markets on dual-listed stocks. An example of such a stock includes Brambles. In Sydney, for example, Brambles makes up 1.3% of the ASX 200 index[11], whereas, in London, it only accounts for 0.191% of the FTSE 100[12]. Therefore, even though it is the 18th biggest Australian stock, it is only the 92nd largest on the London Exchange. Due to this difference in weight, it is found that with Australian stocks investors hold a base amount of the stock in their portfolio regardless of economic performance. This is because of the greater weight the stock occupies in the ASX 200 index. On the other hand, FTSE 100 stocks are not always held as a base amount, as its performance will have little effect on such a portfolio composition. From this effect, it is clear that the local market composition affects the way in which dual-listed stocks are traded (Roosenboom & Van Dijk, 2009:1898).

[11] The ASX 200 is the benchmark stock index for the Australian markets (Investopedia, 2011c:1).
[12] The FTSE 100 is an index of all blue chip stocks on the London Securities Exchange (FTSE, 2011:1).

2.2.3.4 Regional legislation

The existence of differing incentives for domestic investors to hold various lines of stock leads to another potential pricing influence. For example, stamp duty has been abolished in Australia, whereas it still exists in the UK. Furthermore, there is a tax rebate on Australian dividends for domestic investors, which will not be the case for UK investors. These factors could lead to differing performances between dual-listed stocks from the Australian and the London markets (Lynch, 2002:8).

2.2.3.5 Arbitrage effects

If one stock becomes particularly overvalued, arbitrage-seeking investors will look to short[13] that stock against going long[14] in the dual-listed stock in the other market, thereby bringing the pair back into equilibrium due to market powers of supply and demand. By using a chartist[15] approach, it is possible to pick likely levels at which these accounts will become involved (Lynch, 2002:8). Arbitrage will be discussed in more detail in Section 2.5.

2.2.3.6 Regional broker expectations

As the secondary listing of a dual-listed stock is mostly done on a stock exchange in a different country than that of the primary market, investors residing in the primary market often assume the same underlying fundamental analysis for both markets. The local brokers' earning expectations for foreign stocks may differ from those covered in the primary market. This, in turn, may lead to different recommendation changes in local markets to those made in the secondary markets, thereby driving one stock to outperform the other (Roosenboom & Van Dijk, 2009:1898).

By accounting for these factors, an investor may gain insight into plausible causes for the differences in dual-listed stock prices. However, it is also necessary to understand the markets

[13] Taking a short position in a stock refers to the sale of a stock, or borrowed stock, with the expectation that the stock will fall in value (Marx *et al.,* 2008: 222).

[14] A long position in a stock refers to the purchase of a stock with the expectation that the stock will rise in value (Marx *et al.,* 2008: 223).

[15] A chartist approach is a technique where charts are used to identify patterns that can suggest future activity (Investopedia, 2011d:1).

of this study and the dual-listed stocks available in these markets. This study focuses specifically on the JSE and LSE, and the different dual-listed stocks available on these two markets are shown in Table 2.1.

Table 2.1: Dual-listed stocks on the JSE and LSE

DUAL-LISTED STOCK COMPANIES (A-H)	PRIMARILY OR SECONDARILY LISTED ON JSE	DUAL-LISTED STOCK COMPANIES (I-T)	PRIMARILY OR SECONDARILY LISTED ON JSE
Anglo American Plc.	Secondarily	**Impala Platinum Holdings Limited**	Primarily
AngloGold Ashanti Limited	Primarily	**Investec Plc**	Secondarily
African Eagle Resources Plc	Secondarily	**Ipsa Group Plc**	Secondarily
African Rainbow Minerals Limited	Primarily	**Jubilee Platinum Plc**	Primarily
Anglo Platinum Limited	Primarily	**Kiwara Plc**	Primarily
Aquarius Platinum Limited	Secondarily	**Liberty International Plc**	Secondarily
Barloworld Limited	Primarily	**London Finance and Invest.Grp Plc**	Secondarily
BHP Billiton Plc	Secondarily	**Lonmin Plc**	Secondarily
Braemore Resources Plc	Primarily	**Lonrho Plc**	Secondarily
British American Tobacco Plc	Secondarily	**Metorex Limited**	Primarily
Central Rand Gold Limited	Secondarily	**Mondi Plc**	Secondarily
Datatec Limited	Primarily	**Old Mutual Plc**	Secondarily
Diamondcorp Plc	Primarily	**Pan African Resources Plc**	Secondarily
Dimension Data Holdings Plc	Secondarily	**SABMiller Plc**	Primarily
Drdgold Limited	Primarily	**SAPPI Limited**	Primarily
Gold Fields Limited	Primarily	**Stilfontein Gold Mining Company Ltd**	Primarily
Harmony Gold Mining Company Limited	Primarily	**Tongaat Hulett Limited**	Primarily

Source: JSE (2010:1)

2.2.4 Anglo American Plc. as a dual-listed stock

The dual-listed stock that will be used in this study is Anglo American Plc., which is part of the resources sector on the JSE. The resource sector is the most influential sector, according to size, on the JSE (JSE, 2010:1). Anglo American Plc. is primarily listed on the LSE and secondarily listed on the JSE and was first listed on the JSE and the LSE on 1 May 1999 (Anglo American, 2010:1). The Anglo American Corporation of South Africa was founded in 1917, and in 1999 Anglo American Plc. was established by combining the business interests of Anglo and Minorco (Anglo American, 2010:1). With a sweeping restructuring of the Group, it created one of the world's largest mining and natural resource companies in the world.

Anglo American Plc. is active in seven commodity segments, namely platinum (in South Africa), thermal coal (in South Africa), Kumba iron ore (in South Africa), copper (Chile), nickel (Brazil) metallurgical coal, (Australia), and iron ore Brazil (Brazil). Anglo American Plc.'s headquarters are in London, UK. In 2009, Anglo American Plc. had an operating profit of $5 billion, and earnings of $2,569 billion (Anglo American, 2010:1). Anglo American Plc. had a market capitalisation of 462.53 billion as on 22 March 2011 (Anglo American, 2011:1). Furthermore, Anglo American Plc. secured the number one spot on the JSE top 40 index as on 22 March 2011 (FTSE, 2011:1). A further reason why Anglo American Plc. was chosen for this study, above all the other stocks in the resources sector of the JSE, is due to the availability of accurate inter-day stock data.

To summarise; dual-listed stocks have very different characteristics than their single exchange listed counterparts. Dual-listed stocks offer exposure to international markets and offer various taxation benefits (Section 2.2.2). They also provide various efficiency advantages such as possible easier corporate governance and less regulatory consent to conduct business (Section 2.2.2). Apart from these advantages, there are also factors that influence the price of dual-listed stocks. Some of these factors include index exposure (Section 2.2.3.1), geographical risk (Section 2.2.3.2), the degree of exposure to local markets (Section 2.2.3.3), regional legislation (Section 2.2.3.4), arbitrage effects (Section 2.2.3.5), and regional broker expectations (Section 2.2.3.6). In addition to these factors, the following section will elaborate on the composition of a dual-listed stock price. This discussion will start with the Efficient Market Hypothesis (EMH) and information flow as key theories in how stock prices are formed.

2.3 EFFICIENT MARKET HYPOTHESIS AND INFORMATION FLOW

2.3.1 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) is a theory that originated from a study conducted by Bachelier (1900:86) who investigated the mathematical theory of random processes. Bachelier (1900:86) explained that stock price movements followed a Brownian motion[16]. This theory therefore implies that the future price movements of stocks are totally unpredictable empirically. However, the Brownian motion is very difficult to test, requiring complex mathematical computations. Further evidence suggested that stock prices and commodity prices seem to follow a random walk[17] (Kendall, 1953:11), which was also emphasised by the study of Samuelson (1965:48) and Mandelbrot (1966:254). They came to the conclusion that stock prices indeed follow a random walk. This stipulates the possibility that financial information pertinent to the firm may be reflected in the current stock price (Yen & Lee, 2008:308). Based on these findings, Fama (1970:389) was able to formulate the three forms of market efficiency. The first form of market efficiency is known as the *weak form*, which states that past information that is relevant to the stock's parent company is fully reflected in its present stock price. The second form of market efficiency is known as the *semi-strong form*, where public information relevant to the company is fully reflected in the stock's present stock price (Fama, 1970:389). The third and most efficient form of market efficiency is known as the *strong form*, which states that all information, whether publicly available or kept private, relevant to the company is fully and quickly reflected in its present stock price (Fama, 1970:389).

In addition, the EMH claims that it is impossible to gain profit by "beating the market[18]", because of the assumption that stock market efficiency forces stock prices to inherently include and reflect all relevant information (Investopedia, 2010:1). According to this theory, stocks will

[16] Brownian motion is a continuous-time stochastic (or probabilistic) process, explaining the seemingly random movement of particles suspended in a fluid, or the mathematical model used to describe such random movements (Brown, 1828:161).

[17] Random walk refers to the mathematical formalisation of a trajectory that consists of taking successive random steps (Pearson, 1905:294).

[18] Beating the market is when an investor gains a return on his investment, which is larger than the average return of the market (Investopedia, 2010:1).

always trade at their fair value when bought/sold on stock exchanges, thereby making it impossible for anyone to either purchase an undervalued stock or sell their stock at inflated prices (Investopedia, 2010:1). Furthermore, by considering this transparent information system, it should not be possible to outperform the overall market through individual stock selection or by timing the market. Contrary to this, evidence has shown that it is possible to beat the market, for long periods of time, which contradicts the EMH theory (Malkiel, 2003:81).

According to Marx *et al.* (2008:32), the EMH has varying implications for portfolio managers. Fundamental analysts believe that stock values depend on the economic factors underlying the price. This kind of analysis requires that the portfolio manager estimates macroeconomic factors, such as inflation, interest rates, and the gross domestic product (GDP). The portfolio manager then has to estimate which companies are undervalued, and then buy their stocks (Marx *et al.,* 2008:32). The implication for the EMH is, however, that no above-average returns are possible this way, unless the manager has access to reports of superior analysts. Furthermore, if one is able to buy the stocks before the rest of the market realises that there is a difference between the stock's intrinsic and market value (superior market timing), there would also be opportunity for above-average returns. The study by Marx *et al.* (2008:32) elaborated by explaining that the EMH also holds implications for technical analysis. Technical analysts use mathematical and statistical methods, such as graphs and charts, to identify buy and sell signals from the market information. This kind of analyst believes that individual investors never act immediately on analysed information (Marx *et al.,* 2008:32). Analysts tend to believe that some people receive the information first, gradually spreading it to the rest of the market, and believe that stock prices move in persistent trends. The EMH, however, states that stock prices will adjust rapidly and fully reflects all information. This implicates that the use of historical data to determine future prices of stocks is impossible (Marx *et al.,* 2008:32).

To summarise; the way in which stock market information becomes available to investors will influence the price composition of a stock. Fama (1970:389) was able to formulate three forms of market efficiency, which include the *weak form*, the *semi-strong form* and the *strong form.*

These forms imply the inability to predict future stock prices. In addition to market efficiency, is the flow of information from the company to the investor, which will also affect the price composition of a stock and will be discussed in the following section.

2.3.2 Information flow[19]

Information flow is the transaction volume that is signed for the purchase of a stock, indicating whether the transaction is initiated by the buyer or the seller (Lyons, 2002:52). Information flow has a direct influence on the way a stock is priced, which can be illustrated by the information flow model (Figure 2.1). In the information flow model, the information process has three approaches. The first approach is where the fundamental analysis[20] carried out by an investor before the purchase of a stock is done, is based on public information about the stock (Lyons, 2002:52). The second approach is the investor's interpretation of the first analysis. This implies that the investor already possesses all public information, but will gain further information regarding a stock by studying the information flow. The three approaches regarding the information flow on a stock can be illustrated in Figure 2.1 (Lyons, 2002:52).

The first approach in Figure 2.1 is used when public information about a stock will directly influence the price of the stock (Lyons, 2002:52). Under this approach, information about fundamentals is publicly known and will be directly mapped to the price of the stock and consequently the price adjustment will be immediate. In the second approach, known as the *dispersed information approach*, dispersed information of a stock together with the information flow of a stock will influence the stock price. Under this approach, the fundamental information is not known by the public and subsequently information will first be transmitted to the information flow of a stock. The information flow will then indicate to the price setter that the price of the stock needs to be adjusted. In the third approach, public information regarding a stock, together with the information flow, will influence the price of a stock. Under this approach,

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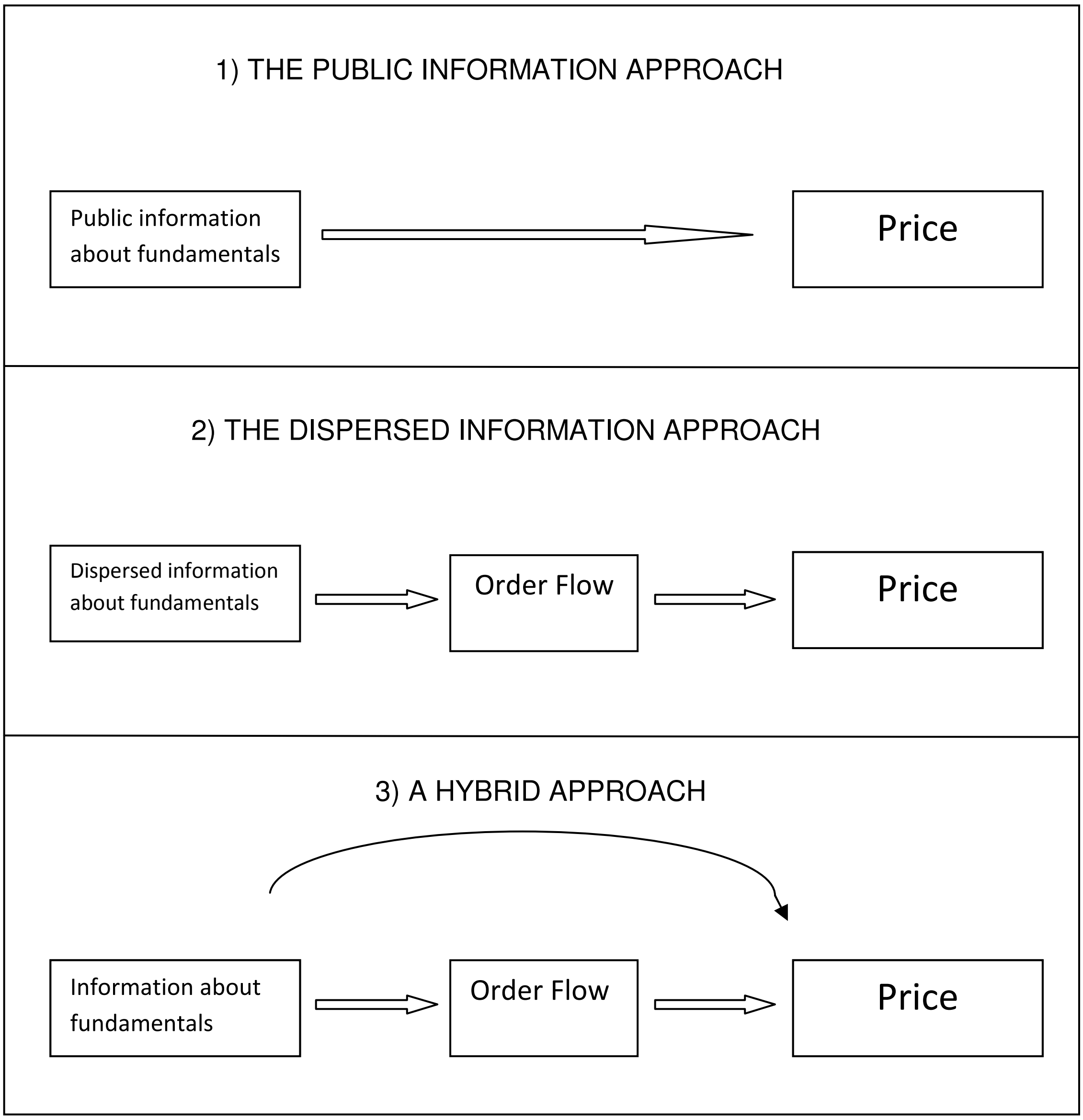
[19] Information flow is also referred to as "order flow" in some studies.

[20] Fundamental analysis is the analysis done on a stock, where an investor looks at factors such as the macro-economic situation, sector behaviour, and company-specific news of a stock (Benjamin & Dodd, 2004:256).

the information is publicly available to investors, and the information flow will directly influence the stock price (Lyons, 2002:52).

Figure 2.1: Information flow and price composition



Source: Lyons (2002:53).

Information flow can also be quantified. If the order for a stock is placed by a buyer, it will influence the information flow positively. This is true where a rise in demand is usually accompanied by a rise in the price. The opposite is true for an order initiated by the seller (Lyons, 2002:52). Consider the following example: If a company decides to sell 10 of its stock, the information flow will be -10. This is because the rise in supply usually causes prices to drop. An investor may also place an order for 10 stocks of a company at a certain price. If the company is satisfied with the price, and the transaction is completed, the information flow will be

+10. Information flow does not depend on the amount of stock, but depends on whether the buyer or seller initiated the transaction (Lyons, 2002:52).

To summarise; the EMH states that all public information regarding a stock will be reflected in the stock's price. This implies that it should not be possible to gain above-average returns on stocks, as stocks are traded at their fair value. However, evidence indicates that prices do deviate from their fair value, making arbitrage possible (Section 2.6.). The study by Lyons (2002:52) examined a different approach, called the *information approach*. Under this approach, information flow has a significant impact on stock prices with orders placed by buyers asserting a positive influence on price (and *vice versa* for orders placed by sellers).

In addition to the information about a stock, there are many other factors that contribute to the stock price composition, which include the trade-off between risk and return. Because a price must sometimes include a premium to compensate for the risk at hand, the following section will discuss the types of risks present (Section 2.4). Only by understanding the risks that investors face can a clear understanding be provided regarding the required return that investors demand (Section 2.4.1.3). Additional insight will then be provided with an overview on asset pricing models. This will elaborate on the factors included in the composition of a stock price.

2.4 SYSTEMATIC AND UNSYSTEMATIC RISK

2.4.1 Introduction

An investor expects a certain level of return from an investment instrument, which is called the required rate of return. This required rate of return can be defined as the minimum return an investor should accept from an investment, in order to compensate for deferring consumption (Marx *et al.*, 2008:4). The three components affecting the required rate of return are the *time value of money* during the period of the investment, the *expected rate of inflation* during the period of the investment, and the *risk* involved when purchasing the stock (Bodie & Kane, 1993:65). The time value of money, also known as the Real Risk-Free Rate (RRFR), is the theoretical rate of return that an investor would receive from an investment with zero risk, or which is risk-free over a period of time. An example of a risk-free asset includes a 91-day Treasury Bill, as Treasury Bills are backed against default by the issuing government (Bodie & Kane, 1993:65).

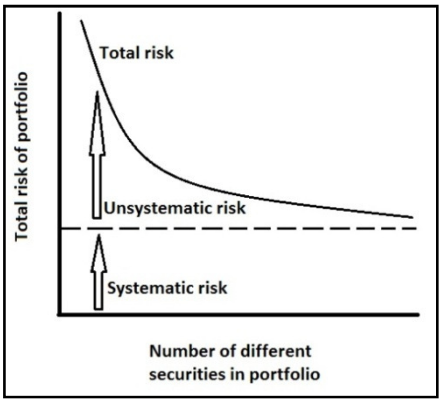
Furthermore, there is a risk that the investor might lose money due to the stock losing value. A higher return than the RRFR is therefore required by the investor in order to compensate for the possible loss (Marx *et al.*, 2008:4). This implies that a higher required return on investment may affect the way in which the stock is priced. Equity stocks also suffer from two kinds of risk, called systematic risk (Section 2.4.1.1), and unsystematic risk (Section 2.4.1.2), which will be discussed in the following section. These risks influence the required rate of return, implying that additional compensation should be made, thereby influencing the stock price, making it an important factor to consider when examining stock price composition.

2.4.1.1 Systematic risk

Systematic risk, also called market risk or un-diversifiable risk, is defined as the risk inherent to the entire market or entire market segment and cannot be diversified away (Marx *et al.*, 2008:34). Examples are interest rate risk[21], equity risk[22], exchange rate risk[23], commodity price risk[24], currency risk[25], recession, war and inflation. Equity stocks always hold some form of systematic risk, which can be illustrated in Figure 2.2:

[21] Interest rate risk is the risk that interest rates and/or the implied volatility will change (Marx *et al.*, 2008:34).
[22] Equity risk is the risk that stock prices and/or the implied volatility will change (Marx *et al.*, 2008:34).
[23] Exchange rate risk is the risk of changes in exchange rates between currencies (Marx *et al.*, 2008:34).
[24] Commodity price risk is the risk that commodity prices (e.g. corn, copper, crude oil) and/or implied volatility will change (Marx *et al.*, 2008:34).
[25] Currency risk is the risk that foreign exchange rates or the implied volatility will change (Marx *et al.*, 2008:34).

Figure 2.2: Systematic and unsystematic risk in an investment



Source: Marx *et al.* (2008:35)

Each stock or portfolio of stocks possesses its own level of systematic risk, as illustrated in Figure 2.2. In order to measure this risk, the beta (β) value of the stock must be calculated, which will be explained in the following section.

2.4.1.1.1 Beta as a risk measurement tool

The beta (β) value of a stock indicates how a stock will react to certain market forces (Gitman & Joehnk, 1990:197). The larger the response of a stock to market forces, the larger the beta value will be. Beta can be estimated by comparing the historical return information of a stock with the historical return information of the market. The value of the market beta is estimated by computing the average return of a large sample of stocks. The following equations can be used to estimate beta (Marx *et al.*, 2008:36):

$$\beta = \frac{Systematic\ risk\ of\ security\ i}{Market\ risk} \tag{2.2}$$

$$\beta = \frac{Covariance_{i,m}}{Variance_m} \tag{2.3}$$

$$\beta = \frac{Corr_{i,m}\sigma_i\sigma_m}{\sigma_m^2} \tag{2.4}$$

Where:

- $Corr_{i,m}$ is the correlation between the individual stock *i* and the market *m*;

- σ_i is the standard deviation[26] of the individual stock; and
- σ_m is the average standard deviation of the market.

If a stock has a beta equal to one, it will react in the same way as the market. For example, if the market moves upward with 1% the stock price will most likely rise with 1%. If the beta value of the stock is smaller than one, it will not react on the same magnitude as the market forces. For example, if a stock has a beta value equal to 0,5 and the market moves upward with 1% the stock price will most likely rise with 0,5%. Lastly, if the stock has a beta value greater than one, it will react heavier to market forces than the market will react. For example, if a stock has a beta value equal to 1,5 and the market moves upward with 1% the stock price will most likely rise with 1,5% (Gitman & Joehnk, 1990:197). Table 2.2 below consists of a summary for the interpretation of beta.

Table 2.2: The interpretation of beta (β)

BETA	COMMENT	INTERPRETATION
2.0	Stock will move in same direction as market.	Twice as responsive as the market.
1.0		Same response or risk as the market.
0.5		Half as responsive as the market.
0	Stock movement unrelated to market movement.	Unaffected by market movements.
-0.5	Stock will move in opposite direction of the market.	Half as responsive as the market.
-1.0		Same response or risk as the market.
-2.0		Twice as responsive as the market.

Source: Gitman & Joehnk (1990:197)

However, the total risk of a stock includes both systematic and unsystematic risk. This leads to the next section that will examine the unsystematic risk of a stock.

[26] Standard deviation refers how much variation or "dispersion" there is from the average (mean, or expected value) in a stock price (Investopedia, 2011e:1).

2.4.1.2 Unsystematic risk

Unsystematic risk refers to a company- or industry specific risk, which is inherent in each investment (See Figure 2.2). The effects of different types of unsystematic risk can be minimised through diversification[27] (Marx *et al.*, 2008:34). The following is a list of unsystematic risks (Reilly & Brown, 2000:19-20):

- Business risk; the extent of certainty (or lack thereof) about a firm's cash flows as a result of the nature of its business.
- Financial risk; the financial leverage (gearing) employed by a firm. The greater the extent to which debt in relation to equity is used to finance the firm, the greater the financial leverage and the greater the financial risk.
- Liquidity risk; the speed at which a company can convert its assets into cash, as well as the ability to receive the right amount of money for its assets. The lower the liquidity of a company's assets, the higher the liquidity risk.
- Operational risk; risk arising from the execution of a company's own business functions, which include risks arising from systems and processes inside of a company. Examples include fraud risks, people risks, legal risks, environmental risks, and physical risks.

In order to remove unsystematic risk, portfolio managers normally diversify portfolios (Gitman & Joehnk, 1990:197). However, even when portfolios are diversified, a certain amount of risk still exists. An investor will, therefore, have to choose between various portfolios that will provide the highest return on investment for the least amount of risk. This is done by studying the Markowitz efficient frontier, which will be discussed in the following section.

2.4.1.3 Markowitz efficient frontier

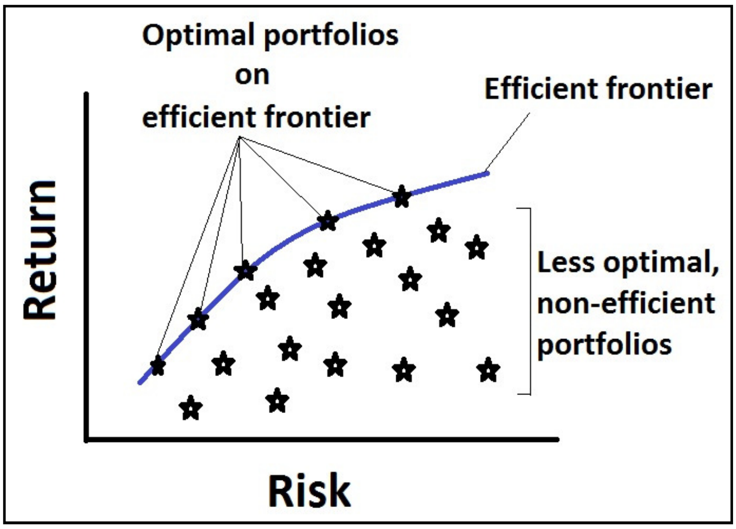
The Markowitz efficient frontier represents that set of portfolios (consisting of risky investments) that has the maximum return for every given level of risk (Figure 2.3). It may also display those

[27] Diversification refers to a method of reducing the systematic risk of a portfolio by investing in more than one asset class (Marx *et al.,* 2008:10).

portfolios displaying the minimum risk, for every level of return (Markowitz, 1952:82). Individual stocks will not be found on the efficient frontier if they consist of an undiversified nature. Every possible combination of the risky assets, without including any holdings of the risk-free asset, can be plotted in a risk-expected return space. The efficient frontier represents the optimal portfolios in terms of return, when risk is controlled for (Marx *et al.*, 2008:34).

Combinations along this upper edge of the efficient frontier represent portfolios (including no holdings of risk-free assets) for which there is lowest risk for a given level of expected return. Equivalently, a portfolio lying on the efficient frontier represents the combination offering the best possible expected return for a given risk level and provides the best possible choice for an investor (Marx *et al.*, 2008:34).

Figure 2.3: The efficient frontier



Source: Markowitz (1952:82)

To summarise; investing in stocks exposes the investor to two different types of risk, namely systematic risk and unsystematic risk. Systematic risk is the risk caused by market conditions, whereas unsystematic risk is the risk inherent to the company and cannot be removed through diversification. Each stock consists of its own level of systematic risk and can be measured by beta (β). A higher beta implies that the stock carries higher systematic risk. Unsystematic risk can be partly removed by diversification.

In order to find a set of portfolios that offers the maximum return for the least amount of risk, the Markowitz efficient frontier can be used. However, to determine how a stock price is determined with the trade-off between risk and return, this study needs to continue investigating the general models used to price equity. These models will provide the insight required to understand how the risk-return trade-off can determine a stock price. This leads to the following section that will provide an overview of the different asset pricing models available.

2.5 ASSET PRICING MODELS

2.5.1 Capital Asset Pricing Model (CAPM)

2.5.1.1 Introduction

Following the development of the Markowitz efficient frontier, Sharpe (1964), Litner (1965), and Mossin (1966) extended the Markowitz efficient frontier model into the general equilibrium asset model. The first assumption made in their studies includes the existence of a risk-free asset [28] (Reilly & Brown, 2003:238). Due to this assumption, investors now have the choice of investing in a portfolio of assets, which can include a risk-free asset that will generate a Risk-Free rate of Return (RFR)[29].

When combining a risk-free asset with a risky portfolio, the average returns as well as the standard deviation of the portfolio are influenced (Reilly & Brown, 2003:240). The expected return on a portfolio when a risk-free asset is incorporated can be illustrated as follows (Reilly & Brown, 2003:241):

$$E(R_{port}) = w_{RF}(RFR) + (1 - w_{RF})E(R_i) \qquad (2.5)$$

Where:

- $E(R_{port})$ is the expected return from the portfolio;
- w_{RF} is the proportion of the asset invested in the risk-free asset;
- $E(R_i)$ is the expected rate of return on risky portfolio *i*; and

28 A risk-free asset is an asset with returns that exhibit zero variance (Reilly & Brown, 2003:240).

29 The Risk-Free rate of Return (RFR) is rate of return received from an investment in a risk-free asset (Reilly & Brown, 2003:240).

- RFR is the risk-free rate of return.

Furthermore, the standard deviation changes when a risk-free asset is combined with the portfolio, and the estimation of the new standard deviation can be illustrated as follows (Reilly & Brown, 2003:241):

$$\sigma_{port} = (1 - w_{RF})\sigma_i \tag{2.6}$$

Where:

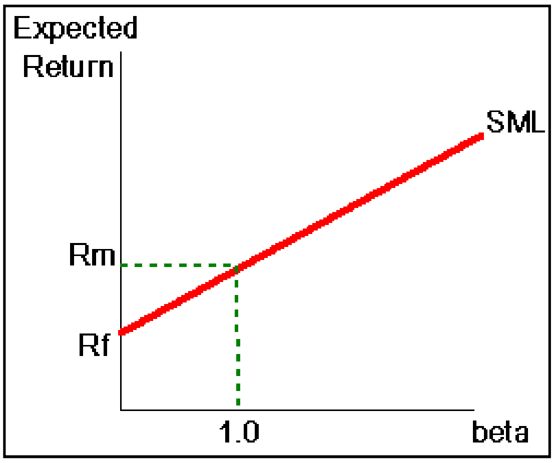
- σ_{port} is the standard deviation of the portfolio;
- σ_i is the variance of asset *i*; and
- w_{RF} is the proportion of the asset invested in the risk-free asset.

The expected return and the standard deviation for such a portfolio are both linear; therefore, a graph of possible portfolio returns and risks forms a straight line between the assets (See Figure 2.4). This graph is depicted as either a Security Market Line (SML) or Capital Market Line (CML), both of which will be discussed in the following section.

2.5.1.2 The Security Market Line (SML) and the Capital Market Line (CML)

One of the greatest developments in capital market theory is the Sharpe-Lintner-Mossin mean-variance equilibrium model of exchange, which is also known as the Capital Asset Pricing Model (CAPM; Sharpe, 1964:425). In modern portfolio theory, the CAPM can be graphically illustrated by the Security Market Line, as illustrated by Figure 2.4 (Marx *et al.*, 2008:33). The Security Market Line (SML) attempts to display the expected rate of return of an individual security as a function of its systematic (non-diversifiable) risk, which is known as the beta (β) (Section 2.2.4.1.). The SML, therefore, identifies the risk-return trade-off an investor must partake in at a given time.

Figure 2.4: The Security Market Line (SML)

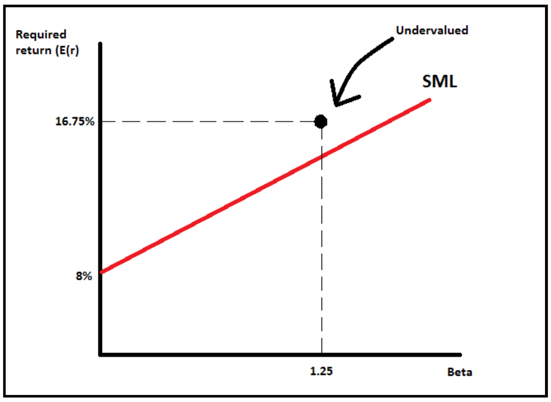


Source: Reilly & Brown (2003:245)

Furthermore, the SML provides the investor with a benchmark return against which a potential investment can be measured. When plotting a single asset against the SML, the risk-return trade-off that accompanies this asset can be determined (See Figure 2.5). Therefore, if the asset falls above the SML, investors consider the asset as a good risk-adjusted return and it should be acquired. However, if it falls below the SML, investors perceive the asset to exhibit a poor risk-adjusted return and it is seen as a sell signal (Marx *et al.*, 2008:34).

In addition to the benchmark returns, the SML also provides investors with information as to whether a stock is undervalued or overvalued. To establish this, an investment's required rate of return is compared to its estimated rate of return (Reilly & Brown, 2003:250). This difference between the required and estimated return is called the alpha (α) value, and can be positive or negative. When the stock's alpha value is positive, the stock is considered to be undervalued, and when the stock's alpha value is negative, the stock is considered to be overvalued. In the case of an undervalued stock, the stock will appear above the SML when the SML graph is plotted (Reilly & Brown, 2003:251). The opposite is also true for an overvalued stock, which can be illustrated by the following figure:

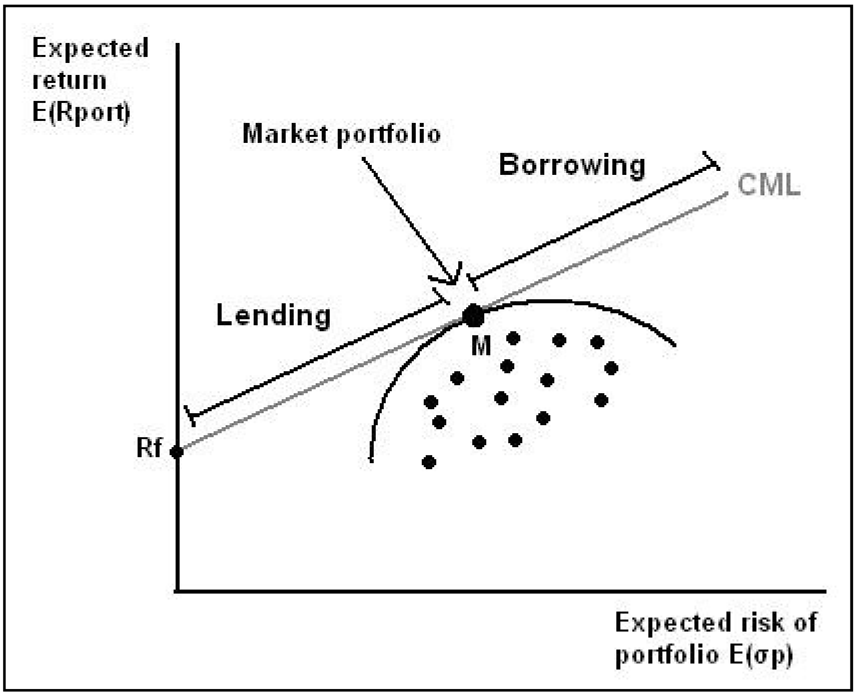
Figure 2.5: The Security Market Line (SML) with an undervalued stock location



Source: Reilly & Brown (2003:245)

Until now, the SML has not included the possibility for investors to lend or borrow money in a portfolio. In practice, investors will borrow against the risk-free rate and because of this the risk and return will increase in a linear fashion along the SML, which leads to the derivation of the Capital Market Line (CML), as illustrated in Figure 2.6. The CML is a straight line, beginning at the risk-free rate (Rf), tangent to point M in Figure 2.6. All portfolios on the CML are perfectly positively correlated (Marx *et al.*, 2008:37). Portfolio M in Figure 2.6 represents a portfolio that lies at the point of tangency to the risk-free rate. This implies that every investor would want to invest in portfolio M and then borrow or lend in order to be somewhere else on the CML (Marx *et al.*, 2008:34). Such a portfolio includes all risky assets in proportion to their individual market value and is therefore also called the market portfolio. The investor could now choose to invest part of his portfolio in the risk-free asset and the rest in the risky portfolio M, or could choose to borrow money at the risk-free rate and invest that amount in the risky portfolio M (Reilly & Brown, 2003:291).

Figure 2.6: Capital Market Line (CML) assuming lending or borrowing at the risk-free rate



Source: Reilly & Brown (2003:243)

One of the differences between the CML and the SML is that risk is measured by means of variance in the CML, whereas in the case of the SML, risk is measured by means of beta (β) (Marx *et al.*, 2008:34). Another difference is that the CML only defines efficient portfolios whereas the SML includes efficient and non-efficient portfolios (Prabhat, 2012:1). The CML is a graphic illustration of the Capital Asset Pricing Model (CAPM) and is considered to be superior to the efficient frontier, since it takes into account the inclusion of a risk-free asset in the portfolio. The Capital Asset Pricing Model (CAPM) further expands the asset pricing theory demonstrating that the market portfolio is essentially the efficient frontier. The following section investigates how the Capital Asset Pricing Model (CAPM) is constructed.

2.5.1.3 Constructing the Capital Asset Pricing Model (CAPM)

Most investors are risk-averse, which implies that for any increase in risk, investors will require an increased rate of return on the investment to compensate for the exposure. The CAPM theory enables the investor to determine the required rate of return with the current risk level. The CAPM also indicates the return an investor should require from an asset, assuming the stock is exposed only to the systematic risk (Section 2.4.1.1). In order to construct an effective CAPM, the following assumptions must be made (Marx *et al.*, 2008:36):

- Investors are rational and mostly risk-averse, and will attempt to invest on the efficient frontier in order to realise a maximum return;
- investors are able to either borrow or lend money at the risk-free rate (R_f);
- investors have homogenous expectations, therefore they estimate future probability distributions of the rate of return in the same way;
- investors have the same (one period) time horizon for their investment;
- investments may be divided, which implies buying or selling fractions of any asset or portfolio;
- there are no transaction costs or any taxes involved in buying or selling assets;
- inflation and interest rate changes are ignored; and
- capital markets are in equilibrium where all assets are priced properly in line with their level of risk.

In addition, the CAPM can be formulated as follows (Marx *et al.*, 2008:36):

$$Required\ return = R_f + \beta_i(k_m - R_f) \quad (2.7)$$

Where:

- R_f is the risk-free rate of return;
- β_i is the sensitivity of the stock *(i)* against market fluctuations; and
- k_m is the return on the market portfolio.

2.5.1.4 Shortcomings of the CAPM

The standard CAPM has been used as the basis for the majority of academic papers[30], and has had a great impact on the financial community (Welles, 1971:79). However, this model has also received much criticism for various theoretical and empirical reasons (Merton, 1973:867). One

[30] Examples include studies such as the ones by Malul *et al.* (2001); Karathanasis *et al.* (2010); Korkmaz *et al.* (2010).

of the CAPM assumptions is that investors compose their portfolios according to the mean-variance criteria of Markowitz (1959:82), which makes the original CAPM subject to all the theoretical objections of the Markowitz (1959:87) criteria[31]. Proponents of the CAPM, such as Yalcýn and Ersahin (2010) and Faff (2001:173), argue that the capital market will operate "as if" the CAPM assumptions are satisfied. These proponents also argue that although the model predicts the expected excess return, it will be proportional to the covariance of its return with the market portfolio (Merton, 1973:867). This may seem like a logical argument in favour of the standard CAPM model; however, the study by Black *et al.* (1973) disagrees. Black *et al.* (1973) found that low beta assets earn a higher return on average, whereas high beta assets earn a lower return on average, which is forecasted by the standard CAPM.

Apart from the criticism mentioned above, the CAPM is still being used, because it serves as an equilibrium model, which provides a strong specification of the relationship among asset yields that can easily be interpreted (Merton, 1973:867). The empirical evidence further suggests that the CAPM also explains a significant fraction of the variation in asset returns (Merton, 1973:868). However, the CAPM also has many other shortcomings, as it assumes that asset returns are normally-distributed random variables. It also assumes that investors employ a quadratic form of utility (Mandlebrot & Hudson, 2004:60). However, evidence shows that prices on equity markets are not normally distributed, which implies that large swings (three to six standard deviations from the mean) may occur in the market on a frequent basis, proving the assumption of a normal distribution to be invalid (Mandlebrot & Hudson, 2004:60). Furthermore, the CAPM assumes that probability beliefs of investors will be the same as the distribution of returns acquired from investments (Kent *et al.,* 2001:965). However, investors rather tend to have biased expectations, causing inefficient information systems in markets. Another shortcoming is that the market portfolio should include all types of assets owned by an investor (including alternative investments such as works of art, real estate). However, in practice, such a market portfolio is unfortunately unobservable and people will substitute a stock index as a proxy for the true market portfolio instead (Roll, 1977:153). Unfortunately, it has been proven

[31] For a full list of the Markowitz criteria consult the study of Markowitz (1959:87).

empirically that this substitution is not innocuous and can lead to false inferences as to the validity of the CAPM. Due to this fact, and the inobservability of the true market portfolio, the CAPM might not be empirically testable (Roll, 1977:176).

To summarise; the use of the CAPM holds advantages for investors, as it provides the investor with a benchmark return that can be used to measure a potential investment. However, the CAPM considers only systematic risk that implies a situation in which most investors have already diversified unsystematic risk. A further disadvantage in using the CAPM is the assumption of a single-period time horizon, which differs from the multi-period nature of investment appraisal. Also, the CAPM uses only one risk measure (beta), and for this reason, a more complex model is required to incorporate multiple aspects of risk, which include the multi-factor model called the Arbitrage Pricing Theory (APT) that will be discussed in the following section.

2.5.2 Arbitrage Pricing Theory (APT)

Due to criticism against the CAPM (Section 2.5.3.1), the Arbitrage Pricing Theory (APT) model was developed by Ross (1976) as an alternative to the CAPM. The following assumptions are required in the APT (Marx *et al.*, 2008:39):

- Capital markets are perfectly competitive;
- investors want less wealth instead of less wealth with certainty; and
- the k factor[32] model used represents a stochastic process that generates asset returns.

The fundamental principle of the APT is that the price of a stock is driven by a number of factors, which can be divided into two groups, namely *macroeconomic factors*, and *company-specific factors*. Sensitivity to changes in each of these various factors is represented by a factor-specific beta coefficient. However, the APT has a weakness, as it is up to the investor to choose these variables, which may lead to a calculation error. This weakness is found because of the incorrect variables that may be chosen and used (Bodie *et al.,* 2010:213).

[32] The *K factor* refers to the fact that the number of factors used in the APT is indefinite (Marx *et al.,* 2008:39).

The APT model can be illustrated as follows (Reilly & Brown, 2003:282):

$$E_i = \lambda_0 + \lambda_1 b_{i1} + \lambda_2 b_{i2} + \dots + \lambda_k b_{ik} \tag{2.8}$$

Where:

- E_i is the expected return on the stock;
- λ_0 is the risk free rate;
- λ_i is the risk premium related to each common factor in the model; and
- b_i is the measure of the relationship between the stock price and the underlying factor.

The common factors may include macroeconomic factors, such as growth in GDP, inflation, and changes in interest rates. Berry *et al.* (1988:30) illustrated an approach that aims at determining the correct factors to be used in the APT. Economic variables that are legitimate risk factors must possess three important properties (Berry *et al.,* 1988:30). Firstly, at the beginning of every period, the market must be unable to predict the factor. Secondly, each APT factor must have a definite influence on stock returns. Thirdly, relevant factors must have an influence on expected return therefore, they must possess non-zero prices. The first property illustrates that for the market as a whole, a risk factor cannot be forecasted either by using its own past value, or by using any other public information. For this factor to be used, it must have an expected value equal to zero at the beginning of every time period (Berry *et al.,* 1988:30).

The second property suggests that firm-specific events may not be used as APT factors. An investor could earn excess returns if he/she has access to firm-specific information, such as the development of a profitable new product. This information may not be incorporated into an APT-based portfolio management strategy, because different types of economy-wide risks are not managed in this way. It may also not be used, as this approach would diversify away firm-specific risks (Berry *et al.,* 1988:30). The third property is an empirical issue, which evaluates if an investor has a correct set of APT variables. The investor may follow his/her instinct and choose a certain APT variable, and still find that a different ATP variable would yield equivalent results. To choose the correct variables, the investor has to consider empirical literature regarding the variables. Empirically, the factors should adequately explain asset returns; they should pass the statistical tests necessary to qualify as legitimate APT factors; the actual asset returns should exhibit plausible sensitivities to the realisations of these factors; and the factors should have non-zero APT prices (Berry *et al.,* 1988:30).

To summarise; the precise types of variables, as well as the number of variables to be used in the model, are still unknown to researchers, as the suggestions only provide guidelines. This is a weakness inherent to the APT model, and explains the conflicting evidence in the empirical results of past studies. However, despite the shortcomings of the CAPM and APT, they are also similar in many ways, as will be explained in the following section.

2.5.2.1 Comparison between APT and CAPM

The difference between CAPM and APT lies in the fact that CAPM has a single non-company factor and a single beta, whereas the APT divides the non-company factors into as many as is needed in the model (Bodie *et al.,* 2010:215). Each one of the factors used in the APT also requires a separate beta in the model (Bodie *et al.,* 2010:215). Therefore, the APT does not rely on measuring the performance of the market, but instead directly relates the price of the security to the fundamental factors driving it. However, this leads to a problem, as no theory can provide an indication as to what these factors might be. Furthermore, a large number of factors are needed and additional betas need to be calculated. This added complexity contributes to why the APT is a far less widely used model than the CAPM (Bodie *et al.,* 2010:215), although the APT relies on fewer assumptions than the CAPM.

The comparison between the APT and CAPM further reveals that the APT can be seen as a "supply-side" model, whereas and the CAPM is a “demand-side” model (Chen *et al.,* 1986:385). The APT is seen as a "supply-side" model since the sensitivity of the underlying asset to economic factors is reflected in the APT’s betas. This means that factor shocks cause structural changes in the assets' expected returns (Chen *et al.,* 1986:385).. The CAPM is considered a "demand side" model, because its results come from maximising each investor's utility function. Furthermore, investors are perceived to be the consumers, thus stimulating the demand for the asset. The resulting market equilibrium function, resulting from this rising demand for an asset, further supports the notion that the CAPM is a "demand side" model (Chen *et al.,* 1986:385).

To summarise; the APT is a proposed alternative to the CAPM, due to many shortcomings in the CAPM. The APT operates on an arbitrage-free assumption and fewer assumptions are needed than in the CAPM. Although the APT and CAPM are very similar, they differ in two major areas. Firstly, the APT uses an unlimited number of explanatory factors, whereas the CAPM only includes unsystematic risk. Furthermore, the APT is seen as a "supply-side" model, whereas the CAPM is seen as a "demand-side" model.

When dual-listed stocks are used in a multinational portfolio, the changes associated with the influence of exchange rates have to be controlled. Neither the APT nor the CAPM in its standard form are sufficient for this purpose. An adjusted version of the CAPM model may, however, prove to be more useful for an international portfolio, which brings various international variables such as the exchange rate between the two countries into account. For this reason, the International Capital Asset Pricing Model (ICAPM) will be investigated in the following section. ICAPM, also, introduces an additional factor to consider in the construction of a dual-listed stock price, namely exchange rate risk.

2.5.3 International Capital Asset Pricing Model (ICAPM)

In addition to the original CAPM model, when purchasing an international stock, Purchasing Power Parity (PPP)[33] does not hold continuously, which means that the investor will be exposed to exchange rate risks (Wu, 2008:175). An investment in a foreign asset leads to the combined outcome between the performance of the foreign asset and the performance of the investor's domestic currency relative to the foreign currency. In order to control for these factors, these risks should also be included in the Capital Asset Pricing Model, when evaluating the price of

[33] It asserts (in the most common form) that the exchange rate change between two currencies over any period of time is determined by the change in the two countries' relative price levels (Dornbusch, 1985:1).

the stock (Solnik, 1974:524; Stulz, 1981:405). Fama and French (1998:1997) developed an alternative three-factor model in order to improve on the original CAPM, which includes international risk factors. They furthermore found that the standard CAPM does not explain returns in a cross-section of national value portfolios, while the multi-factor model was able to include the value premium in international returns. However, the Fama and French three-factor model assumes that capital markets are fully integrated and that investors do not care if PPP fails or holds. By making this assumption, many other possible risks are ignored, and therefore it may be possible that this model would predict international transactions inaccurately (Wu, 2008:176).

Based on the standard CAPM, Dahlquist and Sallstrom (2002:3145) examined whether an international version of the original CAPM would perform better than the international version of the empirical Fama and French (1998) three-factor model. They found that both models capture national market returns fairly well and that an Asset Pricing Model, which controls for foreign exchange risk, may explain 60% of the variation on average returns. However, they do suggest that the ICAPM, controlling for exchange risk, is able to perform equally well to the international three-factor model (Dahlquist & Sallstrom, 2002:60). Zhang (2006:289) conducted an additional study on the performance of the ICAPM without exchange risk, the ICAPM with exchange risk, and the international version of the Fama and French (1998) three-factor model with a size effect. This study found that most of these conditional models were able to quantify the cross-sectional return spreads. Although the Fama and French (1998) three-factor model had some success, the model failed when using conditional models (Zhang, 2006:289). Furthermore, evidence indicated that exchange risk is a very important determinant of the international asset returns, and for this reason, the conditional ICAPM with exchange risk will, therefore, outperform the Fama and French (1998) three-factor model.

The ICAPM can be illustrated as follows (Wu, 2008:177):

$$R - F = \alpha + \beta_1[M - F] + \beta_2[X - F] + \varepsilon_t \qquad (2.9)$$

Where:

- R represents the expected returns of a domestic stock or portfolio;
- F represents the risk-free asset return;
- M represents the global market return;
- X represents the foreign exchange rate;
- $\beta_1; \beta_2$ represents the coefficients of F, M, and X; and
- ε_t represents the error term at time *t.*

Equation 2.9 illustrates how the standard CAPM is expanded in order to include exchange rate risk. The adaptation of the CAPM to a form that controls for multiple currencies leads to a multi-factor solution for asset pricing, which represents the excess returns on assets, which are perfectly correlated with the exchange rate depreciations of the foreign currency (Wu, 2008:177).

In addition to Equation 2.9 as this study involves the use of a dual-listed stock, which is listed in two different currencies, it is also possible to estimate what the return on the investment was in terms of the investor's domestic currency. If an investor chooses to buy a foreign security, and holds it for two periods, the returns on the security ($1+i_2$) must be converted back into the domestic currency after the holding period. In order to determine what the return on the investment was in terms of the investor's domestic currency, the following equation may be used (Wu, 2008:177):

$$Return = \frac{S_1(1+ i_2)}{S_2} \tag{2.10}$$

Where:

- S_1 is the foreign exchange rate at the end of the holding period;
- S_2 is the domestic exchange rate at the end of the holding period; and

- $(1 + i_2)$ is the return of the securities.

If the investor wishes to obtain a continuous net return, the use of a natural logarithm[34] proposed by Wu (2008:177) may be used. However, the risk-free rate remains relatively constant, while the return on the investment will largely be a function of the exchange rate fluctuations.

The following assumptions are needed to form the ICAPM, which adds two additional assumptions (the last two listed) to the original CAPM (Solnik, 2000:165):

- Investors are rational and mostly risk-averse, and will attempt to invest on the efficient frontier in order to realise a maximum return;
- investors are able to either borrow or lend money at the risk-free rate (R_f);
- investors have homogenous expectations; therefore, they estimate future probability distributions of the rate of return in the same way;
- investors have the same (one period) time horizon for their investment;
- investments may be divided, which implies buying or selling fractions of any asset or portfolio;
- there are no transaction costs or any taxes involved in buying or selling assets;
- inflation and interest rate changes are ignored;
- capital markets are in equilibrium where all assets are priced properly in line with their level of risk;
- investors throughout the world have the same consumption baskets; and
- real prices of the consumption goods are identical in every country so that PPP holds exactly at any point in time.

[34] The natural logarithm is the logarithm to the base *e*, where *e* is an irrational and transcendental constant approximately equal to 2.718281828 (Mortimer, 2005:9).

To summarise; after examining the various asset pricing models, the ICAPM was found to be the more superior asset pricing model as ICAPM builds on the standard CAPM, by including exchange rate risk. Furthermore, it is also hard to determine the number of variables as well as the specific factors needed, in order to compose an APT model. Keeping these difficulties in mind, the ICAPM once again seems like the logical choice for pricing a multinational stock, when compared to the APT.

From this chapter, it is evident that a number of factors influence the composition of a stock price. Some of these factors include information flow (Section 2.3.2), risks associated with the stock (Section 2.4), the required rate of return (Section 2.5.1.2) and the risk preference of the investor (Section 2.4.1.3). These previous sections provided an overview required to understand the formulation of a stock price. The next step of this study will continue on using stock prices to identify potential investment opportunities. These investment opportunities are referred to as arbitrage opportunities, which will be discussed in the following section.

The size of the arbitrage opportunities will then be measured in terms of the volatility spillover effect, which will be discussed in Chapter 4. The goal of this study is to measure the volatility spillover effect (arbitrage opportunity) by means of different methods, which will be discussed in Chapter 3.

2.6 ARBITRAGE AND DUAL-LISTED STOCKS

2.6.1 Introduction

According to Sharpe and Alexander (1990:77), investors achieve arbitrage by means of a simultaneous purchase and sale of the same security in two different markets. Arbitrage involves the act of exploiting the mispricing of two or more securities to achieve risk-free profits (Bodie *et al.,* 2010:213). For example, any good sold in one market, should sell for the same price in another, as suggested by the single market hypothesis (Ip & Brooks, 1996:53); however, the prices do differ in the two markets, leading to a possible arbitrage opportunity. Arbitrage, in its purest form, may seem simple, but it has many flaws, as it ignores factors such as the cost of transport, storage, and risk (Bodie *et al.,* 2010:213). True arbitrage requires that there be no market risk involved and a risk-less profit must be realised. Furthermore, stocks are priced differently in the two markets because different fundamental factors may influence the price of these stocks in the various markets, such as varying risk appetite of investors (Section 2.4.1.3), fluctuating demand for the stock, different investor perceptions, information flow (Section 2.3.2), expected return (Section 2.4.1.3) and exchange rate risk (Section 2.5.3) (see Shleifer & Vishny, 1997:35). When arbitrage opportunities arise, investors avidly pursue this strategy until the market forces of supply and demand force prices back into alignment (Bodie *et al.*, 2010:213).

Arbitrage is possible when one of the following four assumptions is met (Bodie *et al.,* 2010:90):

- The same asset must be traded at different prices on all markets;
- Two assets yielding identical cash flows do not trade at the same price;
- An asset with a known price in the future does not trade at its future price discounted at the risk-free interest rate when traded today; or
- The asset does not have costs of storage.

Dybvig *et al.* (1996:2) state that arbitrage in its purest form requires no capital and is virtually risk-free. Unfortunately, in the real world, two other impediments make arbitrage hard to be accomplished (Jogani & Fernandes, 2002:5). The first impediment, as Merton (1987:487) explained, is that arbitrage tends to be a complicated strategy to follow, since the nature of stock mispricing may be unclear to the investor. Due to this uncertainty, many arbitrageurs tend to hesitate in going into such a transaction until all available information regarding that stock is obtained. Furthermore, uncertainty over the distribution of arbitrage returns, with special attention paid to the distribution over the mean, may potentially deter arbitrage activity. This will continue to be the case until investors learn enough about the distribution to decide whether the expected pay-off from the arbitrage opportunity will be large enough to cover the fixed costs of going into the transaction. This may prove to be a negative effect as the opportunity tends to dissipate before such information is gathered. The second impediment, as listed by Shleifer and Summers (1990:26) and Shleifer and Vishny (1997:54), is that investors are unable to engage in successful arbitrage due to the undiversified nature of this strategy. To illustrate the undiversified nature of arbitrage as a strategy, consider the arbitrage specialisation strategy.

Arbitrage specialisation is a strategy that limits the degree of diversification in the arbitrageur's portfolio and causes the investor to bear idiosyncratic risks[35] for which excess return is expected. Consider the following example: If a purely random chance exists that stocks prices may not converge to their fundamental value[36], a highly specialised arbitrageur who is unable to diversify away this risk will be forced to invest less than an investor who is able to do so (Jogani & Fernandes, 2002:5). Prices may not converge to their fundamental values at a steady pace, and while an investor waits for the stock prices to converge, prices may also temporarily deviate from their median value. If this happens and the arbitrageur does not have access to additional capital when the stock prices diverge, the arbitrageur may be forced to prematurely unwind the position and incur a loss (De Long *et al.,* 1990:735).

Furthermore, as dual-listed stocks are listed on different markets, different trading hours apply (Jogani & Fernandes, 2002:5). This means that even in situations where it is possible to exploit mispricing in a risk-less way (by generating perfectly hedged positions and holding on to them until the final pay-off), the following operational aspects need be noted before entering into an arbitrage. Firstly, for arbitrage to be risk-free, the investor is required to trade simultaneously across two markets (Jogani & Fernandes, 2002:5). In inefficient markets, arbitrage opportunities tend to last only for very short periods. This is true because the moment arbitrage takes place the opportunity disappears, because prices converge. Further studies on the existence of arbitrage between dual-listed stocks are summarised in the following table:

[35] Idiosyncratic risk refers to a risk that affects a very small number of assets (Investopedia, 2011f:1).
[36] The fundamental value of a stock refers to the historical moving average price of a stock (Marx *et al.,* 2008:71).

Table 2.3: Arbitrage opportunities in dual-listed stocks

STUDY	SAMPLE	FINDINGS
Eun & Sabherwal (2001)	Canadian stocks that are dual-listed in United States.	Arbitrage leading to price discovery was present on various occasions.
Ding *et al.* (1999)	Stocks that are dual-listed in Malaysia and Singapore.	Many arbitrage opportunities and price discovery were present in both markets.
Ben-Zion *et al.* (1996)	Five Israeli stocks listed on the Tel Aviv stock exchange and United States over-the-counter market	Arbitrage opportunities are generally not available, maybe because of over-the-counter nature.
Domowitz *et al.* (1995)	Four Mexican firm stocks dual-listed also as United States American Depository Receipts (ADRs)[37]	The average returns in both markets are very similar, suggesting existence of arbitrage.
Froot & Dabora (1995)	Three Siamese twin stocks, dual-listed on the New York Stock Exchange and the London Securities Exchange	Each company's stock indicated the existence of cross-border arbitrage.
Pagano & Roell (1993)	16 stocks dual-listed on the London Securities Exchange and the Paris Bourse.	Markets are perfectly arbitraged: In a sample of 380 perfectly time-matched observations, not a single unexploited arbitrage opportunity was found to exist.
Kato, *et al.* (1991)	23 stocks listed in England, Japan and Australia and also as United States American Depository Receipts (ADR's)	No arbitrage opportunities existed.
Jorion & Schwartz (1986)	98 Canadian stocks multiple listed on various United States markets.	Random forms of arbitrage opportunities existed.

Source: Compiled by author

From Table 2.3, arbitrage may be possible when all the relevant factors affecting the possibility of arbitrage to take place, are accounted for. Arbitrage may seem simple and risk free in theory, but additional risks are present when arbitrage strategies are followed. The following section discusses the risks inherent to arbitrage.

2.6.2 Arbitrage risks

Arbitrage strategies involve fairly low risk, but the possibility of mishaps can even lead to extreme measures, like the possibility of bankruptcy (Shleifer & Vishny, 1997:36). Investors tend to perceive arbitrage risk to be minimal because of the relatively small price differences. However, small price differences can be converted to large profits through leverage, but in the rare event of large price movements, large profits and losses may occur (Shleifer & Vishny,

[37] American Depository Receipts (ADRs) are negotiable certificates issued by a United States bank representing a specified number of shares in a foreign stock that is traded on a United States exchange (Investopedia, 2011g:1).

1997:50). This leads to the following subsections, which will discuss the risk factors that may lead to large losses. The risk factors include execution risk (Section 2.6.2.1), counterparty risk (Section 2.6.2.2) and liquidity risk (Section 2.6.2.3).

2.6.2.1 Execution risk

Execution risk describes a situation where one leg of an arbitrage trade remains open, but the other part of the deal is closed (Kondor, 2009:632). Due to technological limits and the existence of computers, this type of trading is impossible, because it is extremely difficult to close more than one transaction at the same time. These limitations may also limit the time that investors have to make investment decisions, which may lead to price changes that will make it even more impossible to close the other open transactions at a profitable price (Kondor, 2009:632). The investor therefore moves from a seemingly risk-less and profitable position into a situation where an inevitable loss is possible, because of the failure to execute the arbitrage strategy in practice. This may also occur when there is counterparty risk[38]. Even though this type of risk may seem relatively small and unlikely, this hazard is essentially very serious, because of the large amounts of an asset that must be traded in order to make a profit on small price differences. This involves leverage that is usually associated with arbitrage trades (Shleifer & Vishny, 1997:50).

2.6.2.2 Counterparty risk

Stock transactions include two parties, known as the buyer and the seller. If one party fails to deliver on the agreed terms, the other party inevitably suffers a loss, which leads to counterparty risk (Kondor, 2009:632). This type of risk may turn out to be a serious risk if one seller or buyer has many related trades with a single counterparty, as this entity may pose a threat if they fail to carry through on their leg of the transaction. This type of failure is usually very common in the event of a financial crisis when many counterparties fail (Kondor, 2009:632).

[38] Counterparty risk is better known as the risk that the other party to one of the deals fails to deliver as agreed (Shleifer & Vishny, 1997:50).

2.6.2.3 Liquidity risk

The inability of an investor to provide additional capital when required is called the liquidity risk (Shleifer & Vishny, 1997:50). If the trader chooses to use leverage, and is subjected to many margin calls[39], the trader may run out of capital in the margin account. This may lead to bankruptcy, even though the trades may be expected to ultimately make money (Shleifer & Vishny, 1997:50). Alternatively, if a trader chooses to purchase a dual-listed stock on one market and sell it for a profit in the other market, liquidity risk may be present. This happens when there are no buyers for this stock on the other market, causing the trader to suffer potential losses because of liquidity risk (Kondor, 2009:633).

To summarise; arbitrage opportunities arise when a dual-listed stock's prices differ in the two markets where it is listed. Investors may then choose to follow an arbitrage strategy, by purchasing the stock in the market with the lower price and selling it for the higher price in the other market, and making a profit. Arbitrage, however, is subject to certain assumptions (Section 2.6.1) and may also lead to large losses. These losses occur because of the risks present when choosing an arbitrage strategy. These risks include execution risk (Section 2.6.2.1), counterparty risk (Section 2.6.2.2) and liquidity risk (Section 2.6.2.3). The size of these arbitrage opportunities may be measured in terms of a volatility spillover effect and this will be discussed in Chapter 3.

2.7 CHAPTER SUMMARY

The goal of this study is to examine whether LSE dual-listed stock price volatility can be utilised as an indicator for determining expected JSE dual-listed stocks price movements, based on the price difference of dual-listed stocks. Dual-listed stocks in separate markets should grow at the same rate, as explained by the single market hypothesis and the Gordon growth model. However, dual-listed stocks do not grow at the same rate, which can lead to arbitrage

[39] A broker's demand on an investor using margin to deposit additional money or securities so that the margin account is brought up to the minimum maintenance margin (Investopedia, 2011h:1).

opportunities (Section 2.6). These price differences may be the result of a volatility spillover effect from one market to the other, which will be discussed in the following chapter.

However, before the volatility spillover effect can be modelled and examined, the composition of a stock's price must first be examined, which was the goal of this chapter. The stock price was found to be influenced by a number of factors, such as information flow (Section 2.3.2), risks associated with the stock (Section 2.4), the required rate of return (Section 2.5.1.2), and the risk preference of the investor (Section 2.4.1.3).

A further investigation also determined some of the factors influencing an arbitrage opportunity, such as execution risk (Section 2.6.2.1), counterparty risk (Section 2.6.2.2) and liquidity risk (Section 2.6.2.3). The following chapter will elaborate on measuring a possible arbitrage opportunity (in terms of the price difference) due to the volatility spillover effect. Chapter 3 sought after establishing a proper understanding behind the mechanics of a volatility spillover effect and how it can be measured.

CHAPTER 3

The volatility spillover effect and methodology

"Fear tends to manifest itself much more quickly than greed"

— Philip Roth

3.1 INTRODUCTION

In the previous chapter, the focus was primarily on the price composition of dual-listed stocks and the existence of arbitrage opportunities, due to different growth rates in dual-listed stock prices. This chapter will continue the investigation on dual-listed stock prices; however, the focus will shift to the influential impact (spillover effect) that the change in prices of one market has on the price movement of another market. The goal of this chapter is, therefore, to examine the interactive relationship between international financial markets. This will consist of determining the different methods available for measuring co-movements and volatility spillover effects. According to Kotze (2005:2), volatility can be seen as the degree (standard deviation) of a stock price movement or the variability of a stock price. Whereas the volatility spillover effect refers to where the volatility (price instability) of one market is transferred to another market. The starting point for investigating the volatility spillover effect is to determine the existence of co-movement in the stock prices between the two markets (JSE and LSE) under investigation. The study by Pretorius (2002:92) found that co-movements can exist among stock markets due to three contributing factors, namely the contagion effect (Section 3.3.2), economic integration (Section 3.3.3), and identical stock market characteristics (Section 3.3.4).

This chapter will also examine past empirical studies on co-movement (Section 3.3.5) and on the volatility spillover effect (Section 3.3.6), in order to determine the most appropriate models (methods) to use for measuring co-movement and the volatility spillover effect. The models chosen will be discussed in greater detail in the latter part of the chapter (Section 3.4). This chapter will commence by examining the volatility theory of stock prices (Section 3.2).

3.2 VOLATILITY

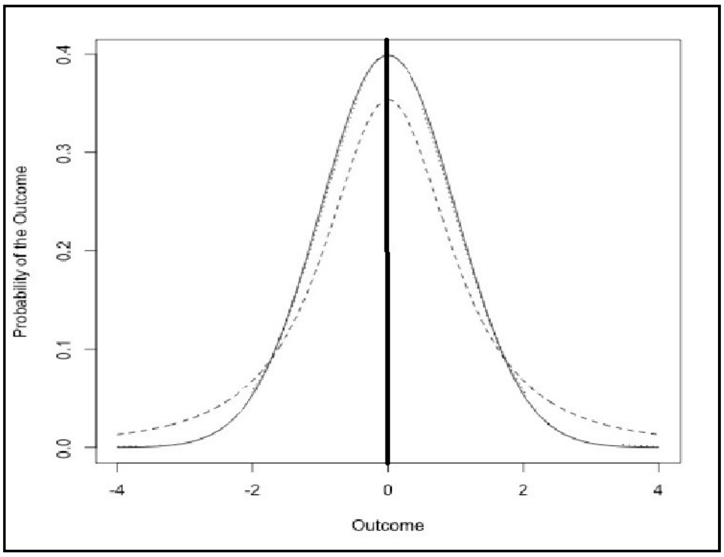
3.2.1 Introduction

Dual-listed stock prices do not grow at the same rate in their various markets, leading to variation in stock prices across markets (Ip & Brooks, 1996:53)[40]. Volatility can be perceived as a measure of the variation of a stock's price, or can be interpreted as the deviation of the stock return from its mean (Kotze, 2005:3). The deviation of the rates of return, around the average rate of return, is frequently used to measure the risk of an investment (Levy, 2002:133). In the case where the rate of return deviates far from the average rate of return, or the standard deviation is large, the relative volatility is high. This implies that there is a higher level of risk associated with such an investment (Levy, 2002:133). Therefore, volatility can be seen as the degree of price movement (risk) in a stock and the probability of price movements (Kotze, 2005:2).

To elaborate on the discussion on volatility, the study of Black and Scholes (1973:640) found that financial stock prices can be viewed as random variables that are log-normally distributed. A normal distribution can be illustrated as a bell-shaped curve (Figure 3.1). In Figure 3.1, two normal curves are noted, the solid line and the dotted curve. Both have the same mean, but the dotted line shows a greater deviation than the continuous line. The dotted line will, therefore, be more risky as it displays higher volatility. These two curves also illustrate that volatility gives an indication of the range of a stock's return movement. Large values of volatility imply that returns will fluctuate over a wider range and will exhibit a greater risk (Kotzè, 2005:2). In addition to the graphic illustration, it is also possible to quantify the volatility of a stock mathematically, which will be briefly discussed in the following section.

40 See also Section 2.1 for a further explanation.

Figure 3.1: A normal distribution curve



Source: (Kotzé, 2005:2)

3.2.2 Mathematical estimation of volatility

Stock prices are commonly observed over fixed intervals of time (hourly, daily, weekly, or monthly). By using time series data, log-relative returns can be mathematically composed as follows (Kotzè, 2005:3):

$$u_i = ln\frac{s_i}{s_{i-1}} \tag{3.1}$$

Where:

- u_i is the log-relative return of the stock;
- s_i is the stock price at the end of the *i* -th interval;
- ln is the natural logarithmic function; and
- S_{i-1} is stock price from the previous period.

Furthermore, volatility can be perceived as a deviation of a stock's returns from its mean (Kotze, 2005:3). In order to calculate the standard deviation of a stock, the following equation can be used (Devore & Farnum, 2005:74):

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(u_i - \bar{u})^2} \tag{3.2}$$

Where:

- σ is the standard deviation of the stock;
- u_i is the log-relative return of the stock as defined in Equation 3.1; and
- n is the number of observations.

In Equation 3.2, the mean ($\bar{u}$) can be defined as follows (Devore & Farnum, 2005:74):

$$\bar{u} = \frac{1}{n}\sum_{j=1}^{n} u_j \tag{3.3}$$

The σ in Equation 3.2 provides the estimated standard deviation per interval. In order to compare volatilities for different interval lengths, volatility must be expressed in annual terms (Kotzè, 2005:4). To achieve this, the volatility estimate must be scaled with an annualisation factor (normalising constant) h, which is the number of intervals per annum. This process can be formulated as follows (Kotzè, 2005:4):

$$\sigma_{an} = \sigma^{*}\sqrt{h} \tag{3.4}$$

Where:

- σ_{an} is the volatility for the certain interval; and
- h is the annualisation factor.

For example, if daily data is used, the interval is one trading day and *h* = 252[41]. For an interval with a weekly length, *h* = 52 and for monthly data, *h* = 12 (Kotzè, 2005:4).

From the above discussion it is clear that volatility can be considered as a useful and important tool for managing a portfolio. It also further implies that increased volatility will require more effective management strategies to limit possible exposure. However, the correct interpretation

41 There are approximately 252 trading days per annum (Kotzè, 2005:4).

of volatility can also provide possible trading options that can be considered. For example, the examination of the effect that one market's volatility has on another (volatility spillover effect), can provide valuable insight for possible arbitrage/trading strategies.

The importance of volatility is further justified by the study of Black and Scholes (1973:640), who found that six inputs are required in order to calculate an expected price for a stock option. These inputs are the current stock price, the strike price, the time to expiry, the risk-free interest rate, the dividends, and the volatility. The most important of the six parameters is considered to be volatility, because changes in volatility will have the largest impact on the price of an option, when compared to the other inputs (Black & Scholes, 1973:641).

In addition, when two markets share a common trend, co-movement may be present. The presence of co-movement between markets can facilitate the volatility spillover effect where volatility is transferred between markets (Pretorius, 2002:90). The composition and causes of co-movements will be discussed in the following section.

3.3 STOCK MARKET CO-MOVEMENT

3.3.1 Introduction

The study of Pretorius (2002:90) found that co-movement may exist between stock markets, which can be due to contagion effects, economic integration, or identical stock market characteristics. Contagion effects are factors that cannot be explained by economic fundamentals and will be discussed in Section 3.3.2. On the other hand, economic integration (Section 3.3.3) explains how two countries' stock markets can become integrated if their economies are integrated. This will be followed by a discussion on identical stock market characteristics (Section 3.3.4), which include market size (Section 3.3.4.1) and volatility (Section 3.3.4.2).

3.3.2 Contagion effect

Contagion can be defined as the co-movement between asset markets that are not caused by fundamental factors, but occurs when there is strong correlation between stock markets during a financial crisis (Bongiglioli & Favero, 2005:1300). In addition, contagion can be explained by institutional and informational factors. Institutional factors include factors such as forced redemption[42] and two-stage investment strategies. Forced redemption causes a large amount of capital inflows to stock markets, because there are open-ended mutual funds[43] in the stock markets (Wolf, 1998:235). When open-ended mutual funds face large reductions in capital inflows, they will be forced into redemption and will cause global mutual funds to sell their assets in the most liquid international stock markets. This will cause markets that were unaffected before to experience different trading volumes, due to the forced redemption (Wolf, 1998:235). The contagion effect will, therefore, occur because of the redemption and will cause several markets to suffer losses without warning from their fundamental factors (Pretorius, 2002:90). In terms of the two-stage strategies, some portions of an investor's portfolio are allocated to the emerging market category. These portions are then sub-allocated according to the index weighting, chosen by the investor, and events in developed markets lead to a contagion effect in the emerging market (Wolf, 1998:235).

In addition, informational factors are based on the comparison between the equity market and the Keynesian "beauty contest" concept (Pretorius, 2002:90). In equity markets, investors will often copy other investors' behaviour. For example, if other investors sell their investments in a specific asset class, the over-supply will cause prices to drop, making their investment worth less. When this occurs, investors will copy this behaviour and will sell their own investments of that specific asset class. On the other hand, in the Keynesian "beauty contest", each judge votes in the same way that other judges will supposedly vote (Pretorius, 2002:90). As a result, investors in the stock market will follow the behaviour of others and will sell their emerging

[42] Redemption refers to the return of an investor's principal in a fixed income security, such as a preferred stock or bond, or the sale of units in a mutual fund (Investopedia, 2011i:1)

[43] An open-ended mutual fund is a type of mutual fund that does not have restrictions on the amount of stocks the fund will issue (Investopedia, 2011j:1).

market securities. This type of selling takes place when a sufficient number of investors take the view that the emerging market has lost its investor confidence (Pretorius, 2002:90). This behaviour generally leads to a fall in stock prices in emerging markets and will lead to a co-movement between markets. Since this co-movement is unexplained by fundamental factors, it is seen as a form of contagion (Pretorius, 2002:90). However, it is important not to confuse interdependence with contagion, as both phenomena share common properties.

Interdependence is found when stock markets are correlated during times of financial stability, as opposed to contagion, which is unaffected by the amount of market stability (Daly, 2003:74). Interdependence can be seen as a normal occurrence of linkages and co-movement between stock markets. To identify whether financial markets undergo co-movement, because of contagion or interdependence, three criteria can be applied. In the first criterion, investor behaviour models are used, where analysts study whether investors behave differently after periods of macroeconomic shocks (Daly, 2003:74). It is, therefore, important to understand how investors react to good news and bad news, as this will influence how macroeconomic shocks are transmitted through international stock markets. For instance, bad news may raise the debt-equity ratio of a company and increase the financial risk. This can ultimately lead to higher volatility in the company's stock prices and may result in contagion (Campbell & Hentschell, 1992:2). The second criterion examines whether the macroeconomic shocks are country-specific. If macroeconomic shocks are country-specific, correlation between local and foreign markets is highly unlikely. The third criterion examines policy-makers and global institutions' views on contagion in financial markets. These entities are concerned with the flow of financial resources from one market to the other, and can provide useful information as to whether a macroeconomic shock will cause co-movement between markets (Daly, 2003:74). This leads to the following section that will provide a more in-depth discussion regarding economic integration.

3.3.3 Economic integration

When considering economic integration, there are two main areas that influence the degree of stock market interdependence, namely *bilateral trade* (Section 3.3.3.1) and *macroeconomic variables* (Section 3.3.3.2), which will be discussed in the following sections.

3.3.3.1 Bilateral trade

When two countries are dependent on each other for trade, their stock markets are more likely to be interdependent (Pretorius, 2002:91). This implies that strong bilateral trade links among countries can lead to a higher degree of co-movement between their stock markets (Pretorius, 2002:91). The relevant stages of economic integration begin with the reduction or removal of trade barriers between countries, in order to establish a trade union (Holden, 2003:1). The trade barriers are removed by establishing a Free Trade Agreement (FTA)[44], a Customs Union (CU)[45], a Common Market (CM)[46], or an economic union. The FTA is seen as the first step towards economic integration, where agreements can be restricted to certain sectors or can include all elements of international trade. Countries involved in FTAs have the same set of regulatory trade rules between each other, but have different policies regarding foreign countries (Pretorius, 2002:91). A good example of an FTA is the North American Free Trade Agreement (NAFTA) between the United States, Canada and Mexico (Holden, 2003:1).

The second stage of economic integration is the establishment of a CU. In a CU, the member countries are forced to synchronise their policies towards external countries, as well as eliminate internal trade barriers (Holden, 2003:2). Policies are, therefore, created in order to benefit all member countries, such as a common external tariff, import quotas for goods coming from third-party countries, and anti-dumping measures[47]. A good example of a CU is the Southern African Customs Union (SACU) between South Africa, Botswana, Lesotho, Namibia

[44] A Free Trade Agreement (FTA) is an agreement between a group of countries that agree to eliminate tariffs, quotas, and preferences on goods and services traded between them (Holden, 2003:1).

[45] A Customs Union (CU) is a type of trade block, which is composed of a free trade area with a common external tariff (Holden, 2003:1).

[46] A Common Market (CM) is formed when a free trade area is formed and capital and services may move freely between countries, but trade barriers are not completely removed (Holden, 2003:1).

[47] Anti-dumping measures refer to a penalty imposed on suspiciously low-priced imports, to increase their price in the importing country and so protect local industry from unfair competition (WTO, 2011:1).

and Swaziland. A further development towards a trade union and economic integration can be achieved with the establishment of a Common Market (CM)(Holden, 2003:1). In a CM, capital, people and other resources, such as services, may move freely between member countries without restrictions. This can affect the independence of countries, as countries have to modify policies in order to be in line with the market policies of other member countries. By following the market structure of other members, countries may become increasingly interdependent, which can ultimately cause fiscal and monetary policies to become similar (Holden, 2003:2).

However, the study of Holden (2003:2) argues that an economic union is the most advanced form of economic integration, because it formally requires that member countries must complement each other's fiscal- and monetary policy, regional development, labour markets, transportation, and industrial policies. The most prominent economic union is the European Union (EU), with twenty-seven European member states[48] that have transferred some of their lawmaking power to the union (WTO, 2011:1). In order to further enhance the functioning of an economic union, the use of a common currency can be employed, together with a merged monetary policy. As the formation of an economic union signifies the most advanced form of economic integration between countries, strong co-movements between stock markets of member countries are usually found (Pretorius, 2002:91). Shared institutional structures as well as shared macroeconomic policies will also cause stock prices to be biased towards regional factors, as opposed to national factors (Pretorius, 2002:92).

In addition, the study of Piesse and Hearn (2002:423) investigated the presence of co-movement, because of stock market integration within the South African Customs Union (SACU). They noted that co-movement is predominantly found between markets that have strong trade links and have common economic reforms within a region. To elaborate on the previous findings, a further cause of co-movement in integrated regions is country-specific shocks, which are often transmitted to other countries' markets (Taing & Worthington, 2002:4). These country-specific shocks take place when foreign stock markets incite reaction on

[48] For a full list of member countries consult the study of Holden (2003:2).

domestic capital markets, a process referred to as *market contagion*. Evidence was also found that larger markets affect smaller markets. An example of this was found within the EU, where countries such as the United Kingdom and Germany transferred country-specific shocks to smaller countries. Taing and Worthington (2002:4) also found that stock price co-movement occurs as a result of sector-specific shocks in each economy. For example, if technology affects a particular sector, co-movement could occur due to links between that particular sector and others within the union (Taing & Worthington, 2002:5).

3.3.3.2 Macroeconomic variables

Several macroeconomic variables, such as interest rates, economic growth, consumer spending, and inflation can influence stock market performance (Pretorius, 2002:92). This implies that the correlation between these variables can give an indication of the correlation between the two countries' stock markets (Pretorius, 2002:92). If the majority of macroeconomic variables are the same in any two countries, their stock market performance should be the same, as the influence on the stock markets will be similar. In order to measure the effect that macroeconomic variables have on stock market performance, the cash flow model can be used and is illustrated as follows (Pretorius, 2002:92):

$$P = \frac{(1+g)D_0}{k-g} \tag{3.5}$$

Where:

- P is the present stock value;
- D_0 is the last dividend paid by a stock;
- g is the constant growth rate in the dividents; and
- k is the discount rate.

From Equation 3.5, it is evident that the dividend of a stock (D_0) can influence the stock's price, since it represents the expected future cash flow from the stock, making it an important factor to consider with stock price movements. Furthermore, the growth rate in dividends (g) is also influenced by systematic factors, which can influence stock performance (Pretorius, 2002:92). These systematic factors include macroeconomic variables such as interest rates, inflation, and the growth rate of industrial production on the expected cash flows. This entails that if these variables in two countries are related, their stock markets will also perform in a similar manner. For example, if two countries' interest rates share a common trend, due to similar monetary policy, there will be co-movement in stock prices (Pretorius, 2002:92).

The following section will conclude the section on stock market co-movement, and will discuss stock market characteristics. This entails a discussion on stock market size (Section 3.3.4.1), stock market volatility (Section 3.3.4.2), and industrial similarity (Section 3.3.4.3).

3.3.4 Stock market characteristics

Stock market characteristics consist of a number of factors. These factors include stock market size (Section 3.3.4.1), volatility (Section 3.3.4.2), and industrial similarity (Section 3.3.4.3). The stock market characteristics is a contributing factor of co-movement and will be discussed in the following sections.

3.3.4.1 Stock market size

Investors usually demand higher returns from the stocks of smaller companies, due to the lower liquidity offered by those stocks and due to the higher transaction costs involved in purchasing those stocks. When a stock market consists mostly of small companies, it can have disadvantages such as lower liquidity and smaller trading volumes. Stock market size may also give a good indication of information available in the market (Pretorius, 2002:93). It is also found that a large disparity in market sizes can provide an indication of the large differences in liquidity, information costs, and transaction costs between two markets, which should result in less co-movement. However, if there is a large similarity in the size of two stock markets, the extent of co-movement will increase (Pretorius, 2002:93).

3.3.4.2 Stock market volatility

Investment models generally insinuate that investors should compensate for the risk they take on. The greater the risk associated with an asset the higher its returns should be[49] (Marx *et al.,* 2008:4). This implies that the returns on stocks should be positively correlated with its risk, where risk is often measured by volatility[50] (Pretorius, 2002:93). Since the return of any stock market is a function of its volatility, two markets with more or less the same volatility should yield the same returns. This implies that if one market's volatility increases relative to another market's volatility, the returns of that market should increase relative to the other market's returns. Therefore, the conclusion is drawn that when stock market volatilities are the same, co-movement between stock markets may occur (Pretorius, 2002:93).

3.3.4.3 Industrial similarity

The performance of a stock market index is partly determined by the sectoral composition of the index and partly obscured by idiosyncratic noise[51] (Wolf, 1998:235). Co-movement will be observable between two stock markets if both markets are dominated by the same type of industry (Pretorius, 2002:93). For example, consider any two markets that are dominated by stocks in the resource sector. A decrease in the world demand for resources may lead to a substantial decrease in the stock prices of both markets; therefore, initiating the presence of co-movement between the two markets (Pretorius, 2002:93).

To summarise; co-movement refers to a similar trend in stock price movements between stock markets. Evidence indicates that the presence of co-movement between two markets will promote a volatility spillover effect in the stock prices. This study will firstly establish the presence of co-movement between the JSE and LSE before the volatility spillover effect will be examined. This section established that co-movement exists due to the contagion effect (section 3.3.2), economic integration (Section 3.3.3) and stock market characteristics (Section 3.3.4). The next section will examine past empirical studies to elaborate on the dominant

49 See also Section 2.4.1 for an explanation of the risk-return trade-off..

50 See also Section 3.2 for a more detailed explanation on vitality.

51 Idiosyncratic noise is a structural or behavioural characteristic of an individual stock's return (Foucalt *et al.,* 2003:2).

models (or methods) used to measure co-movement and the volatility spillover effect. This section on the examination of historical findings is important to the study as it provides valuable guidelines as to which methods are commonly used to determine co-movement and also provides a framework of past results, which can be utilised when interpreting the results of this study.

3.3.5 Historical studies on co-movement

The following reports on the investigation into co-movement between developed markets and developing markets (Section 3.3.5.1). This will be followed by an investigation on co-movement among developing markets (Section 3.3.5.2) and among developed markets (Section 3.3.5.3). The methods used to measure co-movement between these markets will serve as a benchmark when choosing the models for use in this study.

3.3.5.1 Co-movement between developed and developing markets

A number of studies made use of cointegration analysis in order to determine the presence of co-movement between the markets. The reason for this approach is that cointegration can be linked to co-movement between stock markets (Yu & Hassan, 2006:482). By applying the Johanssen (1991) cointegration analysis, the following studies emphasised the presence of co-movement between developed and developing markets:

- The study of Chung and Liu (1994:259) found co-movement to be present between the United States and East Asia. Furthermore, a Vector Error Correction (VEC)[52] model was also applied, supporting evidence of a long-run relationship between markets.
- Masih and Masih (1997:74) found evidence of cointegration between developed and emerging stock markets[53].
- Co-movements between selected United States and Indian stock market indices[54] were found (Abhilash & Ramanathan, 2002:7).

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52 A Vector Error Correction (VEC) model is used in order to determine long-run relationships in VAR models (Asteriou & Hall, 2007:312).

53 The markets that were investigated include Taiwan, South Korea, Singapore, Hong Kong, America, Japan, the United Kingdom, and Germany.

- Yu and Hassan (2006) found that co-movement existed between the Middle East and North African (MENA) region and three developed markets[55].
- The study by Chinzara and Aziakpono (2009b:115) also examined co-movement between South Africa and six major world stock markets[56]. The South African market was found to be co-integrated with the markets of Germany, the United Kingdom, and the United States (Chinzara & Aziakpono, 2009b:115).

Alternative methods for measuring the presence of co-movement were also examined. For example, the study of Boujir and Lahrech (2008) examined the market linkages between Morocco and the United States, after the two countries formed a free trade agreement (FTA) in 2004. They applied the Dynamic Conditional Correlation Generalised Auto Regressive Conditional Heteroskedasticity (DCC-GARCH) model[57] and found no evidence of co-movement. Furthermore, the study of Valadkhani *et al.* (2008:174) used the Factor Analysis technique and a Vector Error Correction (VEC) model to investigate the relationships between stock market returns of developed economies[58] and eight developing countries in Asia[59]. Co-movement was found to be present between the stock markets of the Asian countries (Valadkhani *et al.,* 2008: 172).

3.3.5.2 Co-movement among developing markets

Various studies between developing markets also made use of Johansen (1991) cointegration analysis, which include the following:

- The study of Agathee (2008:17) found co-movements to exist between Mauritius and six African markets[60].

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[54] For the United States the National Association of Securities Dealers Automated Quotations (NASDAQ) composite index and the Dow Jones Industrial Average were examined. For India the National Stock Exchange (NSE), the Nifty and Bombay Stock Exchange (BSE) Sensex indices were examined.

[55] These global markets include the United States, the United Kingdom, and France.

[56] The countries investigated in the study were Australia, China, Japan, Germany, United Kingdom, and the United States.

[57] A Dynamic Conditional Correlation-GARCH model is a multivariate GARCH model together with parsimonious parametric models for the correlations (Engle, 2000:11).

[58] The developed markets were Australia, Germany, Japan, United Kingdom, and the United States.

[59] Hong Kong, Indonesia, Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand.

[60] The countries studied were Botswana, Malawi, Namibia, South Africa, Zambia, and Zimbabwe.

- Alagidede (2009:11) analysed the linkages between major African countries[61], Latin American markets[62], three developed markets[63], and India. Results from the study indicated that there was no co-movement between African markets and that the African markets shared weak trends with the rest of the markets (Alagidede, 2008:29).
- The study of Ratanapakorn and Sharma (2002:108) found evidence for the presence of co-movement between Asian stock markets[64] during the Asian crisis. By applying Granger causality[65] analysis, the study of Floros (2005:178) supported the notion for the presence of co-movement between the same markets during the financial crisis.[66].

Alternative methods were also identified that were used by past empirical studies to establish the presence of co-movement among developing markets. Some of these studies include the study of Onour (2009:11), who found long-term cointegration between Egypt, Morocco, and Tunisia, by applying the Johansen and Juseilus (1989:210) test for linear cointegration and the Breitung (2001) rank test. Evidence was also found by the study of Biekpe and Collins (2003:194), who reported the presence of co-movement between different African markets[67], by applying the adjusted Pearson's correlation coefficient of Forbes and Rigobon (2002).

3.3.5.3 Co-movements among developed markets

A Vector Error Correction (VEC) model was used in the study of Bonfiglioli and Favero (2005:1316), who examined the presence of contagion and co-movements between the United States and German stock markets. Results from this study indicated that normal fluctuations in the United States stock market had very little effect on the German stock market. The Granger causality tests and Principal Component Analysis (PCA)[68] were used by Meric *et al.* (2008:177)

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61 Countries used in the study were South Africa, Egypt, Nigeria, and Kenya.
62 The countries that were investigated include Brazil and Mexico.
63 The countries that were examined in the study included the United States, United Kingdom, and Japan.
64 Countries examined were the United States, Europe, Asia, Latin America, and Eastern Europe.
65 The Granger causality test is used to determine whether one time series can forecast another (Granger, 1969:424).
66 The countries investigated were the United States, Japan, and United Kingdom.
67 Countries examined were Egypt, Kenya, Mauritius, Morocco, Namibia, Nigeria, South Africa, and Zimbabwe.
68 Principal Component Analysis (PCA) is a mathematical procedure that transforms a set of observations that may be correlated into a set of values of uncorrelated variables called principal components (Pearson, 1901:560).

to examine co-movement between developed stock markets[69]. Evidence from this study indicated that co-movement between these markets were more frequent in times of financial crises, which indicates contagion rather than co-movement (Meric *et al.*, 2008:176). These results are emphasised by the study of Arshanapalli and Doukas (1993:208), who examined the October 1987 New York Securities Exchange (NYSE) stock market crash. They found evidence of co-movement between markets in the post-crash period of developed countries[70]. A similar study was also conducted by Meric and Meric (1997:152), who analysed the European stock markets after the October 1987 stock market crash, by using the Johansen (1991) cointegration analysis. The study found that the co-movement between the European stock markets and the United States stock market increased substantially after the 1987 crash (Meric & Meric, 1997:152).

To summarise; various studies have applied different techniques in order to capture the co-movement between markets. Some of the more standard models include the Johansen (1991) cointegration analysis, Factor Analysis, and the Vector Error Correction (VEC) model. This section examined the presence of co-movement between markets of a developing and developed country and found substantial evidence for the presence of co-movement. Most studies applied the Johansen (1991) cointegration analysis and the VEC model to test for the presence of co-movement. Therefore, this study will also make use of these two models to determine if there is co-movement between the JSE and LSE. If establishing the presence of co-movement, the next step will be to determine the extent of volatility spillover between the JSE and LSE. The next section will examine past empirical studies on the volatility spillover effect in order to determine the most appropriate models (or methods).

69 The countries investigated in the study include the United States, the United Kingdom, Germany, France, and Japan.

70 The countries examined were the United States, Germany, United Kingdom, France, and Japan.

3.3.6 Volatility spillover between stock markets

This section will examine past empirical studies that investigated the volatility spillover effect between developed and developing markets (Section 3.3.6.1), among developing markets (Section 3.3.6.2), and among developed markets (Section 3.3.6.3). The results of past studies provide valuable information regarding which models are used to examine for the presence of a volatility spillover effect. The sections are divided in a way that separates developed and developing economies in order to identify how the two different market types influence each other.

3.3.6.1 Volatility spillover effect between developed and developing markets

A group of studies investigated whether volatility spillover is uni-directional[71] from developed markets onto emerging markets. One such study includes that of Lee (2004:12), who applied variance decomposition[72] and found that the United States, Japanese, German, and Indian markets exerted influence over some markets in the MENA region (Egypt and Turkey, in particular). Other authors[73] found similar results for these same markets by applying GARCH[74] models. An example of such a study includes the study of Worthington and Higgs (2004:80), who found a volatility spillover effect between nine Asian markets[75] (Worthington & Higgs, 2004:7). Linkages between African and global stock markets[76] were also examined by Lamba and Otchere (2001:25), by making use of Vector Auto Regressive (VAR) and impulse responses[77]. Their study found that volatility spillover was present between South Africa and Namibia (Lamba & Otchere, 2001:22).

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71 One-directional volatility refers to a volatility spillover from one market onto the other, without being influenced in return (Pretorius, 2002:92).

72 Variance decomposition indicates the amount of information each variable contributes to the other variables in Vector Auto-Regression (VAR) models (Brooks, 2008:30).

73 For future reference, consult the studies of Pagan and Soydernit (2000); Bala and Premarante (2004); Chinzara and Aziakpono (2009b).

74 The GARCH model permits the variances of the forecasted return terms to change with the squared lag values of the previous error terms, treating heteroskedasticity as a variance to be modelled (Nelson1991:350).

75 The developed countries that were examined include Hong Kong, Japan, and Singapore. The emerging markets were Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand.

76 Botswana, Ghana, Kenya, Mauritius, Namibia, South Africa, and Zimbabwe compared to Australia, Belgium, Canada, France, Germany, Japan, the Netherlands, the United Kingdom, and the United States.

77 An impulse response function traces the response to a one-time shock in the innovation. The accumulated response is the accumulated sum of the impulse responses. It can be interpreted as the response to step impulse where the same shock occurs in every period from the first (QMS, 2007:107).

Alternative approaches were also applied in studies that investigated the volatility spillover effect between markets in economic unions. An example of such a study includes that of Tastan (2005:17), who applied a Dynamic Conditional Correlation Multivariate GARCH model in order to determine if countries with close trading and investment links are also closely tied in terms of their financial markets. The study examined interdependence, price and volatility spillover and financial integration between Turkey and developed markets[78] of the European Union (EU) and United States (Tastan, 2005:17). In addition to the previously mentioned studies, the volatility spillover effect between South Africa and major world stock markets[79] was also examined by Chinzara and Aziakpono (2009a:119). By applying GARCH and VAR models, evidence was found for the presence of volatility spillover effect between South Africa and Australia, China and the United States (Chinzara & Aziakpono, 2009a:17).

3.3.6.2 Volatility spillover effect among developing markets

The volatility spillover effect among developing financial markets[80] was investigated by De Santis and Imrohoroglu (1994:39), using a GARCH model. They found evidence of time-varying volatility, implying that volatility clustering may be a major characteristic in emerging markets (De Santis & Imrohoroglu, 1994:14). Furthermore, Piesse and Hearn (2005:53) examined the extent of regional integration of stock markets in Sub-Saharan Africa (SSA). By applying an EGARCH[81] model, they found that the dominant markets of South Africa and Nigeria transmitted their volatility to other regional markets, especially where there were strong trade links (Piesse & Hearn, 2005:53). These results were further supported by the study of Humavindu and Floros (2006:50), who examined the integration and volatility spillovers between South Africa and Namibia, but found no volatility spillover effect to be present.

78 The developed markets include England, Germany, Italy, Finland, France, Germany, and the Netherlands.

79 The world markets examined were Australia, China, and United States.

80 The countries examined in EUROPE\MIDDLE EAST were: Greece, Jordan, Portugal, and Turkey. In ASIA: India, Korea, Malaysia, Pakistan, Philippines, China, Thailand, and in LATIN AMERICA: Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela.

81 The Exponential General Autoregressive Conditional Heteroskedastic (EGARCH) model is another form of the GARCH model that identifies clusters of volatility (Nelson, 1991:348).

In addition, by applying Variance Decomposition analysis, as an alternative method for measuring the volatility spillover effect, Diebold and Yielmas (2007:7) found evidence of a volatility spillover effect between twelve emerging economies[82] . A similar study by Sheng and Tu (2000:346) also examined the presence of volatility spillovers between twelve Asian markets[83]. By applying a Variance Decomposition analysis, they found evidence of volatility spillovers from Hong Kong to Singapore, and from China to Thailand (Sheng & Tu, 2000:346).

3.3.6.3 Volatility spillover among developed markets

Eun and Shin (1989:256) used VAR and impulse response methodology to investigate the linkages of nine international developed markets[84]. The study found that the United States market caused volatility to spill over onto other markets (Eun & Shin, 1989:256). A different group of studies examined the effect of economic integration on the volatility spillover effect and an example includes the study of Baele (2003:114), who analysed thirteen European stock markets[85] of the European Union (EU) as well as the United States market. Regime-switching models[86] were applied in the study and a volatility spillover between the United States and the EU, as well as between EU member countries, was found (Baele, 2003:34).

In addition, other studies[87] focused more on how the announcement of news has an effect on stock returns in different markets. Koutmos and Booth (1995:762) used an EGARCH model and found volatility spillover to be present between the United States, United Kingdom, and Japanese stock markets. Kanas (1998:614) also used an EGARCH model to analyse the volatility spillover between the same markets and found volatility spillovers to occur at less frequent intervals in the period following a stock market crash.

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[82] The countries examined were Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico, and Turkey.

[83] The indices used in the study were Tokyo Nikkei 225, Hong Kong Hang-Seng, Singapore Straits Times, Sydney All Ordinaries, Seoul Composite Index, Taiwan Composite Index, Kuala Lumpur Composite Index, Manila Composite Index, Bangkok Composite Index, Jakarta Composite Index, and Shanghai B-shares index.

[84] Countries examined were Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, United Kingdom, and the United States.

[85] The countries examined include the eight European Monetary Union (EMU) countries (Austria, Belgium, France, Germany, Ireland, Italy, the Netherlands, and Spain), three EU countries that do not participate in the EMU (Denmark, Sweden, and the United Kingdom) and two countries from outside the EU (Norway and Switzerland).

[86] The regime switching models used are an extension of the models proposed by Bekaert and Harvey (1997).

[87] For future reference, consult the studies of Koutmos and Booth (1995:762) and Kanas (1998:614).

To summarise; evidence indicates that a volatility spillover effect can be present between developed and developing countries and also among developed countries and countries in the SSA region. The majority of these past empirical studies made use of VAR models, EGARCH models, and Variance Decomposition analysis to determine the presence of the volatility spillover effect. These three models will, therefore, also be used to measure the volatility spillover effect between the JSE and LSE in this study. The results from these models will be reported in Chapter 4.

3.4 MEASURING CO-MOVEMENT AND THE VOLATILITY SPILLOVER EFFECT BETWEEN THE JSE AND LSE

In Section 2.2, it was established that dual-listed stock prices may differ in their various markets. In this study, these price differences will be examined in terms of the volatility spillover effect. The goal of this chapter is, therefore, to examine the interactive relationship between international financial markets. This will consist of determining the different methods available to measure co-movements and volatility spillover effects. Past empirical studies were examined to determine the most appropriate models (methods) to use to measure co-movement (Section 3.3.5) and the volatility spillover effect (Section 3.3.6). From these past studies, it was established that the standard models to use for this study, in measuring co-movement, are the Johansen (1991) cointegration analysis and the Vector Error Correction (VEC) model. To measure the volatility spillover effect, the Variance Decomposition analysis and the EGARCH model were identified.

In addition, this section will elaborate on the different steps that will be followed in the investigation of the relationship between the JSE and LSE. These steps will consist of the different models that were identified, which will be applied in order to determine, firstly, the presence of co-movement, and finally, the extent of the volatility spillover effect between the JSE and LSE. The first step will be to establish the presence of co-movement between the JSE and LSE, which will be done by applying the Johansen (1991) cointegration analysis (Section 3.4.1). If co-movement is present, the possibility of volatility spillovers will be more likely to occur. The second step will be to establish the direction of causality in order to determine in which market the co-movement originates. Therefore, the second models that will be discussed in this section are the causality tests (Section 3.4.2), which can be used in order to determine which market has the more dominant influence on the other. The next step is to examine the extent of the volatility spillover effect between the JSE and LSE and will consist of the use of two methods, which include the variance decomposition analysis (Section 3.4.3) and the EGARCH model (Section 3.4.4).

3.4.1 Testing for co-movement

The study of Granger (1981) first introduced the concept of cointegration, which was further examined by Engle and Granger (1987:251), who studied the dynamics of cointegration. The foundation of this method is to determine the presence of a co-movement relationship between two series. However, in order to obtain significant results from a cointegration model, the level of stationarity must first be established. An Ordinary Least Squares (OLS) model requires that the variables must be stationary, because regressing one non-stationary (unit root) time series on another will result in spurious results (Gujarati, 2003:822).

However, if two non-stationary time series are regressed onto one another, the stochastic trends may be cancelled out if the error term from the regression is stationary or $I(0)$. If this is the case, the two time series are said to be cointegrated (Gujarati, 2003:822). Therefore, the first step in testing for cointegration is to test for the presence of a unit root in the dual-listed stock series. If a unit root is present and the two series are at the same order of integration, the cointegration method can be applied (Granger, 1986:216). The Augmented Dickey-Fuller (ADF) unit root test will be used to establish the presence of unit roots, which will be discussed in the following section.

3.4.1.1 <u>The Augmented Dickey-Fuller (1979) test</u>

In the basic unit root theory, consider the following AR(1)[88] process (QMS, 2007:384):

$$y_t = \rho y_{t-1} + x_t' \delta + \varepsilon_t \tag{3.6}$$

Where:

- x_t is an optional exogenous regressor that consists of a constant and a trend, or only a constant;
- ρ and δ are parameters to be estimated; and
- ε_t is assumed to be a white noise[89].

If $|\rho| \geq 1$, y_t is a non-stationary series and the variance of y_t increases with time and approaches infinity. If $|\rho| < 1$, then y_t is a trend-stationary series. The basic unit root test can be evaluated according to the absolute value of ρ. The null hypothesis is that $H_0\colon \rho < 1$ against the one-sided alternative $H_1\colon \rho = 1$. Therefore, if the ρ value is smaller than 0.05, the null hypothesis is rejected and indicates that there is no unit root present. However, if the ρ value is greater than 0.05, the null hypothesis is not rejected, indicating that there is presence of a unit root. To determine if ρ is statistically equal to 1, y_t can be regressed on its lagged value, y_{t-1}. By extracting y_{t-1} from both sides of Equation 3.6, the following equation can be estimated (QMS, 2007:384):

$$\Delta y_t = \alpha y_{t-1} + x_t' \delta + \varepsilon_t \tag{3.7}$$

Where:

- α is equal to $p - 1$.

The null and alternative hypotheses can be illustrated as follows (QMS, 2007:92):

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[88] An Autoregressive (AR) model is a type of random process which attempts to predict an output of a system based on the previous outputs (Mills, 1990:3).

[89] White noise refers to a random process or a random sample of variables (Diebold, 2007:324).

$$H_0\colon \propto = 0$$

$$H_1\colon \propto < 0 \tag{3.8}$$

The Dickey-Fuller test make the assumption that ε_t is a white noise; however, if ε_t is correlated, an Augmented Dickey-Fuller (ADF) test can be used (QMS, 2007:93). The ADF can be formulated by means of a parametric correction for higher-order correlation by assuming that the y_t series follows an AR(p) process[90] and by adding p lagged difference terms of the dependant variable y_t to the right-hand side of the equation, which can be illustrated as follows (QMS, 2007:93):

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + v_t \tag{3.9}$$

The ADF specification test estimates Equation 3.7 by using the t-ratio from Equation 3.10. The asymptotic distribution of the t-ratio for α is independent of the number of lagged first differences in the ADF regression.

$$t_\alpha = \frac{\hat{a}}{se(\hat{a})} \tag{3.10}$$

Where:

- $\hat{a}$ is the estimate of α; and
- $se(\hat{a})$ is the coefficient standard error.

The ADF unit root test will be performed by using EViews 7 econometric software (QMS, 2007). To conclude, the study of King and Watson (1997:69) stated that cointegration methods should be applied only when variables have a unit root, or are integrated to the same order. The two variables will only be cointegrated if the error term contains no unit roots. This leads to the following section, which will discuss cointegration.

90 An Autoregressive (AR) model is a type of random process which attempts to predict an output of a system based on the previous outputs(Mills, 1990:3). In order to determine the impact from previous outputs the series is lagged (Mills, 1990:3).

3.4.1.2 <u>The Johansen (1991) cointegration approach</u>

This study will use the Johansen (1991) cointegration approach, which is a Vector Autoregressive (VAR)-based cointegration approach and will be performed in EViews 7 (QMS, 2007). The first step in the Johansen (1991) approach is to estimate a standard VAR model. The next step is to determine if the VAR model is stable by using an AR root table and graph. The final step, before executing the Johansen (1991) cointegration test, is to determine the suitable lag structure. This is done by using the lag length criteria in EViews 7 (QMS, 2007), which determine the appropriate lag length. The lag length criteria consist of the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwartz Criterion (SC) and the Hannan & Quinn (HQ). The data will be tested at all lag lengths suspected by the criteria.

The null hypothesis of the Johansen (1991) cointegration approach is that there is no cointegration present. By considering the process X_t as integrated to the order one, it can be defined by an unrestricted VAR system of order (n x 1), it is possible to express this process as a Vector Error Correction (VEC) model, which will be discussed in the following section.

3.4.1.2.1 <u>Vector Error Correction (VEC) model</u>

A Vector Error Correction (VEC) model is a restricted VAR designed for the use with non-stationary series that are known to have a cointegrated relationship (QMS, 2007:478). A VAR model of the process X_t can be illustrated as follows (Johansen, 1998:232):

$$\Delta X_t = \Pi_1 \Delta X_{t-1} + \Pi_2 \Delta X_{t-2} + \cdots + \Pi_k \Delta X_{t-k} + \mu_t \qquad (3.11)$$

Where:

- X_t= (n x 1) is the vector of $I(1)$ variables;
- Π_i= (n x n) i = 1,2,...,k is the matrix of unknown parameters to be estimated;
- μ_t is the independant and identically distributed (i.i.d) (n x 1) vector of error terms; and
- t =1,2,...,m subsequent observations.

By incorporating $\Delta = (1 - L)$, where L is the lags operator, Equation 3.11 can be parameterised in the following error correction form (Johansen & Juselius, 1990:170):

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \, \Delta X + \Pi X_{t-1} + u_t \tag{3.12}$$

Where:

- $\mathrm{X_t}$ is an $I(0)$ vector;
- $\Pi = \sum_{j=1}^{k} \Pi_j - I$;
- $\Gamma_i = \sum_{i=1}^{k-1} \Pi_j - I \; where \; i = 1,2, \ldots, k-1$; and
- I is a (n x n) identity matrix.

Johansen (1991:233) derived the maximum likelihood estimators of the cointegration vectors for the autoregressive process by incorporating independent errors. According to Johansen and Juselius (1990:169), (n x n) matrix Π can also be illustrated as the product of two matrices β and α, each of the rank r, in order for $\Pi = \alpha\beta'$. If the matrix Π has reduced rank $r < k$, then there exist k x r matrices β and α, each of the rank r. The α is also known as the adjustment parameter in the VEC model (QMS, 2007:364). The number of cointegrating relations can be symbolised by r and each column of β is the cointegrating vector (Johansen & Juselius, 1990:169). Equation 3.12 can, therefore, be rewritten as follows (Johansen & Juselius, 1990:171):

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \, \Delta X + (\alpha\beta') X_{t-k} + u_t \tag{3.13}$$

The hypothesis of r cointegration relationships between the elements of X_t can now be tested (Johansen & Juselius, 1990:170):

$$H_0 : \Pi = \alpha\beta' \tag{3.14}$$

The null hypothesis of no cointegrating relationships is therefore where $r = 0$ that implies $\Pi = 0$. When estimating the Johansen (1991) cointegration test the Π matrix from an unrestricted VAR is estimated and used to determine whether the restrictions from the reduced rank of Π could be rejected or not (QMS, 2007:364). In other words, by examining whether the eigenvalues of Π are significantly different to zero, the rank r of the Π matrix (or the number of co-integrating vectors) can be determined. Furthermore, the Trace (Tr) statistic[91] and the maximum eigenvalue (L-max) statistic can be used to evaluate the rank of the Π matrix (Johansen & Juselius, 1990:181). The Tr likelihood statistic is illustrated as follows (Johansen, 1991:1555):

$$-2\ln Q = -T\sum_{i=r+1}^{p=2}(1-\lambda_i) \tag{3.15}$$

Where:

- $\lambda_{r+1}, \ldots, \lambda_p$ are the estimated $p - r$ smalls Eigenvalues.

The null hypothesis states that r is the maximum amount of cointegrating vectors. Therefore, a rejection of the first hypothesis, $r \leq s - 1$, will imply that $r \geq 1$, while the alternative hypothesis will be $r \leq s$ and will be reduced to $r = s$. This process will continue until the null hypothesis is not rejected (Burke & Hunter, 2005:103).

In the L-max statistic, the null hypothesis of r cointegrating vectors $r = 0$, is tested against the alternative $r + 1$ cointegrating vector $r = 1$. The original $r + 1$ cointegrating vector $(r = 1)$ is then tested against the other alternative $r + 1$ cointegrating vector $r = 2$, and so forth (Burke & Hunter, 2005:100). The L-max statistic can be illustrated as follows (Burke & Hunter, 2005:100):

$$-2\ln Q = -T\ln(1 - \lambda\lambda_{r+1}) \tag{3.16}$$

91 In linear algebra, the Trace of an n-by-n square matrix A is defined to be the sum of the elements on the main diagonal (the diagonal from the upper left to the lower right) of A, i.e., where a_{ii} represents the entry on the i^{th} row and i^{th} column of A (Devore & Farnum, 2005:74).

When the Johansen (1991) test is executed in EViews 7 (QMS, 2007), there are several options available in the programme, enabling the user to include a deterministic trend[92]. The first option excludes a deterministic trend from the level data y_t and the cointegration equations include no intercepts. This option is used when the series has a zero mean (QMS, 2007:687):

$$H_2(r)\colon \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha\beta' y_{\mathrm{t}-1} \tag{3.17}$$

The second option excludes a deterministic trend from the level data y_t and includes intercepts in the cointegrating equations. This option is used if none of the series has a trend (QMS, 2007:687):

$$H_1^*(r)\colon \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0) \tag{3.18}$$

The third option includes a linear trend in the level data y_t, but excludes intercepts in the cointegrating equations. This option is used when the trends of the series are stochastic (QMS, 2007:687):

$$H_1(r)\colon \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0) + \alpha_\perp \gamma_0 \tag{3.19}$$

The fourth option includes linear trends in both the level data y_t and in the cointegrating equations (Equation 3.21). This option is used when the trends of the series appear to be stationary (QMS, 2007:687):

$$H^*(r)\colon \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_\perp \gamma_0 \tag{3.20}$$

[92] A deterministic trend is a stationary trend (Dickey & Fuller, 1979:427).

The fifth option includes quadratic trends in the level data y_t and linear trends in the cointegrating equations (Equation 3.17). This option is able to produce a good in-sample fit, but it may produce implausible estimates in the case of out-of-sample forecasts (QMS, 2007:687):

$$H(r)\colon \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_{\perp}(\gamma_0 + \gamma_1 t) \tag{3.21}$$

The terms $\alpha_{\perp}$ are the deterministic terms that lie outside the cointegration relationships. Johansen (1995) states that the $\alpha_{\perp}$ term is the null space of α such that $\alpha' \alpha_{\perp} = 0$. EViews 7 (QMS, 2007) identifies the part inside the error correction term by regressing the cointegration relationships $\beta' y_t$ on a constant and on a linear trend (QMS, 2007:366).

The Johansen (1991) cointegration test generates two estimates that can be used to evaluate the presence of a cointegrating relationship at the defined lag length. Both the Trace and maximum eigenvalue statistics utilise a sequential testing procedure, where the rank of cointegration equations (r) tested depends on the number of variables (p) in the cointegration model and can continue as long as $r \leq p$ (Mitchell-Innes, 2006:63). This implies that as long as the Trace and maximum eigenvalue statistics are smaller than the critical value, the hypothesis will be rejected, with a maximum number of hypotheses of p. For example, if the null hypothesis $(r = 0)$ is rejected, then the sequential testing procedure will continue to the next hypothesis $(r \leq 1)$, and to the alternative $r + 1$ cointegration equations. This process will continue for a maximum of p cointegration equations until the hypothesis is not rejected, which means that the Trace and maximum eigenvalue statistics will be greater than the critical value (Mitchell-Innes. 2006:63).

After establishing the presence of a cointegration relationship between the JSE and LSE, the VEC model will be estimated. The following section will examine how the output from a VEC model can be interpreted.

3.4.1.2.2 Interpreting the output of a Vector Error Correction model

The VEC model is used to estimate the speed of adjustment to equilibrium of two non-stationary cointegrated variables (Asteriou and Hall, 2007:310). For example, if a dual-listed stock on the JSE experienced a shock, the VEC model will determine the period it will take for the dual-listed stock on the LSE and JSE to return to equilibrium. The speed of adjustment variable ranges between 0 and 1, with 1 indicating that 100% adjustment will take place in one time period and an estimate of 0 indicating that no adjustment will occur[93].

In addition, Asteriou and Hall (2007:310) listed four reasons for the use of the VEC model:

- It is a convenient model to use when measuring the speed of adjustment of a regression and explaining how long it takes for disequilibrium to be rectified.
- When a VEC model is estimated, the model makes use of first differenced variables, which eliminate trends in the data giving more accurate results.
- The VEC model fits into a general-to-specific approach to econometric modelling, which is in fact the most parsimonious model that fits the given datasets.
- The disequilibrium error term is a stationary variable (by definition of cointegration) and therefore the error term is prevented from becoming larger and larger over time.

To summarise; the first step of establishing the presence of co-movement is to determine if there is a unit root present. The next step, which consists of the Johansen (1991) cointegration analysis, can only be implemented if the two variables in a model consisted of the same level of stationarity. With the presence of cointegration established, where the Trace and maximum eigenvalues exceeded the critical value, the final step can be executed. In this step, a speed of adjustment variable for each of the dual-listed stocks will be estimated.

However, the estimated coefficients of the VEC model can be difficult to interpret (Maroney *et al.,* 2004:141). Therefore, to elaborate on the results found on co-movement, using the VEC model, the variance decomposition model will be applied as the first method in examining the

[93] For more information regarding speed of adjustment, consult Asteriou and Hall (2007:312-314).

volatility spillover effect (Section 3.4.3). However, before the volatility spillover effect will be examined, the next section will conclude the discussion on measuring co-movement by elaborating on causality tests that will determine the direction of volatility spillovers and from which market the volatility spillover effect will originate.

3.4.2 Causality tests

3.4.2.1 Introduction

Volatility spillovers from one market onto the other may be caused by the price differences of dual-listed stocks in their various markets (Pretorius, 2002:90). In order to determine from which market the volatility spillovers originate, the direction of causality must first be determined. Causality, therefore, refers to the situation where the value of one variable can be better predicted by using past values of the other variable (Asteriou & Hall, 2007:281). If two variables exist, for example X_t and Y_t, and affect each other with distributed lags, the relationship can be captured by a VAR model. The effect can be explained by any of the following four possible scenarios (Asteriou & Hall, 2007:281):

- X_t causes Y_t;
- Y_t causes X_t;
- Bi-directional feedback can exist; or
- The two variables are independent.

The problem, however, is to determine which of the four scenarios are true. In order to accomplish this, the following sections will discuss the two different causality methods that will be applied, which include the Sims (1972) causality test (Section 3.4.2.2) and the Granger (1969) causality test (Section 3.4.2.3). The Sims (1972) causality test has the ability to test for bi-directional feedback, whereas the Granger (1969) causality test can only test for uni-directional causality. The Granger (1969) causality test will, therefore, be used to justify the results found for the Sims (1972) causality test.

3.4.2.2 Sims (1972) causality test

The study by Sims (1972:542) introduced a causality test that includes leading values, which differentiates the Sims (1972) method from the Granger (1969) method. The Sims (1972) test is based on the premise that the future values of a series cannot influence the present value of a series (Gujarati, 2003:712). Furthermore, in Sims' (1972) causality test, the dependent variable is regressed on the independent variable's lagging and leading values. Therefore, to identify if a variable Y_t causes X_t, equations 3.22 and 3.23 can be estimated by (Asteriou & Hall, 2007:283):

$$Y_t = \alpha_1 + \sum_{i=1}^{n} \beta_i X_{t-i} + \sum_{j=1}^{m} \gamma_j Y_{t-j} + \sum_{p=1}^{k} \zeta_p X_{t+p} + \varepsilon_t \tag{3.22}$$

Where:

- Y_t is the dependent variables;
- X_t is the independent variables;
- X_{t-i} is the lag value of X_t;
- Y_{t-j} is the lag value of Y_t;
- X_{t+p} is the lead value of X_t;
- α_1 is the intercept coefficient;
- β_i, γ_j and ζ_p are the slope coefficients; and
- ε_t is the stochastic error term.

and:

$$X_t = \alpha_2 + \sum_{i=1}^{n} \theta_i Y_{t-i} + \sum_{j=1}^{m} \delta_j X_{t-j} + \sum_{p=1}^{k} \xi_p Y_{t+p} + \epsilon_t \tag{3.23}$$

Where:

- X_t is the dependent variables;
- Y_t is the independent variables;
- X_{t-j} is the lag value of X_t;
- Y_{t-i} is the lag value of Y_t;
- Y_{t+p} is the lead value of Y_t;

- α_1 is the intercept coefficient;
- θ_i, δ_j and ξ_p are the slope coefficients; and
- ϵ_t is the stochastic error term.

If X_t is said to cause Y_t in Equation 3.22, the sum of the coefficients of X_t must be statistically equal to zero (Gujarati, 2003:713). In Equation 3.23, where Y_t is regressed on X_t, if the future coefficient values of X_t are insignificant to zero, the causality runs from X_t, to Y_t, (Sims, 1972:545). In other words, the lagging and leading variables are compared to the critical t-statistic and are statistically significant if their t-statistics are greater than the critical t-statistic. Therefore, if the lagging and leading variables of the independent variable are statistically significant, causality will run from the independent to the dependent variable. The dependent variable is, therefore, found to be dependent on the past and future values of the independent variable.

The first step in the Sims (1972) causality test is to estimate an unrestricted model, which includes a large amount of both lagging and leading variable of the independent variable (Van der Westhuizen, 1991:151). After estimating the unrestricted model, the statistically significant variables to be used in the rest of the process are identified. The second step is to estimate a restricted model using only the statistically significant variables from the unrestricted model. The final step is to identify whether the variables in the restricted model are statistically significant. The statistically significant variables indicate that the direction of causality flows in the direction of the dependant variable (Van der Westhuizen, 1991:151)..

The Sims (1972) test results can be verified by estimating a Granger (1969) causality test, in order to determine if the direction of causality is correct. The Granger (1969) method will be discussed in the following section.

3.4.2.3 Granger (1969) causality test

A variable Z_t is said to granger-cause variable Y_t, if variable Y_t can be predicted with greater accuracy by using past values of the Z_t variables (Granger, 1969:424). The purpose of the method is to include past values of the dependent and independent variable, with all the other terms remaining unchanged. The following equation illustrates the Granger (1969) causality relationship (Wooldridge, 2006:650):

$$E(Y_t/I_{t-1}) \neq E(Y_t/J_{t-1}) \quad (3.24)$$

Where:

- I_{t-1} contains past information on Y_t and Z_t; and
- J_{t-1} contains past information on Y_t.

If Equation 3.24 holds, the past values of Z_t and Y_t can be useful to predict Y_t. Furthermore, if this is true, the conclusion is drawn that Z_t granger causes Y_t (Wooldridge, 2006:650). To illustrate the Granger causality test, consider the following two-variable VAR model (Asteriou & Hall, 2007:282):

$$Y_t = \alpha_1 + \sum_{i=1}^{n} \beta_i X_{t-i} + \sum_{j=1}^{m} \gamma_j Y_{t-j} + \varepsilon_t \quad (3.25)$$

and

$$X_t = \alpha_2 + \sum_{i=1}^{n} \theta_i Y_{t-i} + \sum_{j=1}^{m} \delta_j X_{t-j} + \epsilon_t \quad (3.26)$$

Where:

- Y_t and X_t are the dependent variables in Equation 3.25 and 3.26, respectively;
- X_t and Y_t are the independent variables in Equation 3.25 and 3.26, respectively;
- X_{t-i} is the lag values of X_t;
- Y_{t-j} is the lag values of Y_t;
- α_1 and α_2 are the intercept coefficients in Equation 3.25 and 3.26, respectively;
- β_i and γ_j are the slope coefficients in Equation 3.25;

- θ_i and δ_j are the slope coefficients in Equation 3.26; and
- ε_t and ϵ_t are the stochastic error terms in Equation 3.25 and 3.26, respectively.

Equation 3.25 represents the unrestricted model, and is further expanded into Equation 3.27, which can be denoted as the restricted model (Asteriou & Hall, 2007:282). Furthermore, Equation 3.27 includes only the lagged values of $\mathrm{Y_t}$, and can be illustrated as follows (Asteriou & Hall, 2007:282):

$$Y_t = \alpha_3 + \sum_{1=j}^{m} \gamma_{j_1} Y_{t-j} + \varepsilon_t \tag{3.27}$$

Where:

- Y_t is the dependent variable;
- Y_{t-j} is the lag values of Y_t;
- α_3 is the intercept coefficient;
- γ_j is the slope coefficient; and
- ε_t is the stochastic error term.

After denoting the unrestricted and restricted models, the Residual Sum of Squares (RSS) can be obtained to calculate the F statistic as follows (Asteriou & Hall, 2007:283):

$$F = \frac{(RSS_R - RSS_u)/m}{RSS_u/(n-k)} \tag{3.28}$$

Where:

- RSS_R is the residual sum of squares of the restricted model (Equation 3.25);
- RSS_u is the residual sum of squares of the unrestricted model (Equation 3.27);
- n is the number of observations;
- k is the number of explanatory variables; and
- $m = k - n - 1$.

Once the F statistic is obtained, the null hypothesis can be presented as follows (Asteriou & Hall, 2007:282):

$$H_0: \sum_{i=1}^{n} \beta_i = 0 \tag{3.29}$$

and

$$H_1: \sum_{i=1}^{n} \beta_i \neq 0 \tag{3.30}$$

Where:

- According to Equation 3.29, X_t does not cause Y_t; and
- According to Equation 3.30, X_t does cause Y_t.

The null hypotheses also entails that if the slope coefficients (β_i)[94] equal zero, X_t does not cause Y_t. If the computed F value exceeds the F-critical value, the H_0 is rejected (Asteriou & Hall, 2007:282).

To summarise; the first step in the empirical study will be to use the Johansen (1991) cointegration analysis and the VEC model to determine the presence of co-movement. To further the investigation on co-movement, the Sims (1972) and Granger (1969) causality tests will be employed, and were examined in this section. The Sims (1972) and Granger (1969) tests will determine the direction of causality, indicating in which market the volatility spillover originated. After the direction of causality is determined (between the JSE and LSE), the next step will establish the impact of the volatility spillover between the JSE and LSE. The Variance Decomposition (VDC) model will be able to provide a more accurate indication of the information flow (volatility spillover) between the JSE and LSE. These results will, therefore, be able to shed light on price movements that are caused by the volatility of the domestic market or by the volatility spillovers from the other market and are discussed in the next section.

[94] The slope coefficients (β_i) that influence the lagged value of the independent variable (X_{t-i}), refer to Equation 3.13.

3.4.3 Variance decomposition model

The variance decomposition model is an adjusted Vector Auto-Regressive (VAR) model. While a standard VAR traces the effects of one shock from an endogenous variable onto the other variables, the variance decomposition model separates the variation in the endogenous variable into component shocks (QMS, 2007:470). Therefore, the amount of information that each variable contributes to the other variables can be illustrated by the variance decomposition model[95] (Brooks, 2008:175). The variance decomposition model is also able to explain the forecast error variance of each variable[96]. In other words, the model measures the proportion of the movements in the stock market that are as a result of its "own" innovations, as opposed to those carried over from other stock markets (Eun & Shin, 1989:241) The study of Brooks (2008:175) found that "own" innovations explain the largest share of the forecast error variance found in a VAR equation.

In addition, if X_t and Y_t are random variables on the same probability space, then the variance decomposition model of Xt can be illustrated as follows (Weiss, 2005:385):

$$var(X_t) = E\left(\frac{varX_t}{Y_t}\right) + varE\left(\frac{X_t}{Y_t}\right) \tag{3.31}$$

Where:

- $var(X_t)$ is the variance of the variable X_t;
- $E\left(\frac{varX_t}{Y_t}\right)$ is the unexplained component of the variance of X_t; and
- $varE\left(\frac{X_t}{Y_t}\right)$ is the explained component of the variance of X_t.

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95 Variance decomposition models are sometimes referred to as the forecast error variance decomposition models (Brooks, 2008:30).

96 The forecast error variance is influenced by the exogenous shocks on the other variables (Brooks, 2008:30).

The first step of the variance decomposition model, in EViews 7 (QMS, 2007), is to select the variables required for the variance decomposition model [97]. Once the model is generated, the output displays a separate variance decomposition model for each endogenous variable selected. In the output, the second column, labelled "S.E.", contains the forecast error of the variable at the given forecast horizon. The source of this forecast error is the variation in the current and future values of the innovations to each endogenous variable in the VAR. In other words, the higher the value, the greater the variable is attributable to an "own shock". Furthermore, when interpreting the output generated it is important to remember that the variance decomposition model is based on the Cholesky factor[98] and can change dramatically if you alter the ordering of the variables in the VAR. For example, the first period decomposition for the first variable in the VAR ordering is completely due to its own innovation. In order to establish the decomposition for the following periods, the order of the variables can be rearranged.

To summarise; the variance decomposition model illustrates the amount of information that each variable contributes to the other variables. This implies that the variance decomposition model is able to indicate whether volatility in a market is the result of volatility spillovers from other markets or a product of "own innovations" in the market. However, to provide a more comprehensive measure of the volatility spillover effect between the JSE and LSE, a univariate EGARCH model will be used, which will be discussed in the following section.

3.4.4 Exponential GARCH (EGARCH) model

The use of Autoregressive Conditional Heteroskedasticity (ARCH) models to study volatility spillover clusters is very common, as illustrated by past studies[99]. However, the study of Bollerslev (1986:308) stated that GARCH models have the ability to be a more plausible learning mechanism than the ARCH model and provide a better fit compared to ARCH models.

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97 Since non-orthogonal factorisation will yield decompositions that do not satisfy an adding up property, your choice of factorisation is limited to the Cholesky orthogonal factorisations (QMS, 2007:470).

98 In linear algebra, the Cholesky factor is a decomposition of a Hermetical, positive-definite matrix into the product of a lower triangular matrix and its conjugate transpose (Watkins, 1991:84).

99 Studies that can be consulted include Booth *et al.* (1997:437), Boujir and Lahrech (2008:123), Gallo (2007:117), De Santis and Imrohoroglu (1994:39) and Solnik *et al.* (1997:524).

Karolyi (1995:17) also stated that the spillover effect is better explained by the GARCH model than by VAR model, because the VAR model seems to overestimate the dependence between markets.

However, GARCH models have a number of shortcomings that must be taken under consideration, which include the following (Nelson, 1991:347):

- The GARCH models impose parameter restrictions that may restrict the dynamics of the conditional variance process and are often violated by estimated coefficients.
- Evidence of a negative correlation between future returns and current returns volatility have been found, which is in contrast with the GARCH assumptions.
- The persistence of shocks to the conditional variance is difficult to interpret in GARCH models

In an attempt to capture the asymmetric impact of shocks on volatility, Nelson (1991:350-353) developed the exponential GARCH (EGARCH) model. A rival model called the Quadratic GARCH model was also proposed by Engle (1990:103), which allows volatility to respond asymmetrically to innovations. However, the study by Engle and Ng (1993:1752) stated that the Quadratic GARCH does not capture the asymmetric effect or size effect, and for this reason the EGARCH model is superior. Engle and Ng (1993:1753) also stated that the standard GARCH model and the EGARCH model differ in two ways. Firstly, EGARCH allows immanent news to have a larger impact on volatility. Secondly, EGARCH allows bad news and good news to have different effects on volatility (Engle & Ng, 1993:1753). Koutmos and Booth (1995:749) also stated that the EGARCH model does not require parameter restrictions to ensure positive variances at all times. Hamao *et al.* (1990:292-305) emphasised this notion, because their results indicated that there are coefficients in the conditional variance specification that violated the non-negative assumption, which is in contrast with the assumptions of the standard GARCH model.

The EGARCH(1,1) model consists of two equations, namely the returns equation and the variance equation. The returns equation can be formulated as follows (St Pierre, 1998:168):

$$R_t = \alpha_0 + \sum_{i-1}^{p} \emptyset_i R_{t-i} + \delta\sigma_t^2 + \varepsilon_t, \tag{3.32}$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t^2) \tag{3.33}$$

Where:

- R_t is the daily return for day t;
- α_0 is the intercept;
- $\emptyset_i$ is the order autocorrelation in daily returns;
- δ is the degree of correlation between daily returns and conditional variance (it can also be thought of as a risk aversion parameter); and
- σ_t^2 is the variance on day t.

The variance equation can be illustrated as follows (Ogum *et al.,* 2002:109):

$$\ln(\sigma_t^2) = \theta_0 + \theta_1\left\{|\varepsilon_{t-1}/\sigma_{t-1}| - \sqrt{2/\pi}\right\} + \frac{\gamma\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2), \tag{3.34}$$

Where:

- θ_1 measures the impact of innovation on conditional volatility at time t;
- γ permits the asymmetric response of conditional variance to innovations of a differing sign (positive or negative); and
- β is the shock persistence measure.

As stated above, the error term (ε_t) is assumed to follow a normal distribution with Ω_{t-1} being the set of relevant information available at time t. Furthermore, the equation also allows for a risk factor in the form of the "in-mean" parameter (δ). This parameter is introduced in order to determine whether or not investors are rewarded for their exposure to market risk. According to the CAPM mean-variance hypothesis, large standard deviations (variances or volatility) are expected to be associated with large returns (Litterman, 2003:37). For this reason, it follows that (δ) is expected to be greater than zero. Consequently, the parameter (δ) determines the relationship between returns and volatility.

The conditional variance Equation 3.34 follows an EGARCH(1,1) process, which allows for time-varying heteroskedasticity in the errors (Nelson, 1991:348). As previously mentioned, the EGARCH model differs from the standard GARCH model, in that it allows innovations of different signs to have a differential impact on volatility and allows bigger shocks to have a larger impact on volatility. In Equation 3.34, the parameter (θ_1) measures the impact of innovation on conditional volatility at time t. The parameter (γ) permits the asymmetric response of conditional variance to innovations of a differing sign (positive or negative). In the case of (γ) in Equation 3.32 being negative, negative realisations of the innovation (risk factor) in Equation 3.32 will generate more volatility than positive realisations. If, however, (γ) is positive, negative realisations of the innovation in Equation 3.32 will generate less volatility than positive realisations.

The presence of the leverage effect can be tested by the assumption that $\gamma < 0$. The impact is asymmetric in the case where $\gamma \neq 0$ and the most recent residual term impact is exponential, rather than quadratic. 'Good' news ($\varepsilon_t > 0$) will have an impact of $(\theta + \gamma)/\sigma_{t-1}$ while 'bad' news ($\varepsilon_t < 0$) will have an impact of $(\theta - \gamma)/\sigma_{t-1}$ (Ogum *et al.*, 2002:11). The parameter (β) is the autoregressive term on lagged conditional volatility, consequently reflecting the weight given to the previous period's conditional volatility in the conditional volatility at time t. It measures the persistence of shocks to the conditional variance.

To summarise; the EGARCH model is considered to be the most superior model in examining volatility spillover effects, because it has the ability to capture the asymmetric impact of shocks on volatility. The EGARCH model can provide information on how a stock market will react to positive or negative shocks with both a size effect and the asymmetric effect estimate. This study will apply the EGARCH model to generate a more comprehensive measure of the volatility spillover effect between the JSE and LSE, where the results will be reported in Chapter 4.

3.5 CHAPTER SUMMARY

The main goal of this study is to examine whether LSE dual-listed stock price volatility can be utilised as an indicator to determine expected JSE dual-listed stocks price movements. To assist in achieving this main goal, this chapter examined the interactive relationship between international financial markets. This was primarily achieved by determining the different methods available to measure co-movements and volatility spillover effects. Volatility can be seen as the degree (standard deviation) of a stock price movement or the variability of a stock price, whereas the volatility spillover effect refers to where the volatility (price instability) of one market is transferred to another market.

The volatility spillover effect can be facilitated by the presence of co-movement between markets and for this reason the investigation of co-movement was the starting point in determining the cause of the volatility spillover effect. Past studies indicated that co-movements can exist among stock markets due to three contributing factors, namely the *contagion effect* (Section 3.3.2), *economic integration* (Section 3.3.3) and *identical stock market characteristics* (Section 3.3.4).

Furthermore, to establish the appropriate models to be used in Chapter 4, past empirical studies on co-movement (Section 3.3.5) and on the volatility spillover effect (Section 3.3.6) were examined. The first method to measure co-movement identified was the Johansen (1991) cointegration analysis, which includes a Vector Error Correction (VEC) model. These tests examine the presence of a long-run relationship between JSE and LSE and determine the speed of adjustment required for the markets to return to their equilibrium prices. The second measure of co-movement includes causality tests, which will determine the direction of causality. The causality tests that will be used in this study, are the Sims (1972) and Granger (1969) causality tests (Section 3.5.1). In addition to testing for co-movement, the impact of a volatility spillover effect will also be examined. The first measure of the volatility spillover effect includes the Variance Decomposition (VDC) model, which will be applied to separate the variations in the endogenous variables into the component shocks to the VAR (Section 3.4.3). The VDC will, therefore, indicate the amount of information that each dual-listed stock price contributes to the other.

The Exponential GARCH (EGARCH) model (Section 3.4.4) was also employed in the majority of past studies and will be used in this study to measure the volatility spillover effect between the JSE and LSE. The EGARCH model will provide a size effect, shock persistence, and an asymmetric effect of a shock (change in stock price), which will provide additional information regarding the influential strength that the two markets have on each other. This chapter only provided the methodology that will be applied in this study, whereas the following chapter will provide the empirical results obtained from the various models.

CHAPTER 4

Empirical results

"Historical methodology is a product of common sense applied to circumstances."

— Samuel E. Morison

4.1 INTRODUCTION

The speed of globalisation in the capital markets has increased the ability to trade stocks around the world. Stocks, therefore, became an important source of cross-border capital flows (Karolyi, 2004:2), making investing in dual-listed stocks more attractive. Dual-listed stocks should grow at the same rate in their various markets as explained by the single market hypothesis (Section 2.1). However, they do not grow at the same rate, which leads to price differences in the dual-listed stocks, making arbitrage opportunities a possibility (Ip & Brooks, 1996:53). Evidence from past empirical studies[100] suggests that these price differences may be due to a volatility spillover effect between the various markets. By providing a better understanding of this volatility, the spillover effect can aid investors in making better cross-border investment decisions. **The main goal of this study is to examine whether LSE dual-listed stock price volatility can be utilised as an indicator for determining expected JSE dual-listed stocks price movements.** This chapter will commence by examining the data that were applied in this study (Section 4.2), which will be followed by a discussion on the data-screening process. In the data-screening process, the descriptive statistics and a graphical presentation of the variables will be analysed to ensure the required reliability and usefulness of the data. This will be followed by the results from the first step of the empirical study, which includes the estimation of a Johansen (1991) cointegration test (Section 4.4.1) and a Vector Error Correction (VEC) model (Section 4.4.2) as the first measures of co-movement. The Johansen (1991) cointegration test will determine the presence of a long-run relationship between the JSE and LSE, whereas the VEC model will generate a speed of adjustment

[100] For further references see De Santis and Imrohoroglu (1994:39), Worthington and Higgs (2004:80), and Baele (2003:114).

estimate, which illustrates the time horizon required to eliminate the disequilibrium between the two markets. The second step is testing for the direction of causality (Section 4.5). As was previously mentioned, the presence of co-movement between markets will facilitate the volatility spillover effect, where volatility is transferred between markets (Pretorius, 2002:90). The direction of causality is able to elaborate on the direction the volatility spillovers and from which market the volatility spillover effect originated

The next step is to examine the extent to which the markets are affected by a volatility spillover effect. The first model that will be used in the investigation of the volatility spillover effect is the Variance Decomposition (VDC) model, which separates the variations in the endogenous variables into the component shocks to the VAR (Section 4.6). The VDC will, therefore, indicate the amount of information that each Anglo American Plc. stock price in one market contributes to the other. In addition to the VDC, the Exponential GARCH (EGARCH) model (Section 4.7) will be estimated as the final step in the volatility spillover analysis. Results from the EGARCH model will be used in this study to measure the volatility spillover effect between the JSE and LSE in terms of a size effect, the shock persistence, and an asymmetric effect of the shock (change in stock price). These results will provide additional information regarding the influential strength that the two markets[101] have on each other.

4.2 THE DATA

Due to limited access to intra-day data, the data that were collected for this study ranged from 14 October 2009 to 4 February 2010. This timeframe falls in the middle of the global financial crisis, which started in September 2008 when the Lehman Brothers were declared bankrupt. The data is in an hourly format, commencing from 08:00am and ends at 15:00pm, which consist of eight observations per day and 2344 observations in total. Hourly format data is preferable to daily/weekly data, as it captures volatility in the short term.

[101] The two markets mentioned are the JSE and LSE.

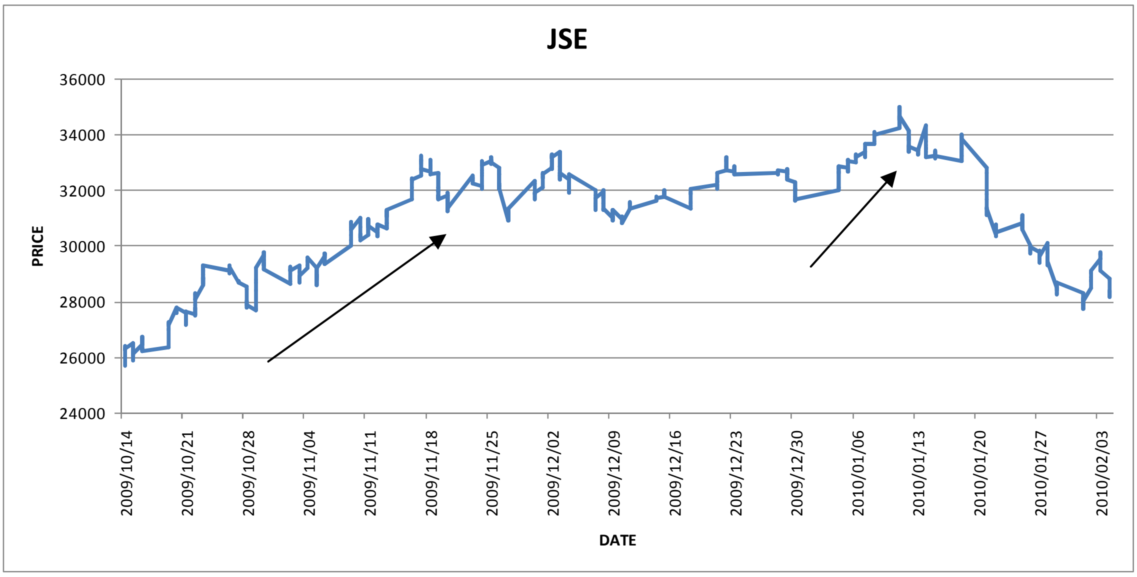
The hourly intra-day ZAR/USD spot exchange rate was obtained from the Reuters database (Reuters, 2010). This specific exchange rate was chosen because dual-listed stocks on the JSE are quoted in ZAR and dual-listed stocks on the LSE are quoted in USD. The LSE dual-listed stock prices were, therefore, converted in ZAR terms by using the ZAR/USD spot exchange rate, before using it in the empirical study. The hourly intra-day Anglo American Plc. dual-listed stock prices from both the JSE and LSE were obtained from the Reuters database (Reuters, 2010).

Before commencing with the reporting of the empirical results, the data will be examined on a micro-level. Mangani (2005:10) indicated that it is important to examine some of the characteristics of the underlying data before the main analysis is conducted, which leads to the following section that will provide a brief discussion on the data-screening process.

4.3 DATA-SCREENING PROCESS

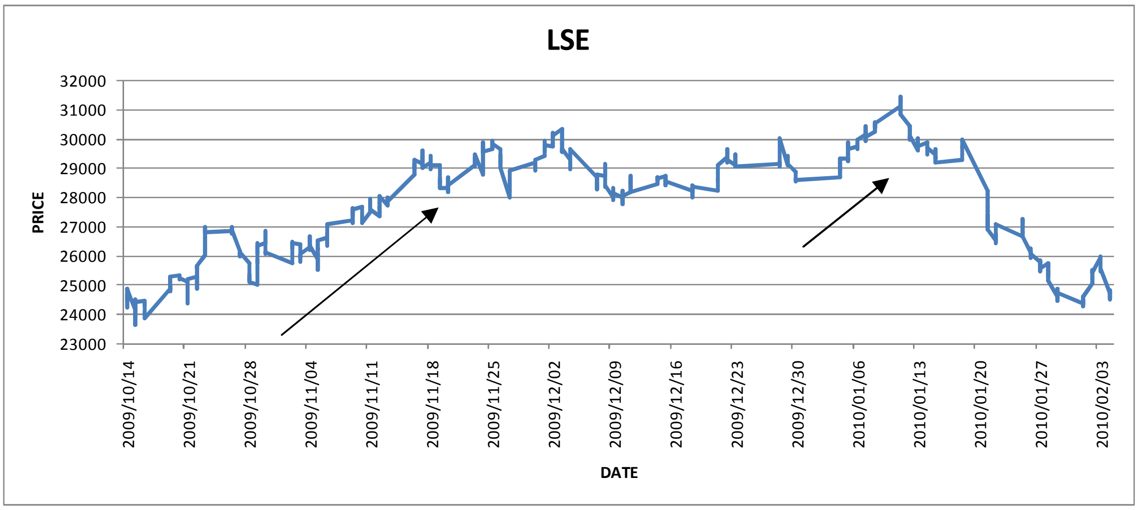
The first step in the data-screening process is to provide an overview of the descriptive statistics of the dual-listed stocks. EViews 7 (QMS, 2009) econometric software is used to obtain the graphs and the descriptive statistics of the data, which are illustrated by Figures 4.1 to 4.2 and Table 4.1, respectively. Figures 4.1 to 4.3 illustrate the graphical representation of the variables used in this study. The vertical axis represents the nominal value and the horizontal axis represents the time horizon. The Anglo American Plc. stock prices on the JSE (Figure 4.1) and the LSE (Figure 4.2) show an upward trend from October 2009 to January 2010 (indicated by the arrows), followed by a downward trend. This can be because the markets were very volatile during the time of the European sovereign debt crisis, which ranged from 5 November 2009 to 10 June 2010 (Matlock, 2010:1; Reuters, 2011:1). During this period, investors lost confidence in the European markets, when the rating agencies Moody's, Fitch, and Standard & Poor's delivered the credit rating of Greece from A- to BBB+. Uncertainty intensified among investors, which led to a high level volatility within the LSE (Reuters, 2011:1).

Figure 4.1: Anglo American Plc. stock prices on the JSE (in ZAR terms)



Source: Compiled by author from data gathered on the Reuters database (Reuters, 2010:1)

Figure 4.2: Anglo American Plc. stock prices on the LSE (in ZAR terms)



Source: Compiled by author from data gathered on the Reuters database (Reuters, 2010:1)

In addition to the graphical analysis, Table 4.1 reports the descriptive statistics of the 586 observations of each variable (2344 observations in total). The kurtosis of all the variables is less than 3, which indicates that the distribution of each of the variables is relatively flat (platykurtic) (QMS, 2007:318). All the variables are negatively skewed, according to the negative sign before the skewness coefficient, which is a familiar property of stock prices (Henry, 2002:727). Furthermore, the null hypothesis for the Jarque-Bera test, which states that the data is normally distributed, is rejected at the 95% statistical significance level for the Anglo

American Plc. dual-listed stock prices on the JSE and LSE. This illustrates that the dual-listed stocks are not normally distributed, which is supported by the study of Mangani (2005:10), who found that the stock prices of the JSE are not normally distributed.

Table 4.1: Descriptive statistics of the variables

VARIABLES	JSE (in ZAR)	LSE (in USD)	LSE (in ZAR)
Mean	30905.89	2529.69	27719.34
Maximum	35000.00	2958.80	31428.32
Minimum	25700.00	2170.00	23624.28
Std. Dev.	2083.41	188.47	1853.28
Skewness	-0.47	-0.035	-0.34
Kurtosis	2.23	2.029	1.90
Jarque-Bera	33.24*	23.16*	40.73*
Observations	586	586	586

**Reject H_0 that the data are normally distributed at the 95% level of statistical significance.*
Source: Compiled by author

The next step is to determine the level of integration using the Augmented Dickey-Fuller (ADF) test (Section 3.4.2), as reported in Tables 4.2 and 4.3. The data were tested in level format with an intercept (Table 4.2) and in the first differential format with an intercept (Table 4.3)[102]. The results from Table 4.2 report that all the variables are not stationary in level format, as the null hypothesis of the unit root cannot be rejected for all the variables.

The results from Table 4.3 show that the variables are all integrated of order one, $I(1)$, where the null hypothesis of the unit root is rejected for all the differenced variables. The ADF results, therefore, emphasise the fact that the dual-listed stock variables are suitable for the Johansen (1991) cointegration analysis, because the Johansen procedure requires that the two variables have the same order of integration (Section 4.5). Furthermore, each data variable was differenced in order to achieve stationarity before further analysis was conducted.

[102] The data assumption of an intercept was included as a strong trend was not expected based on prior knowledge and literature. Furthermore, the analysis of Elder and Kennedy (2001) indicated that an intercept is suitable.

Table 4.2: Unit root tests (level form)

		t-statistic	t-probability
JSE	ADF test statistic	-2.24	0.19
	1% level	-3.44	
	5% level	-2.87	
	10% level	-2.57	
LSE	ADF test statistic	-1.65	0.45
	1% level	-3.44	
	5% level	-2.87	
	10% level	-2.57	
ZAR/USD	ADF test statistic	-0.76	0.83
	1% level	-3.44	
	5% level	-2.87	
	10% level	-2.57	

Model assumption: Intercept was included in the ADF equation.
Source: Compiled by author

Table 4.3: Unit root tests (first differential format)

		t-statistic	t-probability
JSE	ADF test statistic	-22.80	0.00*
	1% level	-3.44	
	5% level	-2.87	
	10% level	-2.57	
LSE	ADF test statistic	-24.47	0.00*
	1% level	-3.44	
	5% level	-2.87	
	10% level	-2.57	
ZAR/USD	ADF test statistic	-26.12	0.00*
	1% level	-3.44	
	5% level	-2.87	
	10% level	-2.57	

Model assumption: Intercept was included in the ADF equation.
**Reject H_0 that the data has a unit root at the 95% level of statistical significance.*
Source: Compiled by author

To summarise; the data-screening process reported that the Anglo American Plc. stock prices on the JSE and the LSE illustrated normal stock data behaviour, which means that the time series are not normally distributed and are negatively skewed. Furthermore, all the variables were found to be integrated to the order of one. These results emphasised the fact that the dual-listed stock variables are suitable for the Johansen (1991) cointegration analysis.

The next step is to commence with the empirical study by estimating the first measure of co-movement, where the presence of co-movement facilitates volatility spillovers between markets. The analysis on co-movement is initialised by applying the Johansen (1991) cointegration approach. The Johansen (1991) cointegration approach will determine if there is a long-run relationship present between the JSE and LSE. The co-movement analysis will also continue by estimating a Vector Error Correction (VEC) model.

4.4 THE COINTEGRATION APPROACH

The cointegration approach is the first step in examining the presence of co-movement between the two financial markets. This section is divided into the Johansen (1991) cointegration analysis (Section 4.4.1) and the Vector Error Correction (VEC) model (Section 4.4.2). In addition to examining the presence of a long-run relationship with the Johansen (1991) cointegration analysis, the VEC model also generates a speed of adjustment estimate (Section 4.4.2). The speed of adjustment estimate indicates how long the markets will take to return to their equilibrium price levels after a shock.

4.4.1 The Johansen (1991) cointegration analysis

The first step in the Johansen (1991) cointegration analysis is to determine the order of integration of the variables. Only variables that have the same order of integration can be used for the Johansen (1991) cointegration analysis. The ADF test in Table 4.3 illustrated that the JSE and LSE stock price variables are all integrated to the same order of integration, $I(1)$, and can, therefore, be used to compose a VAR-based cointegration test. The second step in the Johansen (1991) cointegration analysis is to determine if the VAR model is stable. The graphical analysis for the stability test, as illustrated in Figure D.1 in Appendix D, indicates that the VAR is stable.

The next step in the Johansen (1991) cointegration analysis is to identify the appropriate lag structure for the VAR-based cointegration test (Agung, 2009:30). The results of the lag structure test are reported in Table 4.4. The Schwartz criterion (SC) indicated that the optimal lag length is equal to two lags, whereas the Akaike information criterion (AIC) and Final Prediction Error (FPE) criterion indicated that the optimal lag length is equal to five lags. By examining the different lag lengths, the lag structure of two lags yielded the most statistically significant results, suggesting that the Schwartz criterion (SC) was sufficient in computing the lag structure.

Table 4.4: Lag structure test

LAG	LOGL	LR	FPE	AIC	SC	HQ
0	-7891.74	NA	2.62	27.36	27.36	27.37
1	-7736.70	308.47	1.55	26.84	26.88	26.86
2	-7700.13	72.50	1.39	26.72	26.80*	26.76
3	-7689.78	20.45*	1.36	26.70	26.81	26.74*
4	-7685.65	8.12	1.35	26.70	26.84	26.76
5	-7681.29	8.57	1.35*	26.70*	26.87	26.77

**Indicates the optimal lag length.*
Source: Compiled by author

Once the optimal lag length is determined, the Johansen (1991) cointegration test can be estimated in EViews 7 (QMS, 2007). In the Johansen (1991) cointegration test, both the Trace (Tr) and maximum eigenvalue (L-max) statistics are used in order to determine the number of cointegrating relationships. If the Trace (Tr) and maximum eigenvalue (L-max) statistics are smaller than the critical value, the hypothesis cannot be rejected, which will imply the presence of a cointegration relationship (Hawtrey 1997:341).

The null and alternative hypothesis of the two tests can be presented as follows:

$$H_0: r = 0 \text{ (no cointegration relationship present)} \quad (6.1)$$

$$H_1: r \leq 1 \text{ (one cointegration relationship present)} \quad (6.2)$$

$$H_2: r \leq 2 \text{ (two cointegration relationships present)} \quad (6.3)$$

The results reported in Tables 4.5 and 4.6 indicate that the Trace statistic (Tr) and the maximum eigenvalue (L-max) statistic are greater than the critical value at the H_0 hypothesis, implying that the H_0 hypothesis could be rejected in both tests. However, according to the Trace (Tr) and maximum eigenvalue (L-max) statistics, the H_1 hypothesis could not be rejected, implying the presence of one cointegration relationship between the Anglo American Plc. dual-listed stock prices on the JSE and the LSE. These results, therefore, confirm that there is a long-run cointegration relationship between the Anglo American Plc. dual-listed stock prices on the JSE and the LSE.

Table 4.5:Johansen (1991) cointegration test results (Tr statistic)

HYPOTHESIZED	TRACE STATISTIC	0.5 CRITICAL VALUE	t-prob
$H_0: r = 0$	27.67	18.40	0.00*
$H_1: r \leq 1$	0.94	3.84	0.33

Model assumption: Intercept and trend were allowed in cointegration equation, but not in VAR, with a 2 lag interval.
*Reject hypothesis at the 95% confidence level.
Source: Compiled by author

Table 4.6:Johansen (1991) cointegration test results (L-max statistic)

HYPOTHESIZED	L-MAX STATISTIC	0.5 CRITICAL VALUE	t-prob
$H_0: r = 0$	26.72	17.15	0.00*
$H_1: r \leq 1$	0.94	3.84	0.33

Intercept and trend were allowed in cointegration equation, but not in VAR, with a 2 lag interval.
*Reject hypothesis at the 95% confidence level.
Source: Compiled by author

In addition to the Johansen (1991) cointegration analysis, the results of the VEC model will be reported in the following section, which will elaborate on the long-run relationship found by the Johansen (1991) cointegration analysis. The VEC model will provide a speed of adjustment estimate that will indicate how long the markets will take to return to their equilibrium price levels after a shock.

4.4.2 Vector Error Correction (VEC) model

The VEC model estimated can be illustrated as follows (Asteriou & Hall, 2007:310):

$$\Delta Y_t = \gamma_0 \Delta X_t - (1-\alpha)\left[Y_{t-1} - \frac{\alpha_0}{1-\alpha_1} - \frac{\gamma_0+\gamma_1}{1-\alpha_1} X_{t-1}\right] \tag{6.4}$$

where:

- γ_0 is the short-run effect (impact multiplier) of Y_t after a change in X_t;
- $\frac{\gamma_0+\gamma_1}{1-\alpha_1}$ is the long-run coefficient;
- it is assumed that $\alpha_1 < 1$ in order for the short-run model to convert to a long-run solution; and
- $(1-\alpha)$ or π is the speed of adjustment needed in the case of disequilibrium. π is also known as the adjustment or feedback effect.

The α estimate ranges between 0 and 1, with $\alpha = 1$ illustrating that 100% adjustment will take place in one time period and an estimate of $\alpha = 0$ indicating that no adjustment will take place (Asteriou & Hall, 2007:314). The results found for the VEC model are reported in Table 4.7.

Table 4.7: Vector Error Correction (VEC) model output (JSE as dependant variable)

LAGS:2	LONG-RUN COEFFICIENT	t-statistic (LONG –RUN COEFFICIENT: β)	SPEED OF ADJUSTMENT (α)	t-statistic (α)	Adjusted R^2	R^2
JSE	1	-	-0.06	[-3.94]*	0.42	0.42
LSE	-1.05	[-16.14]*	-0.03	[-1.23]	0.01	0.00

Model assumption: Intercept and trend were allowed in cointegration equation, but not in VAR, with a 2 lag interval.
**Statistically significant at the 1% level.*
Source: Compiled by author

The results reported in Table 4.7 illustrate that the long-run coefficient is statistically significant and has a negative sign. This suggests the presence of an inverse relationship between the stock prices on the JSE and on the LSE, but greater than unity. Furthermore, the α estimate of the Anglo American Plc. stock prices on the JSE is equal to 6% for an estimated period (1 hour), which implies that it will take approximately two days to eliminate the disequilibrium between the two markets. The π estimate, therefore, emphasises a level of co-movement between the JSE and LSE.

To summarise; The Johansen (1991) cointegration analysis indicated that a long-run cointegration relationship between the JSE and LSE exists. The VEC model elaborated on this long-run relationship by reporting the presence of an inverse relationship between the JSE and the LSE, but more than unity. Furthermore, results indicated that it will take approximately two days to eliminate the presence of disequilibrium between these two financial markets. These results, therefore, indicate the existence of long-run co-movement between the JSE and the LSE. In the next step, the Sims (1972) and Granger (1969) causality tests are estimated as the second measure of co-movement and will elaborate on the direction of the volatility spillovers and from which market the volatility spillover effect originated.

4.5 THE DIRECTION OF CAUSALITY

The Sims (1972) causality test produces a bi-directional output, which will be compared with the results found in the Granger (1969) causality test. The estimated models are explained in detail in Section 3.4. In the Sims (1972) causality test, the dependent variable is regressed on both lagging and leading variables of the independent variable (Sims, 1972:545). The sums of the lagging and leading variables' t-statistics are compared to the critical t-statistic, respectively and are statistically significant if their t-statistics are greater than the critical t-statistic. Therefore, if the lagging and leading variables of the independent variable are statistically significant, causality will run from the independent to the dependent variable. The dependent variable is, therefore, found to depend on the past and future values of the independent variable.

Therefore, to estimate the Sims (1972) causality test, the first step is to estimate an unrestricted model, which includes a large number of both lagging and leading variables of the independent variable (Van der Westhuizen, 1991:151). After estimating the unrestricted model, the statistically significant variables are identified and are incorporated in the rest of the process. In the unrestricted model, with the Anglo American Plc. dual-listed stock prices on the JSE as the dependent variable, only the first and second lagged variable and the first leading variable of the Anglo American Plc. dual-listed stock prices on the LSE were found to be statistically significant. However, the unrestricted model with the Anglo American Plc. dual-listed stock prices on the LSE as the dependent variable produced no statistically significant coefficients for leading or lagging values. This implies that the JSE has no significant influential effect on the LSE.

The second step is to estimate a restricted model using only the statistically significant variables from the unrestricted model. The results from the restricted model are reported in Table 4.8, which include only the statistically significant variables from the unrestricted model[103]. The final step is to identify whether the variables in the restricted model are statistically significant. By examining the lagging variables in Table 4.8, it is found that the sum of the t-statistics of the lagging variables of the LSE Anglo American Plc. dual-listed stock prices is equal to 14.88, which is greater than the critical t-statistic of 2.326. This implies that the coefficients of the first and second lagged variables of the LSE Anglo American Plc. dual-listed stock prices as a group are statistically significant at a 1 percent level of significance. Therefore, causality is present between the markets of the LSE and JSE and the direction of causality is from the LSE to the JSE (Koutsoyiannis, 1977:660). In addition to the lagged variables, by examining the leading variables, it was found that the t-statistic is equal to 2.50, which is greater than the critical t-statistic of 2.326. Therefore, the variable is statistically significant at a 99 percent confidence level. This implies that the JSE is influenced by both leading and lagging values of the LSE.

In addition to the Sims (1972) causality test, the Granger (1969) causality test was estimated in order to justify the results obtained by the Sims (1972) causality test. The estimation of the Granger (1969) causality test differs from the Sims (1972) causality test in terms of the usage of lagged variables in the equation. In the Granger (1969) causality test, only lagged variables of

[103] The unrestricted models are reported in Tables C.1 and C.2 in Appendix C.

the independent variable are used. The model examined in Section 3.4 was employed in the estimation of the Granger (1969) causality test.

Table 4.8: Sims (1972) causality test results (JSE Anglo American Plc. dual-listed stock price as the dependant variable)

VARIABLE	COEFFICIENT	Std. Error	t-Statistic	PROBABILITY
LSE (FIRST LAG PERIOD)	0.56	0.05	12.07	0.00
LSE (SECOND LAG PERIOD)	0.083	0.03	2.81	0.01
LSE (FIRST LEAD PERIOD)	0.068	0.03	2.50	0.01

Source: Compiled by author

When estimating the Granger (1969) causality test, it is important to remember that the results are sensitive to the number of lags that are used (Shan & Tian, 1998:202). For this reason, a lag structure test was performed in order to establish the optimal lag length, which is reported in Table 4.4. From the results in Table 4.4, the Schwartz criterion (SC) indicates that the optimal lag length is equal to two lags, whereas the Akaike information criterion (AIC) and Final Prediction Error (FPE) criterion indicate that the optimal lag length is equal to five lags. Due to the different lag structure suggestions, the Granger (1969) causality test was estimated using two to five lags. The results for the Granger (1969) causality test are reported in Table 4.9, which are also robust to the different lag lengths.

Table 4.9: Granger (1969) causality test results

DIRECTION OF CAUSALITY	LAG(S)	F-STATISTIC	PROBABILITY	DECISION
LSE=>JSE **JSE=>LSE**	1	31.95 0.05	2.48 0.83	Rejection No rejection
LSE=>JSE **JSE=>LSE**	2	164.78 1.19	2.24 0.30	Rejection No rejection
LSE=>JSE **JSE=>LSE**	3	126.04 1.07	9.12 0.36	Rejection No rejection
LSE=>JSE **JSE=>LSE**	4	98.02 1.08	1.59 0.36	Rejection No rejection
LSE=>JSE **JSE=>LSE**	5	78.06 0.77	2.62 0.57	Rejection No rejection

Source: Compiled by author

As reported in Table 4.9, the null hypothesis for the LSE not granger causing the JSE is rejected at the 99% level of statistical significance for all lag lengths. In addition, the null hypothesis that the JSE is not granger causing the LSE is not rejected at the 99% level of statistical significance for all lag lengths. This implies that the direction of causality originates in the LSE and spills over to the JSE, which justifies the results found by the Sims (1972) causality test.

To summarise; the Johansen (1991) and VEC models indicated the presence of co-movement between the JSE and LSE. By estimating the Sims (1972) and Granger (1969) causality tests, as the second measure of co-movement, the results illustrated that the direction of causality runs from the LSE to the JSE. These results imply that the origin of a volatility spillover effect will be from the LSE and will spill over to the JSE.

The next step in this empirical study is to examine the extent to which the markets are affected by a volatility spillover effect. The first measure that will be examined includes the Variance Decomposition (VDC) model, which has the ability to elaborate on the long-run coefficient from the VEC model (Maroney *et al.*, 2004:141). Furthermore, the VDC model is able to indicate the amount of volatility that each market contributes to the other. This leads to the following section that will report the results of the VDC model.

4.6 VARIANCE DECOMPOSITION (VDC) ANALYSIS

The VDC model elaborates on the amount of volatility that each market contributes to the other. The model used in the analysis is explained in greater detail in Section 3.4. The output from the Variance Decomposition model is reported in Table 4.10. The first column represents the time horizon, whereas the second column labelled “S.E.” represents the variations between current and future values of the endogenous variable due to a shock. The higher the value, the greater the variable is attributable to an "own shock". Therefore, the results report how the JSE deviates from its mean value due to an "own shock" and also due to a shock from the LSE. The results reported in Table 4.10 illustrate that all the variations in the JSE during period 1 are mainly due to "own shocks", but decrease as the time horizon increases. From period 2, the influential ability of the LSE increases, contributing an average variance of 38.58% over the estimated period. From Table 4.10, it is evident that although the LSE has an influential effect on the JSE, the JSE is still responsible for most of the movements of its Anglo American Plc. stock prices ("own shocks")[104].

Table 4.10: Variance Decomposition (VDC) model output

JSE			
Period	**S.E.**	**JSE**	**LSE**
1	175.79	100.00	0.00
2	226.20	60.74	39.26
3	228.03	61.32	38.68
4	228.59	61.21	38.79
5	228.69	61.16	38.84
6	228.71	61.15	38.85
7	228.71	61.15	38.85
8	228.71	61.15	38.85
9	228.71	61.15	38.85
10	228.71	61.15	38.85

Source: Compiled by author

To summarise; the volatility of the LSE has an impact on the Anglo American Plc. stock prices of the JSE, as suggested by the direction of causality (Section 4.4). However, the "own shocks" of the JSE are found to be the dominant cause for the volatility of the Anglo American Plc. stock price on the JSE over the estimated period. In addition, the output of the VEC model suggests that there is a greater than unity relationship between the markets, but the output from the VDC model suggests that the impact of the LSE on the JSE is of a smaller scale.

In addition to the VDC model, the final step in the empirical analysis is the estimation of the Exponential GARCH (EGARCH) model. The EGARCH model measures the impact that the volatility spillover from the LSE has on the JSE. The volatility spillover effect will be measured in

[104] The results of the VDC model with the LSE as dependent variable are reported in Table E.1 in the Appendix E.

terms of a size effect, shock persistence, and an asymmetric effect of a shock (change in stock price). The results obtained from the EGARCH model are reported in the following section.

4.7 Exponential GARCH (EGARCH) model

In an attempt to enhance the techniques used to capture the asymmetric impact of shocks on volatility, Nelson (1991:350-353) developed the Exponential GARCH (EGARCH) model. This model is examined in greater detail in Section 3.4. The first step is to determine if the EGARCH(p, q)[105] model is properly specified and correctly estimated. In this study, various formats were examined to make the data stationary before applying it in the EGARCH(p, q) model. The various formats include the log-format and the first differential format, where the first differential format entails the use of the change in the variables from period t to period $t + 1$. The first differential format yielded the best result as the data was found to be stationary as required. For this reason the first differential format was applied in the EGARCH(p, q) model. This stationarity approach is also supported by the study of Granger and Newbold (1974:118), who argued that no information in the time series will be lost by using difference format changes.

In addition to stationarity, the EGARCH(p, q) model must be properly specified in terms of the p^{th} order autoregressive GARCH term and the q^{th} order moving average ARCH term. Different EGARCH specifications were examined, where the AIC and SIC criterion indicated that the best model was an EGARCH(1,1) model. This model was also tested for serial correlation and autocorrelation and no evidence was found for serial correlation[106]. Furthermore, the null hypothesis of the Ljung-Box Q-statistic[107] was not rejected at one lag length, indicating that no

[105] In an EGARCH(p, q) model, p is a nonnegative integer indicating the number of lagged log conditional variances included in the EGARCH model, and q is a nonnegative integer indicating the number of lagged standardized innovations included in the EGARCH model. If p is greater than zero, then q must also be greater than zero (Mathworks, 2012:1).

[106] The corellograms of the variables are reported in Figures B.1 to B.8 Appendix B.

[107] The Ljung–Box test is a type of statistical test of whether any of a group of autocorrelations of a time series are different from zero (Ljung and Box, 1978:297)

autocorrelation was present in the error terms[108]. These results, therefore, supported the use of an EGARCH(1,1) model to test for the volatility spillover effect between the JSE and LSE.

The second step in the EGARCH process includes estimating both Equations 3.34 and 3.36[109], which are reported in Table 4.11.

Table 4.11: EGARCH(1,1) model output

RETURN EQUATION			
VARIABLE	**COEFFICIENT**	***Z*-STATISTIC**	**PROBABILITY**
$\emptyset_i$	0.24*	10.29	0.00*
VARIANCE EQUATION			
VARIABLE	**COEFFICIENT**	***Z*-STATISTIC**	**PROBABILITY**
$\boldsymbol{\theta_0}$	21.39*	191.64	0.00*
$\boldsymbol{\theta_1}$	-0.08*	-4.33	0.00*
$\boldsymbol{\gamma}$	0.03*	2.43	0.02*
$\boldsymbol{\beta}$	-0.99*	-129.31	0.00*
DESCRIPTIVE STATISTICS			
Durbin-Watson	2.23		
AIC	13.56	**Schwarz Criterion (SIC)**	13.60
R^2	0.09	**Adjusted R^2**	0.09

**Statistically significant at the 99% level.*
Model assumption: Asymmetric order of one.
Source: Compiled by author

Results from Table 4.11 indicate that all the variables are statistically significant at the 99% level. The first important coefficient, θ_1 in Equation 3.36, is statistically significant, indicating that a volatility spillover effect is present between the JSE and LSE. The second coefficient of importance is the γ parameter in Equation 3.36, which measures the asymmetry or the leverage effect of volatility. If $\gamma = 0$, the model is symmetric, whereas, if $\gamma < 0$, negative shocks (bad news) generate more volatility than positive shocks (good news). If $\gamma > 0$, positive shocks (good news) will have a greater impact on volatility than negative shocks (bad news). The results from

[108] The correlogram and Ljung-Box Q statistic are reported in Figure G.1 in Appendix G.

[109] The model was also estimated with a structural dummy included into the model. The dummy was found not to be statistically significant and is reported in Figure H.2 in the appendix.

Table 4.11 report that γ is greater than zero, implying that the volatility of the Anglo American Plc. stock prices on the JSE has a greater reaction to positive shocks (good news) than to negative shocks (bad news). Furthermore, the β coefficient in Equation 3.36, which is the autoregressive term on lagged conditional volatility, reflects the weight given to previous periods' conditional volatility in the conditional volatility at time t. Table 4.11 reports that the coefficient is close to one, indicating that the volatility on the JSE will remain in the market for an extended period and that the market will converge to the steady state at a slow pace.

In addition to the output from the EGARCH(1,1), the residuals of the model were tested for any remaining ARCH effects by employing the Lagrange Multiplier (LM) test[110,111]. The null hypothesis of homoskedasticity was not rejected, illustrating that no remaining ARCH effects were present. The residuals were also tested for a unit root by employing an ADF test. The null hypothesis of a unit root was rejected, implying that there was no unit root present. The null hypothesis of a normal distribution was, however, rejected which is similar to the results found by Lynch *et al.* (2004:57) and Chang (2009:5) who also rejected the null hypothesis of a unit root.

To conclude the EGARCH analysis, a conditional variance series was generated and incorporated into a VEC model in order to confirm the significance of the existing volatility spillover effect and is reported in Table 4.12. The conditional variance, which can be considered as a measure for expected changing stock price volatility on the JSE, indicates the statistically significant dependence on past stock price movements on the LSE. These results also justify the statistically significant long-run convergence presence between the JSE and LSE.

[110] In mathematical optimization, the method of Lagrange multipliers provides a strategy for finding the local maxima and minima of a function subject to equality constraints (QMS, 2007:107).
[111] The results of the heteroskedasticity test are reported in Figure F.1 in Appendix F.

Table 4.12: Vector Error Correction (VEC) model with a conditional variance series

LAGS:2	LONG-RUN COEFFICIENT	t-statistic (LONG-RUN COEFFICIENT β)	SPEED OF ADJUSTMENT (α)	t-statistic (α)	Adjusted R^2	R^2
JSE	1	-	-0.02	[-2.22]*	0.40	0.41
LSE	-1.12	[-13.56]*	-0.01	[-0.67]	0.03	0.41
CONDITIONAL VARIANCE SERIES	-0.19	[-4.83]*	0.89	[4.42]*	0.98	0.99

Model assumption: Intercept and trend were allowed in cointegration equation, but not in VAR, with a 2 lag interval.
**Statistically significant at the 1% level.*
Source: Compiled by author

To summarise; the EGARCH model was estimated as the final measure to elaborate on the volatility spillover effect between the JSE and LSE and to provide additional information regarding the influential strength that the two markets have on each other. The results from the EGARCH(1,1) model identified the presence of a volatility spillover effect between the JSE and LSE. The results on the asymmetry effect reported that stock prices on the JSE have a greater reaction to positive shocks than to negative shocks. Furthermore, when a volatility spillover occurs, the volatility persistence on the JSE will remain for an extended period, converging to the steady state at a slow pace.

4.8 CHAPTER SUMMARY

The purpose of this chapter was to establish the existence of co-movement between the JSE and LSE. The presence of co-movement facilitates the influential effect that the two markets have on each other. This influential effect was measured in terms of a volatility spillover effect between the JSE and LSE, based on the price differences of a dual-listed stock.

To initialise the analysis, the first measure of co-movement, namely the Johansen (1991) cointegration test, was estimated. The results indicated the presence of a long-run cointegrating relationship between the two markets, emphasising the presence of co-movement between the markets. The Vector Error Correction (VEC) model elaborated on this long-run relationship by reporting that when a volatility spillover occurs from the LSE onto the JSE market, it takes approximately two days for the JSE to recover and return to its equilibrium price level (Section 4.4.2). The VEC also suggested that the long-run impact from the LSE on the JSE is greater than unity. The second measure of co-movement was the direction of causality and was estimated to determine the origin of the volatility spillover effect. Results from both the Sims (1972) and the Granger (1969) causality tests also indicated that co-movement is present between the two international markets. The co-movement originates in the LSE (primary market) and spills over to the JSE (secondary market).

With the presence of co-movement established between the two markets, the next step was to initiate a further investigation into measuring the volatility spillover effect on the JSE. The results from the Variance Decomposition (VDC) model reported that the impact from the LSE on the JSE was less than unity. These results suggested that the "own shocks" of the JSE were the dominant cause for the volatility of the Anglo American Plc. stock price over the estimated period (Section 4.6). In addition to the VDC model, the EGARCH(1,1) model justified the presence of a volatility spillover effect between the JSE and LSE (Section 4.7). Evidence of a significant level of volatility persistence was found to be present in the JSE market. Furthermore, stock prices on the JSE were found to have a greater reaction to positive shocks than to negative shocks. To conclude the EGARCH analysis, a conditional variance series was also generated and incorporated into a VEC model in order to confirm the significance of the existing volatility spillover effect. The conditional variance indicated the statistically significant dependence on past stock price movements on the LSE. These results also justify the statistically significant long-run convergence presence between the JSE and LSE.

These results, therefore, confirm the influential effect that stock price movements on the LSE have on the stock price behaviour of the JSE. In conclusion, these results justify the usage of LSE dual-listed stock price movements as a partial indicator that can be consulted in the decision-making processes of investing in JSE dual-listed stocks. The following chapter will provide concluding remarks and suggestions for this study.

CHAPTER 5

Conclusion

"Ask five economists and you'll get five different answers."

— Edgar R Fiedler

5.1 INTRODUCTION

This study posed the following research question: Can LSE dual-listed stock price volatility be utilised as an indicator for determining expected JSE dual-listed stocks price movements? The goal of this study was, therefore, to examine the volatility spillover effect of a dual-listed stock between two international markets, based on the price difference of dual-listed stocks, which can assist the future decision-making processes of portfolio managers.

This chapter will commence with a brief summary on how the goal of the study was achieved, by providing a broad review of the literature study and of the results found in the empirical study (Section 5.2). This chapter will conclude with recommendations for future studies (Section 5.3).

5.2 STUDY REVIEW: LITERATURE AND EMPIRICAL RESULTS

The 2008 financial crisis caused a dramatic increase in volatility in world markets, which further escalated in the post-crisis period. The increased volatility in stock price movements posed a threat to portfolio managers, because it can affect the returns of the overall stock portfolio. Minimising the negative effect of increased volatility implied that portfolio managers had to rethink their diversification strategies. This study proposed a possible diversification instrument, which used the dual-listed stock price volatility in the LSE to determine possible buy opportunities in the JSE. Dual-listed stocks were the ideal assets for this strategy, because dual-listed stocks are exposed to volatility fluctuations of more than one market (Section 2.2), which can be exploited to ensure more significant portfolio diversification.

However, before stock price volatility could be examined, a better understanding had to be provided regarding the price composition of dual-listed stocks (Section 2.1). It is important to understand the formulation of a stock price before the movement of stock prices could be understood. Factors that were examined that influence the composition of a dual-listed stock price included index exposure (Section 2.2.3.1), geographical risk (Section 2.2.3.2), local markets (Section 2.2.3.3), regional legislation (Section 2.2.3.4), arbitrage effects (Section 2.2.3.5), and regional broker expectations (Section 2.2.3.6). In addition to these factors, the information flow and the efficient market hypothesis (Section 2.3), risks associated with the stock (Section 2.4), the required rate of return (Section 2.5.1.2), and the risk preference of the investor (Section 2.4.1.3) were also discussed.

However, the focus of this study was on dual-listed stock price movements due to volatility spillovers. Dual-listed stock prices should grow at the same rates in their separate markets, as emphasised by the single market hypothesis (Section 2.1); however, evidence indicated the presence of a dual-listed stock price differential between the JSE and LSE (see for example Figures 4.1 & 4.2). This led to Chapter 3, where volatility spillovers were investigated as the reason for the dual-listed stock price differential. Chapter 3 commenced by examining the concept of volatility (Section 3.2), which was followed by an examination of the transference of volatility spillovers between markets. This entailed investigating the concept of co-movement (Section 3.3) and the volatility spillover effect (Section 3.3.6). Historical studies on co-movement and the volatility spillover effect were examined in order to determine the most appropriate models to measure the presence of co-movement and a volatility spillover effect between the JSE and LSE, which were discussed in Section 3.4.

To build on the previous chapter, the empirical study in Chapter 4 reported the results found on the presence of co-movement and the volatility spillover effect between the JSE and LSE. The Johansen (1991) cointegration test was used as the first measure to establish the presence of co-movement. Results indicated the presence of a long-run cointegration relationship present between the JSE and LSE over the estimated period[112], which indicates the presence of co-movement (Section 4.4). The Johansen (1991) cointegration analysis was followed by the Vector Error Correction (VEC) model, which further confirmed the presence of co-movement. Evidence from the VEC model illustrated that it will take approximately two days to eliminate the presence of disequilibrium between the JSE and LSE. The second measure of co-movement that was used included the Sims (1972) and Granger (1969) causality tests, which justified that co-movement was present between the JSE and LSE, illustrating that volatility spillovers will originate in the LSE and will spill over into the JSE (Section 4.5).

With the presence of co-movement established between the JSE and LSE, the next step was to examine the extent of the volatility spillover effect between the two markets. The two measures that were used included the Variance Decomposition (VDC) model (Section 4.6) and the EGARCH model (Section 4.7). The results from the VDC model reported that the impact from the LSE on the JSE was less than unity. These results further suggested that the "own shocks[113]" of the JSE were the dominant cause for the volatility of the Anglo American Plc. stock price over the estimated period (Section 4.6). In addition to the VDC model, the EGARCH(1,1) model justified the presence of a volatility spillover effect between the JSE and LSE (Section 4.7). Evidence of a significant level of volatility persistence was also found to be present in the JSE market. Further evidence reported that stock prices on the JSE had a greater reaction to positive shocks than to negative shocks. The conditional variance of the EGARCH model also indicated the statistically significant dependence on past stock price movements on the LSE, which justifies the statistically significant long-run convergence present between the JSE and LSE. These results, therefore, confirmed the influential effect that stock price movements on the LSE have on the stock price behaviour of the JSE.

[112] The period mentioned ranges from 14 October 2009 to 4 February 2010.
[113] "Own shocks" refer to endogenous variables in the market which lead to market fluctuations.

5.3 CONCLUSION

This study obtained substantial clarification regarding the volatility spillover effect between the JSE and LSE. By using the price differences of a dual-listed stock, the presence of co-movement and of a volatility spillover effect was found between the JSE and LSE over the estimated period. The results from this study justified the usage of LSE dual-listed stock price movements as a partial indicator that can be consulted in the decision-making processes for investing in JSE dual-listed stocks. By effectively implementing this approach, the volatility spillover effect can be exploited, which can be implemented to ensure advanced international portfolio diversification in times of great market fluctuations.

5.4 FUTURE RESEARCH RECOMMENDATIONS

In addition to these results, the following recommendations may provide more insight into exploiting the volatility spillover effect. Incorporating a longer inter-day time series over the pre-financial crisis and for the post-financial crisis may provide additional insight into the extent of the exponential volatility changes as a result of the 2008 financial crisis. Besides examining volatility spillovers outside a portfolio, further studies could also focus on the possibilities of diversifying volatility spillovers within the portfolio, minimising correlation in terms of stock returns. This entails adapting diversification strategies in terms of examining the statistical characteristics of different stocks, which should be used to determine which shocks should be replaced in the portfolio, thereby minimising the standard deviation and covariance of a portfolio.

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APPENDIX A

Figure A.1 to A.8 presents the individual ADF tests on each variable in order to determine the presence of unit roots.

Figure A.1: Anglogold plc stock price on the JSE (in ZAR; Level form)

Null Hypothesis: JSEZAR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.237526	0.1933
Test critical values:	1% level	-3.441299	
	5% level	-2.866262	
	10% level	-2.569344	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(JSEZAR)
Method: Least Squares
Date: 08/04/11 Time: 15:32
Sample (adjusted): 10/14/2009 09:00 2/04/2010 14:00
Included observations: 585 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
JSEZAR(-1)	-0.010122	0.004524	-2.237526	0.0256
C	317.4760	140.1500	2.265258	0.0239

R-squared	0.008514	Mean dependent var	4.594872
Adjusted R-squared	0.006814	S.D. dependent var	228.4562
S.E. of regression	227.6766	Akaike info criterion	13.69714
Sum squared resid	30220752	Schwarz criterion	13.71209
Log likelihood	-4004.414	Hannan-Quinn criter.	13.70297
F-statistic	5.006521	Durbin-Watson stat	1.879483
Prob(F-statistic)	0.025629		

Source: Compiled by author from estimations in EViews 7 (QMS, 2009).

Figure A.2: Anglogold plc stock price on the JSE (in ZAR; 1st differenced form)

Null Hypothesis: D(JSEZAR) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.80731	0.0000
Test critical values:	1% level	-3.441318	
	5% level	-2.866270	
	10% level	-2.569348	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(JSEZAR,2)
Method: Least Squares
Date: 08/04/11 Time: 15:33
Sample (adjusted): 10/14/2009 10:00 2/04/2010 14:00
Included observations: 584 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(JSEZAR(-1))	-0.942583	0.041328	-22.80731	0.0000
C	3.845625	9.443351	0.407231	0.6840

R-squared	0.471953	Mean dependent var	-0.431507
Adjusted R-squared	0.471045	S.D. dependent var	313.7167
S.E. of regression	228.1639	Akaike info criterion	13.70142
Sum squared resid	30298196	Schwarz criterion	13.71639
Log likelihood	-3998.816	Hannan-Quinn criter.	13.70726
F-statistic	520.1736	Durbin-Watson stat	2.008570
Prob(F-statistic)	0.000000		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure A.3: Anglogold plc stock price on the LSE (in ZAR; Level form)

Null Hypothesis: LSEZAR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.653187	0.4547
Test critical values:	1% level	-3.441299	
	5% level	-2.866262	
	10% level	-2.569344	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LSEZAR)
Method: Least Squares
Date: 08/04/11 Time: 15:35
Sample (adjusted): 10/14/2009 09:00 2/04/2010 14:00
Included observations: 585 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSEZAR(-1)	-0.008809	0.005329	-1.653187	0.0988
C	244.7335	148.0609	1.652925	0.0989

R-squared	0.004666	Mean dependent var	0.503444
Adjusted R-squared	0.002959	S.D. dependent var	238.5951
S.E. of regression	238.2419	Akaike info criterion	13.78786
Sum squared resid	33090614	Schwarz criterion	13.80281
Log likelihood	-4030.950	Hannan-Quinn criter.	13.79369
F-statistic	2.733027	Durbin-Watson stat	2.006120
Prob(F-statistic)	0.098831		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure A.4: Anglogold plc stock price on the LSE (in ZAR; 1st differenced form)

Null Hypothesis: D(LSEZAR) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.47117	0.0000
Test critical values:	1% level	-3.441318	
	5% level	-2.866270	
	10% level	-2.569348	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LSEZAR,2)
Method: Least Squares
Date: 08/04/11 Time: 15:36
Sample (adjusted): 10/14/2009 10:00 2/04/2010 14:00
Included observations: 584 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LSEZAR(-1))	-1.012163	0.041361	-24.47117	0.0000
C	-0.309312	9.854777	-0.031387	0.9750

R-squared	0.507130	Mean dependent var	-1.349686
Adjusted R-squared	0.506283	S.D. dependent var	338.9301
S.E. of regression	238.1492	Akaike info criterion	13.78709
Sum squared resid	33008160	Schwarz criterion	13.80206
Log likelihood	-4023.830	Hannan-Quinn criter.	13.79292
F-statistic	598.8384	Durbin-Watson stat	1.991930
Prob(F-statistic)	0.000000		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure A.5: Anglogold plc stock price on the LSE (in USD; Level form)

Null Hypothesis: LSEUSD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.665456	0.4484
Test critical values:	1% level	-3.441299	
	5% level	-2.866262	
	10% level	-2.569344	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LSEUSD)
Method: Least Squares
Date: 08/04/11 Time: 15:37
Sample (adjusted): 10/14/2009 09:00 2/04/2010 14:00
Included observations: 585 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSEUSD(-1)	-0.008137	0.004885	-1.665456	0.0964
C	20.75481	12.39451	1.674516	0.0946

R-squared	0.004735	Mean dependent var	0.169231
Adjusted R-squared	0.003028	S.D. dependent var	22.28412
S.E. of regression	22.25035	Akaike info criterion	9.046006
Sum squared resid	288630.6	Schwarz criterion	9.060951
Log likelihood	-2643.957	Hannan-Quinn criter.	9.051830
F-statistic	2.773743	Durbin-Watson stat	1.896542
Prob(F-statistic)	0.096359		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure A.6: Anglogold plc stock price on the LSE (in USD; 1st differenced form)

Null Hypothesis: D(LSEUSD) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-23.09286	0.0000
Test critical values:	1% level	-3.441318	
	5% level	-2.866270	
	10% level	-2.569348	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LSEUSD,2)
Method: Least Squares
Date: 08/04/11 Time: 15:38
Sample (adjusted): 10/14/2009 10:00 2/04/2010 14:00
Included observations: 584 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LSEUSD(-1))	-0.955162	0.041362	-23.09286	0.0000
C	0.094740	0.920535	0.102918	0.9181

R-squared	0.478158	Mean dependent var	-0.112158
Adjusted R-squared	0.477261	S.D. dependent var	30.76692
S.E. of regression	22.24468	Akaike info criterion	9.045502
Sum squared resid	287988.7	Schwarz criterion	9.060467
Log likelihood	-2639.287	Hannan-Quinn criter.	9.051335
F-statistic	533.2803	Durbin-Watson stat	1.992634
Prob(F-statistic)	0.000000		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure A.7: ZAR/USD exchange rate (Level form)

Null Hypothesis: ZAR_USD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.759415	0.8291
Test critical values:	1% level	-3.441299	
	5% level	-2.866262	
	10% level	-2.569344	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ZAR_USD)
Method: Least Squares
Date: 08/04/11 Time: 15:38
Sample (adjusted): 10/14/2009 09:00 2/04/2010 14:00
Included observations: 585 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ZAR_USD(-1)	-0.003262	0.004295	-0.759415	0.4479
C	0.035209	0.047127	0.747114	0.4553

R-squared	0.000988	Mean dependent var	-0.000567
Adjusted R-squared	-0.000725	S.D. dependent var	0.030379
S.E. of regression	0.030390	Akaike info criterion	-4.145993
Sum squared resid	0.538431	Schwarz criterion	-4.131047
Log likelihood	1214.703	Hannan-Quinn criter.	-4.140168
F-statistic	0.576712	Durbin-Watson stat	2.149946
Prob(F-statistic)	0.447911		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure A.8: ZAR/USD exchange rate (1st differenced form)

Null Hypothesis: D(ZAR_USD) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-26.12074	0.0000
Test critical values:	1% level	-3.441318	
	5% level	-2.866270	
	10% level	-2.569348	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ZAR_USD,2)
Method: Least Squares
Date: 08/04/11 Time: 15:39
Sample (adjusted): 10/14/2009 10:00 2/04/2010 14:00
Included observations: 584 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(ZAR_USD(-1))	-1.078420	0.041286	-26.12074	0.0000
C	-0.000665	0.001254	-0.530376	0.5961

R-squared	0.539664	Mean dependent var	-6.64E-05
Adjusted R-squared	0.538873	S.D. dependent var	0.044633
S.E. of regression	0.030308	Akaike info criterion	-4.151362
Sum squared resid	0.534626	Schwarz criterion	-4.136397
Log likelihood	1214.198	Hannan-Quinn criter.	-4.145530
F-statistic	682.2929	Durbin-Watson stat	1.993999
Prob(F-statistic)	0.000000		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

APPENDIX B

Figures B.1 to B.8 presents the corellograms and partial correlograms for the stocks and the exchange rates in this study. The asterisks represent the degree of autocorrelation: the more asterisks the greater the degree of autocorrelation.

Figure B.1: Correlogram and partial correlogram (Anglogold plc in ZAR on the JSE)

Date: 08/04/11 Time: 16:37
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 586

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|*******</td><td>.|*******</td><td>1</td><td>0.987</td><td>0.987</td><td>574.27</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>2</td><td>0.975</td><td>-0.012</td><td>1134.8</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>3</td><td>0.962</td><td>0.001</td><td>1681.9</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>4</td><td>0.949</td><td>-0.025</td><td>2215.3</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>5</td><td>0.935</td><td>-0.046</td><td>2733.9</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>6</td><td>0.922</td><td>0.021</td><td>3238.7</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>7</td><td>0.909</td><td>-0.004</td><td>3730.0</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>8</td><td>0.897</td><td>0.054</td><td>4209.6</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>9</td><td>0.886</td><td>0.030</td><td>4678.4</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>10</td><td>0.875</td><td>-0.032</td><td>5136.0</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>11</td><td>0.863</td><td>-0.004</td><td>5582.5</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>12</td><td>0.852</td><td>-0.017</td><td>6018.1</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>13</td><td>0.840</td><td>-0.011</td><td>6442.5</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>14</td><td>0.828</td><td>-0.007</td><td>6855.9</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>15</td><td>0.816</td><td>-0.013</td><td>7258.2</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>16</td><td>0.805</td><td>0.003</td><td>7649.5</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>17</td><td>0.794</td><td>0.057</td><td>8031.7</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>18</td><td>0.784</td><td>0.006</td><td>8405.0</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>19</td><td>0.776</td><td>0.041</td><td>8770.7</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>20</td><td>0.767</td><td>-0.003</td><td>9128.9</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>21</td><td>0.758</td><td>-0.024</td><td>9479.5</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>22</td><td>0.749</td><td>-0.015</td><td>9822.3</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>*|. |</td><td>23</td><td>0.738</td><td>-0.068</td><td>10156.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>24</td><td>0.727</td><td>-0.016</td><td>10480.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>25</td><td>0.716</td><td>-0.013</td><td>10795.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>26</td><td>0.705</td><td>0.039</td><td>11101.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>27</td><td>0.695</td><td>0.022</td><td>11399.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>28</td><td>0.685</td><td>0.001</td><td>11689.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>29</td><td>0.676</td><td>0.016</td><td>11972.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>30</td><td>0.667</td><td>-0.028</td><td>12248.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>31</td><td>0.659</td><td>0.021</td><td>12517.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>32</td><td>0.649</td><td>-0.034</td><td>12779.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|* |</td><td>33</td><td>0.642</td><td>0.079</td><td>13036.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>34</td><td>0.635</td><td>-0.001</td><td>13288.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>35</td><td>0.627</td><td>-0.025</td><td>13533.</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>36</td><td>0.619</td><td>0.009</td><td>13773.</td><td>0.000</td></tr>
</table>

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure B.2: Correlogram and partial correlogram (Anglogold plc in ZAR on the JSE; first differenced form)

Date: 08/04/11 Time: 16:38
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 585

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.057	0.057	1.9384	0.164
.|. |	.|. |	2	0.059	0.056	3.9925	0.136
.|. |	.|. |	3	0.012	0.006	4.0813	0.253
.|. |	.|. |	4	0.071	0.067	7.0576	0.133
.|. |	.|. |	5	-0.017	-0.026	7.2330	0.204
.|. |	.|. |	6	0.005	0.000	7.2500	0.298
*|. |	*|. |	7	-0.098	-0.098	12.991	0.072
.|. |	.|. |	8	-0.008	-0.002	13.028	0.111
.|. |	.|. |	9	0.001	0.015	13.029	0.161
.|. |	.|. |	10	0.052	0.053	14.615	0.147
.|. |	.|. |	11	-0.014	-0.007	14.736	0.195
.|. |	.|. |	12	-0.002	-0.010	14.737	0.256
.|. |	.|. |	13	-0.025	-0.026	15.105	0.301
.|. |	.|. |	14	-0.024	-0.038	15.441	0.349
.|. |	.|. |	15	-0.009	-0.001	15.489	0.417
*|. |	*|. |	16	-0.075	-0.071	18.856	0.276
.|. |	.|. |	17	0.010	0.034	18.915	0.333
*|. |	*|. |	18	-0.093	-0.089	24.186	0.149
.|. |	.|. |	19	-0.046	-0.039	25.473	0.146
.|. |	.|. |	20	-0.031	-0.017	26.064	0.164
.|. |	.|. |	21	0.003	0.002	26.070	0.204
.|* |	.|* |	22	0.110	0.132	33.437	0.056
.|. |	.|. |	23	-0.007	-0.031	33.467	0.073
.|. |	.|. |	24	0.042	0.045	34.540	0.076
.|. |	.|. |	25	0.012	-0.016	34.626	0.095
.|. |	.|. |	26	-0.027	-0.052	35.060	0.110
.|. |	.|. |	27	0.016	0.018	35.218	0.133
.|. |	.|. |	28	-0.040	-0.040	36.195	0.138
.|. |	.|. |	29	0.016	0.051	36.350	0.164
.|. |	.|. |	30	-0.046	-0.051	37.672	0.158
.|* |	.|* |	31	0.074	0.084	41.102	0.106
*|. |	*|. |	32	-0.069	-0.102	44.016	0.077
.|. |	.|. |	33	-0.014	-0.017	44.141	0.093
.|. |	.|. |	34	0.033	0.035	44.821	0.101
.|. |	.|. |	35	0.009	-0.009	44.876	0.122
.|. |	.|. |	36	-0.027	-0.001	45.349	0.137

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure B.3: Correlogram and partial correlogram (Anglogold plc in ZAR on the JSE)

Date: 08/04/11 Time: 16:39
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 586

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*******	.|*******	1	0.986	0.986	572.80	0.000
.|*******	.|. |	2	0.974	0.048	1132.3	0.000
.|*******	.|. |	3	0.961	-0.019	1678.2	0.000
.|*******	.|. |	4	0.949	-0.000	2210.9	0.000
.|*******	.|. |	5	0.935	-0.041	2729.3	0.000
.|*******	.|. |	6	0.922	0.011	3234.4	0.000
.|*******	.|. |	7	0.909	0.007	3726.6	0.000
.|******|	.|* |	8	0.899	0.081	4208.5	0.000
.|******|	.|. |	9	0.887	-0.060	4678.6	0.000
.|******|	.|. |	10	0.877	0.046	5138.5	0.000
.|******|	.|. |	11	0.865	-0.054	5586.8	0.000
.|******|	.|. |	12	0.853	-0.020	6023.7	0.000
.|******|	.|. |	13	0.841	-0.023	6448.6	0.000
.|******|	.|. |	14	0.828	-0.029	6861.2	0.000
.|******|	.|. |	15	0.816	0.049	7262.8	0.000
.|******|	.|. |	16	0.805	0.012	7654.2	0.000
.|******|	.|. |	17	0.794	0.028	8036.1	0.000
.|******|	.|. |	18	0.784	0.016	8409.3	0.000
.|******|	.|. |	19	0.775	0.011	8774.4	0.000
.|******|	.|. |	20	0.766	0.010	9131.9	0.000
.|***** |	.|. |	21	0.757	-0.026	9481.4	0.000
.|***** |	.|. |	22	0.748	-0.000	9822.9	0.000
.|***** |	.|. |	23	0.738	-0.030	10156.	0.000
.|***** |	.|. |	24	0.726	-0.048	10479.	0.000
.|***** |	.|. |	25	0.716	0.027	10794.	0.000
.|***** |	.|. |	26	0.706	0.002	11101.	0.000
.|***** |	.|. |	27	0.695	-0.024	11398.	0.000
.|***** |	.|. |	28	0.684	-0.004	11687.	0.000
.|***** |	.|. |	29	0.674	-0.007	11968.	0.000
.|***** |	.|. |	30	0.664	0.020	12242.	0.000
.|***** |	.|. |	31	0.654	-0.046	12507.	0.000
.|***** |	.|. |	32	0.645	0.062	12766.	0.000
.|***** |	.|. |	33	0.635	-0.021	13017.	0.000
.|***** |	.|. |	34	0.626	0.002	13261.	0.000
.|**** |	.|. |	35	0.616	-0.014	13498.	0.000
.|**** |	.|. |	36	0.606	-0.001	13728.	0.000

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure B.4: Correlogram and partial correlogram (Anglogold plc in ZAR on the JSE; first differenced form)

Date: 08/04/11 Time: 16:39
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 585

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.012	-0.012	0.0866	0.769
.|. |	.|. |	2	0.002	0.001	0.0882	0.957
.|. |	.|. |	3	0.002	0.002	0.0908	0.993
.|. |	.|. |	4	0.031	0.031	0.6426	0.958
.|. |	.|. |	5	-0.042	-0.041	1.6710	0.893
.|. |	.|. |	6	0.002	0.001	1.6733	0.947
.|. |	.|. |	7	-0.032	-0.032	2.2662	0.944
.|. |	.|. |	8	0.021	0.019	2.5190	0.961
.|. |	.|. |	9	-0.026	-0.023	2.9086	0.968
.|. |	.|. |	10	0.070	0.068	5.8226	0.830
.|. |	.|. |	11	-0.011	-0.008	5.8934	0.880
.|. |	.|. |	12	0.019	0.015	6.1033	0.911
.|. |	.|. |	13	-0.004	-0.002	6.1145	0.942
.|. |	.|. |	14	-0.024	-0.031	6.4700	0.953
.|. |	.|. |	15	-0.054	-0.048	8.2115	0.915
.|. |	.|. |	16	-0.029	-0.033	8.7018	0.925
*|. |	.|. |	17	-0.066	-0.060	11.327	0.839
.|. |	.|. |	18	-0.013	-0.016	11.425	0.875
*|. |	.|. |	19	-0.068	-0.064	14.209	0.771
.|. |	.|. |	20	0.010	0.001	14.267	0.817
.|. |	.|. |	21	-0.001	-0.000	14.268	0.858
.|. |	.|. |	22	0.015	0.008	14.409	0.886
.|. |	.|. |	23	0.029	0.032	14.938	0.897
.|. |	.|. |	24	0.030	0.026	15.501	0.905
.|. |	.|. |	25	-0.014	-0.006	15.626	0.926
.|. |	.|. |	26	0.023	0.021	15.946	0.937
.|. |	.|. |	27	0.007	0.018	15.978	0.953
.|. |	.|. |	28	0.002	0.001	15.980	0.966
.|. |	.|. |	29	-0.056	-0.047	17.944	0.945
.|. |	.|. |	30	0.043	0.035	19.077	0.938
.|. |	.|. |	31	-0.011	-0.015	19.157	0.952
.|. |	.|. |	32	0.048	0.040	20.611	0.940
.|. |	.|. |	33	-0.043	-0.052	21.762	0.933
.|. |	.|. |	34	0.015	-0.006	21.902	0.946
.|. |	.|. |	35	-0.007	-0.010	21.937	0.958
.|. |	.|. |	36	0.033	0.017	22.598	0.960

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure B.5: Correlogram and partial correlogram (Anglogold plc in USD on the LSE)

Date: 08/04/11 Time: 16:39
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 586

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|*******</td><td>.|*******</td><td>1</td><td>0.990</td><td>0.990</td><td>577.45</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>2</td><td>0.980</td><td>0.003</td><td>1144.6</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>3</td><td>0.970</td><td>-0.017</td><td>1701.3</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>4</td><td>0.960</td><td>-0.021</td><td>2247.2</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>5</td><td>0.949</td><td>-0.031</td><td>2781.8</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>6</td><td>0.939</td><td>-0.000</td><td>3305.4</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>7</td><td>0.928</td><td>0.002</td><td>3818.3</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|* |</td><td>8</td><td>0.919</td><td>0.083</td><td>4322.3</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>*|. |</td><td>9</td><td>0.909</td><td>-0.067</td><td>4816.1</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>10</td><td>0.900</td><td>0.046</td><td>5301.1</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>11</td><td>0.890</td><td>-0.062</td><td>5776.1</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>12</td><td>0.880</td><td>-0.020</td><td>6240.9</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>13</td><td>0.869</td><td>-0.018</td><td>6695.4</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>14</td><td>0.859</td><td>-0.016</td><td>7139.4</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>15</td><td>0.849</td><td>0.073</td><td>7574.4</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>16</td><td>0.840</td><td>0.017</td><td>8001.1</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>17</td><td>0.832</td><td>0.053</td><td>8420.3</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>18</td><td>0.825</td><td>0.019</td><td>8833.0</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>19</td><td>0.818</td><td>0.020</td><td>9239.7</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>20</td><td>0.812</td><td>0.019</td><td>9641.0</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>21</td><td>0.805</td><td>-0.033</td><td>10036.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>22</td><td>0.798</td><td>-0.004</td><td>10426.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>23</td><td>0.791</td><td>-0.032</td><td>10809.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>24</td><td>0.782</td><td>-0.063</td><td>11184.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>25</td><td>0.774</td><td>0.017</td><td>11552.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>26</td><td>0.766</td><td>0.005</td><td>11912.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>27</td><td>0.758</td><td>-0.004</td><td>12266.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>28</td><td>0.750</td><td>-0.010</td><td>12613.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>29</td><td>0.742</td><td>-0.001</td><td>12953.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>30</td><td>0.734</td><td>0.013</td><td>13287.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>31</td><td>0.726</td><td>-0.037</td><td>13615.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>32</td><td>0.719</td><td>0.068</td><td>13936.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>33</td><td>0.712</td><td>-0.009</td><td>14251.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>34</td><td>0.704</td><td>0.010</td><td>14561.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>35</td><td>0.697</td><td>-0.015</td><td>14865.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>36</td><td>0.689</td><td>-0.015</td><td>15162.</td><td>0.000</td></tr>
</table>

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure B.6: Correlogram and partial correlogram (Anglogold plc in USD on the LSE; first differenced form)

Date: 08/04/11 Time: 16:40
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 585

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.045	0.045	1.1756	0.278
.|. |	.|. |	2	0.002	-0.000	1.1770	0.555
.|. |	.|. |	3	0.037	0.037	1.9782	0.577
.|. |	.|. |	4	0.024	0.020	2.3097	0.679
.|. |	.|. |	5	-0.015	-0.017	2.4354	0.786
.|. |	.|. |	6	0.010	0.010	2.4960	0.869
.|. |	.|. |	7	-0.048	-0.050	3.8453	0.797
.|. |	.|. |	8	0.019	0.025	4.0708	0.851
.|. |	.|. |	9	-0.019	-0.021	4.2847	0.892
.|. |	.|. |	10	0.061	0.067	6.5357	0.768
.|. |	.|. |	11	0.002	-0.003	6.5379	0.835
.|. |	.|. |	12	0.007	0.006	6.5676	0.885
.|. |	.|. |	13	-0.017	-0.020	6.7403	0.915
.|. |	*|. |	14	-0.065	-0.070	9.2429	0.815
.|. |	.|. |	15	-0.040	-0.031	10.228	0.805
*|. |	*|. |	16	-0.071	-0.072	13.248	0.655
*|. |	.|. |	17	-0.073	-0.054	16.476	0.490
.|. |	.|. |	18	-0.028	-0.022	16.954	0.526
*|. |	.|. |	19	-0.071	-0.063	20.036	0.392
.|. |	.|. |	20	0.017	0.025	20.220	0.444
.|. |	.|. |	21	0.014	0.009	20.336	0.500
.|. |	.|. |	22	0.016	0.020	20.498	0.552
.|. |	.|. |	23	0.047	0.044	21.865	0.528
.|. |	.|. |	24	0.045	0.044	23.098	0.514
.|. |	.|. |	25	-0.018	-0.017	23.294	0.560
.|. |	.|. |	26	-0.005	-0.005	23.306	0.616
.|. |	.|. |	27	0.010	0.016	23.368	0.665
.|. |	.|. |	28	0.003	-0.003	23.373	0.714
.|. |	.|. |	29	-0.039	-0.034	24.330	0.712
.|. |	.|. |	30	0.024	0.014	24.674	0.741
.|. |	.|. |	31	-0.010	-0.025	24.731	0.780
.|. |	.|. |	32	0.027	0.013	25.176	0.799
.|. |	.|. |	33	-0.026	-0.052	25.603	0.817
.|. |	.|. |	34	0.004	-0.007	25.615	0.849
.|. |	.|. |	35	0.012	0.004	25.700	0.874
.|. |	.|. |	36	0.041	0.037	26.741	0.869

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure B.7: Correlogram and partial correlogram (ZAR/USD exchange rate)

Date: 08/04/11 Time: 16:40
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 586

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|*******</td><td>.|*******</td><td>1</td><td>0.992</td><td>0.992</td><td>579.69</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>2</td><td>0.985</td><td>0.059</td><td>1152.3</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>3</td><td>0.978</td><td>-0.042</td><td>1717.0</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>4</td><td>0.970</td><td>-0.020</td><td>2273.8</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>5</td><td>0.961</td><td>-0.035</td><td>2822.0</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>6</td><td>0.953</td><td>-0.026</td><td>3361.5</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>7</td><td>0.944</td><td>-0.041</td><td>3891.5</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>8</td><td>0.934</td><td>-0.043</td><td>4411.6</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>9</td><td>0.925</td><td>0.017</td><td>4922.2</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>10</td><td>0.915</td><td>-0.029</td><td>5422.7</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>11</td><td>0.905</td><td>-0.006</td><td>5913.4</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>12</td><td>0.895</td><td>0.025</td><td>6394.7</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>13</td><td>0.885</td><td>-0.058</td><td>6865.7</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>14</td><td>0.875</td><td>-0.014</td><td>7326.5</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>15</td><td>0.864</td><td>0.007</td><td>7777.3</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>16</td><td>0.854</td><td>0.013</td><td>8218.4</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>17</td><td>0.844</td><td>-0.025</td><td>8649.5</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>18</td><td>0.833</td><td>-0.023</td><td>9070.6</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>19</td><td>0.823</td><td>0.033</td><td>9482.3</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>20</td><td>0.813</td><td>0.031</td><td>9885.2</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>21</td><td>0.804</td><td>-0.021</td><td>10279.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>22</td><td>0.794</td><td>-0.021</td><td>10664.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>23</td><td>0.783</td><td>-0.035</td><td>11039.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|* |</td><td>24</td><td>0.774</td><td>0.082</td><td>11406.</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>25</td><td>0.765</td><td>0.007</td><td>11766.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>26</td><td>0.756</td><td>-0.022</td><td>12117.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>27</td><td>0.746</td><td>-0.018</td><td>12460.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>28</td><td>0.737</td><td>-0.025</td><td>12796.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>29</td><td>0.727</td><td>-0.004</td><td>13123.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>30</td><td>0.718</td><td>0.026</td><td>13443.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>31</td><td>0.709</td><td>-0.003</td><td>13755.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>32</td><td>0.700</td><td>-0.032</td><td>14060.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>33</td><td>0.691</td><td>0.010</td><td>14357.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>34</td><td>0.682</td><td>0.029</td><td>14647.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>35</td><td>0.674</td><td>0.023</td><td>14931.</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>36</td><td>0.666</td><td>-0.007</td><td>15209.</td><td>0.000</td></tr>
</table>

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure B.8: Correlogram and partial correlogram (ZAR/USD exchange rate; first differenced form)

Date: 08/04/11 Time: 16:41
Sample: 10/14/2009 08:00 2/04/2010 14:00
Included observations: 585

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.078	-0.078	3.6155	0.057
.|. |	.|. |	2	0.039	0.033	4.5290	0.104
.|. |	.|. |	3	0.007	0.013	4.5593	0.207
.|. |	.|. |	4	0.017	0.017	4.7306	0.316
.|. |	.|. |	5	0.045	0.047	5.9177	0.314
.|. |	.|. |	6	0.029	0.035	6.4139	0.378
.|. |	.|. |	7	0.059	0.061	8.4852	0.292
.|. |	.|. |	8	-0.034	-0.029	9.1853	0.327
.|. |	.|. |	9	0.051	0.040	10.711	0.296
.|. |	.|. |	10	-0.023	-0.019	11.025	0.356
.|. |	.|. |	11	-0.033	-0.044	11.658	0.390
.|. |	.|. |	12	0.070	0.060	14.554	0.267
.|. |	.|. |	13	0.001	0.012	14.555	0.336
.|. |	.|. |	14	0.024	0.017	14.907	0.385
.|. |	.|. |	15	-0.024	-0.019	15.249	0.434
.|. |	.|. |	16	0.041	0.033	16.240	0.436
.|. |	.|. |	17	0.028	0.037	16.699	0.475
.|. |	.|. |	18	-0.056	-0.060	18.626	0.415
.|. |	.|. |	19	-0.037	-0.059	19.468	0.427
.|. |	.|. |	20	0.022	0.024	19.757	0.473
.|. |	.|. |	21	0.029	0.026	20.276	0.504
.|. |	.|. |	22	0.039	0.044	21.190	0.509
.|. |	.|. |	23	-0.024	-0.018	21.556	0.547
.|. |	.|. |	24	-0.010	-0.011	21.616	0.602
.|. |	.|. |	25	0.027	0.032	22.049	0.633
.|. |	.|. |	26	0.025	0.022	22.422	0.665
.|. |	.|. |	27	0.004	0.007	22.432	0.715
.|. |	.|. |	28	-0.020	-0.027	22.677	0.749
.|. |	.|. |	29	-0.024	-0.044	23.025	0.775
.|. |	.|. |	30	-0.013	-0.013	23.123	0.810
.|. |	.|. |	31	0.050	0.056	24.674	0.782
.|. |	.|. |	32	-0.034	-0.024	25.383	0.790
.|. |	.|. |	33	-0.040	-0.054	26.399	0.785
.|. |	.|. |	34	-0.006	-0.017	26.423	0.820
.|. |	.|. |	35	0.023	0.042	26.762	0.840
*|. |	*|. |	36	-0.072	-0.066	29.998	0.749

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

APPENDIX C

Figures C.1 to C.4 present the results obtained from the Sims (1972) causality tests. Figures C.1 and C.2 represent the unrestricted models, and Figures D.1 and D.2 represent the restricted models.

Figure C.1: Sims (1972) causality test results – unrestricted model (Anglogold plc JSE stock price as dependant variable)

Dependent Variable: DIFF_JSEZAR
Method: Least Squares
Date: 08/05/11 Time: 13:00
Sample (adjusted): 10/15/2009 08:00 2/04/2010 09:00
Included observations: 573 after adjustments
Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFF_LSEZAR	0.321881	0.029641	10.85931	0.0000
DIFF1_LSEZAR	0.556597	0.029505	18.86475	0.0000
DIFF2_LSEZAR	0.071557	0.029651	2.413291	0.0161
DIFF3_LSEZAR	0.014046	0.029658	0.473619	0.6360
DIFF4_LSEZAR	0.005951	0.029731	0.200167	0.8414
DIFF5_LSEZAR	0.047417	0.027242	1.740568	0.0823
DIFF1_LSEZARLEADING	0.071059	0.029890	2.377330	0.0178
DIFF2_LSEZARLEADING	-0.018810	0.029941	-0.628236	0.5301
DIFF3_LSEZARLEADING	0.030956	0.029962	1.033174	0.3020
DIFF4_LSEZARLEADING	0.001498	0.030003	0.049926	0.9602
DIFF5_LSEZARLEADING	-0.003558	0.027253	-0.130548	0.8962
C	3.579427	3.880988	0.922298	0.3568
AR(1)	-0.451718	0.041814	-10.80305	0.0000
AR(2)	-0.199737	0.041844	-4.773384	0.0000

R-squared	0.558678	Mean dependent var	4.301920
Adjusted R-squared	0.548415	S.D. dependent var	228.2425
S.E. of regression	153.3792	Akaike info criterion	12.92783
Sum squared resid	13150572	Schwarz criterion	13.03414
Log likelihood	-3689.824	Hannan-Quinn criter.	12.96930
F-statistic	54.43450	Durbin-Watson stat	2.033294
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.23-.39i	-.23+.39i

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure C.2: Sims (1972) causality test results – unrestricted model (Anglogold plc LSE stock price as dependant variable)

Dependent Variable: DIFF_LSEZAR
Method: Least Squares
Date: 08/05/11 Time: 13:33
Sample (adjusted): 10/15/2009 08:00 2/04/2010 09:00
Included observations: 573 after adjustments
Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFF_JSEZAR	0.313765	0.034712	9.039106	0.0000
DIFF1_JSEZAR	0.025507	0.034714	0.734774	0.4628
DIFF2_JSEZAR	-0.042694	0.034564	-1.235211	0.2173
DIFF3_JSEZAR	0.007388	0.034367	0.214960	0.8299
DIFF4_JSEZAR	-0.036324	0.034361	-1.057120	0.2909
DIFF5_JSEZAR	0.017251	0.030124	0.572653	0.5671
DIFF1_JSEZARLEADING	0.583518	0.034529	16.89913	0.0000
DIFF2_JSEZARLEADING	0.036871	0.034528	1.067878	0.2860
DIFF3_JSEZARLEADING	-0.034520	0.034412	-1.003120	0.3162
DIFF4_JSEZARLEADING	-0.004617	0.034412	-0.134173	0.8933
DIFF5_JSEZARLEADING	0.005218	0.030035	0.173725	0.8621
C	-3.248200	3.862962	-0.840857	0.4008
AR(1)	-0.499870	0.040931	-12.21236	0.0000
AR(2)	-0.254372	0.041469	-6.134024	0.0000

R-squared	0.552158	Mean dependent var	-0.545127
Adjusted R-squared	0.541743	S.D. dependent var	239.0970
S.E. of regression	161.8560	Akaike info criterion	13.03542
Sum squared resid	14644332	Schwarz criterion	13.14173
Log likelihood	-3720.648	Hannan-Quinn criter.	13.07689
F-statistic	53.01590	Durbin-Watson stat	2.036758
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.25+.44i	-.25-.44i

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure C.3: Sims (1972) causality test results – restricted model (Anglogold plc JSE stock price as dependant variable)

Dependent Variable: DIFF_JSEZAR
Method: Least Squares
Date: 08/23/11 Time: 11:19
Sample (adjusted): 10/14/2009 13:00 2/04/2010 13:00
Included observations: 580 after adjustments
Convergence achieved after 4 iterations
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFF_LSEZAR	0.315338	0.049604	6.357122	0.0000
DIFF1_LSEZAR	0.561651	0.046526	12.07186	0.0000
DIFF2_LSEZAR	0.083439	0.029670	2.812229	0.0051
DIFF1_LSEZARLEADING	0.067979	0.027184	2.500680	0.0127
C	3.247031	3.844249	0.844646	0.3987
AR(1)	-0.455641	0.050829	-8.964140	0.0000
AR(2)	-0.197444	0.045006	-4.387059	0.0000

R-squared	0.556388	Mean dependent var	3.551724
Adjusted R-squared	0.551743	S.D. dependent var	228.3460
S.E. of regression	152.8822	Akaike info criterion	12.90921
Sum squared resid	13392706	Schwarz criterion	12.96186
Log likelihood	-3736.670	Hannan-Quinn criter.	12.92974
F-statistic	119.7783	Durbin-Watson stat	2.051830
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.23-.38i	-.23+.38i

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure C.4: Sims (1972) causality test results – restricted model (Anglogold plc LSE stock price as dependant variable)

Dependent Variable: DIFF_LSEZAR
Method: Least Squares
Date: 08/23/11 Time: 12:24
Sample (adjusted): 10/14/2009 12:00 2/04/2010 13:00
Included observations: 581 after adjustments
Convergence achieved after 5 iterations
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFF_JSEZAR	0.310546	0.053949	5.756256	0.0000
DIFF1_JSEZAR	-0.003886	0.036945	-0.105192	0.9163
DIFF1_JSEZARLEADING	0.600782	0.057198	10.50348	0.0000
C	-2.961761	3.851322	-0.769025	0.4422
AR(1)	-0.498831	0.068126	-7.322198	0.0000
AR(2)	-0.251082	0.044178	-5.683455	0.0000

R-squared	0.546798	Mean dependent var	0.282050
Adjusted R-squared	0.542857	S.D. dependent var	238.0991
S.E. of regression	160.9844	Akaike info criterion	13.01076
Sum squared resid	14901679	Schwarz criterion	13.05584
Log likelihood	-3773.627	Hannan-Quinn criter.	13.02834
F-statistic	138.7499	Durbin-Watson stat	2.062981
Prob(F-statistic)	0.000000		

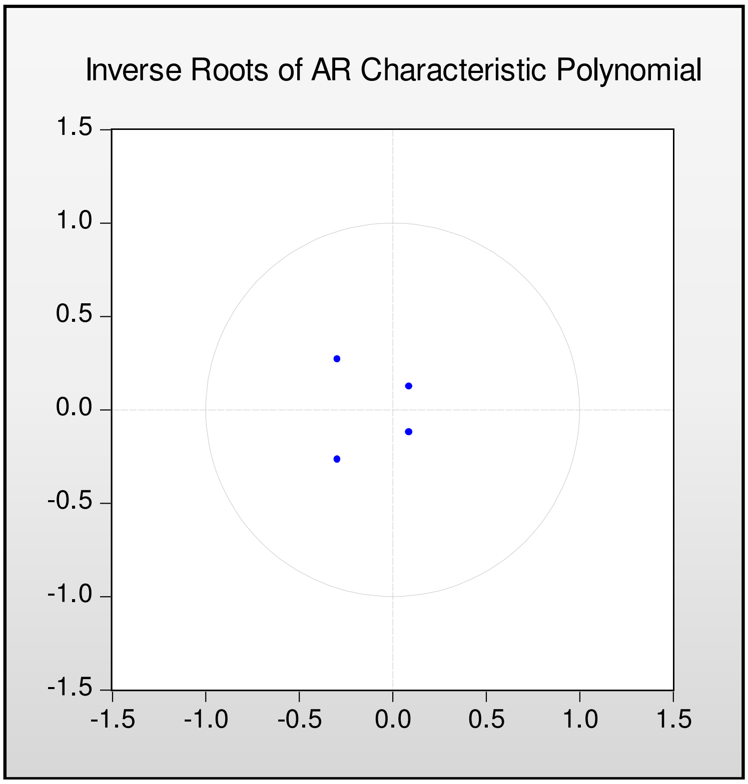
Inverted AR Roots	-.25+.43i	-.25-.43i

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

APPENDIX D

Figure D.1 represents the Graphical Vector Autoregressive (VAR) stability test results obtained from the cointegration approach.

Figure D.1: Inverse roots of AR Characteristic Polynomial



Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

APPENDIX E

Figure E.1 represents the results obtained from the VDC with LSE as the dependant variable.

Figure E.1: VDC test with LSE as the dependant variable

Variance Decomposition of DIFF_LSEZAR			
Period	S.E.	DIFF_LSEZAR	DIFF_JSEZAR
1	237.6452	100.0000	0.000000
2	238.7158	99.10917	0.890833
3	238.8481	98.99942	1.000577
4	238.8802	98.99565	1.004354
5	238.8920	98.99556	1.004436
6	238.8934	98.99523	1.004771
7	238.8935	98.99515	1.004846
8	238.8935	98.99515	1.004850
9	238.8935	98.99515	1.004850
10	238.8935	98.99515	1.004850
Variance Decomposition of DIFF_JSEZAR:			
Period	S.E.	DIFF_LSEZAR	DIFF_JSEZAR
1	175.7901	21.64387	78.35613
2	226.2033	46.93833	53.06167
3	228.0298	46.76460	53.23540
4	228.5865	47.00741	52.99259
5	228.6933	47.04974	52.95026
6	228.7052	47.05072	52.94928
7	228.7061	47.05040	52.94960
8	228.7063	47.05050	52.94950
9	228.7064	47.05053	52.94947
10	228.7064	47.05053	52.94947

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

APPENDIX F

Figure F.1 represents the results obtained from the heteroskedasticity test after he EGARCH was performed.

Figure F.1: Heteroskedasticity results (ARCH LM)

Heteroskedasticity Test: ARCH

F-statistic	0.487004	Prob. F(1,582)	0.4855
Obs*R-squared	0.488269	Prob. Chi-Square(1)	0.4847

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/17/11 Time: 18:56
Sample (adjusted): 10/14/2009 10:00 2/04/2010 14:00
Included observations: 584 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.966691	0.095342	10.13922	0.0000
WGT_RESID^2(-1)	0.028919	0.041439	0.697857	0.4855

R-squared	0.000836	Mean dependent var	0.995527
Adjusted R-squared	-0.000881	S.D. dependent var	2.075491
S.E. of regression	2.076405	Akaike info criterion	4.302572
Sum squared resid	2509.268	Schwarz criterion	4.317537
Log likelihood	-1254.351	Hannan-Quinn criter.	4.308404
F-statistic	0.487004	Durbin-Watson stat	1.997867
Prob(F-statistic)	0.485546		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

APPENDIX G

Figure G.1 represents the results obtained from the correlogram test after he EGARCH was performed, including the Ljung-Box Q statistic.

Figure G.1: Corellogram with Q statistics

Date: 10/18/11 Time: 13:19
Sample: 10/14/2009 09:00 2/04/2010 14:00
Included observations: 585

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.029	0.029	0.4915	0.483
.|. |	.|. |	2	-0.006	-0.007	0.5110	0.775
.|. |	.|. |	3	0.018	0.018	0.6985	0.874
.|. |	.|. |	4	-0.008	-0.009	0.7350	0.947
.|. |	.|. |	5	-0.035	-0.034	1.4545	0.918
.|. |	.|. |	6	-0.033	-0.031	2.0856	0.912
.|. |	.|. |	7	0.053	0.054	3.7290	0.810
.|* |	.|. |	8	0.075	0.073	7.0383	0.533
.|. |	.|. |	9	-0.008	-0.011	7.0777	0.629
.|. |	.|. |	10	0.005	0.002	7.0935	0.717
.|. |	.|. |	11	0.019	0.015	7.3158	0.773
.|. |	.|. |	12	-0.017	-0.014	7.4867	0.824
.|. |	.|. |	13	-0.008	0.001	7.5218	0.873
.|. |	.|. |	14	0.019	0.020	7.7477	0.902
.|. |	.|. |	15	0.009	0.001	7.7994	0.932
.|. |	.|. |	16	0.060	0.058	9.9911	0.867
.|. |	.|. |	17	0.032	0.029	10.596	0.877
.|. |	.|. |	18	-0.005	-0.010	10.611	0.910
.|. |	.|. |	19	-0.017	-0.019	10.782	0.931
*|. |	*|. |	20	-0.082	-0.078	14.844	0.785
.|. |	.|. |	21	-0.062	-0.057	17.189	0.700
.|. |	.|. |	22	0.029	0.035	17.706	0.723
.|. |	.|. |	23	0.010	0.008	17.773	0.770
.|* |	.|* |	24	0.086	0.076	22.268	0.563
.|. |	.|. |	25	-0.016	-0.032	22.423	0.611
.|. |	.|. |	26	0.041	0.038	23.462	0.607
.|. |	.|. |	27	0.008	0.009	23.504	0.658
.|. |	.|. |	28	-0.012	0.009	23.592	0.703
.|. |	.|. |	29	-0.019	-0.011	23.814	0.738
.|* |	.|* |	30	0.083	0.082	28.077	0.566
.|. |	.|. |	31	0.028	0.018	28.547	0.593
.|. |	.|. |	32	0.041	0.034	29.571	0.590
.|. |	.|. |	33	0.000	-0.010	29.571	0.639
.|. |	.|. |	34	-0.001	-0.007	29.572	0.685
.|. |	.|. |	35	-0.006	-0.002	29.592	0.726
*|. |	.|. |	36	-0.067	-0.049	32.436	0.639

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

APPENDIX H

Figure H.1 represents the results obtained from the Augmented Dickey-Fuller test on the residual series of the EGARCH output. In addition, Figure H.2 represents the EGARCH model output with a dummy variable included.

Figure H.1: Augmented Dickey Fuller results

Null Hypothesis: RESID01 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.23877	0.0000
Test critical values:	1% level	-3.441318	
	5% level	-2.866270	
	10% level	-2.569348	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID01)
Method: Least Squares
Date: 10/19/11 Time: 19:02
Sample (adjusted): 10/14/2009 10:00 2/04/2010 14:00
Included observations: 584 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID01(-1)	-1.120502	0.041136	-27.23877	0.0000
C	6.867228	8.917018	0.770126	0.4415

R-squared	0.560407	Mean dependent var	-0.105535
Adjusted R-squared	0.559651	S.D. dependent var	324.6001
S.E. of regression	215.4007	Akaike info criterion	13.58630
Sum squared resid	27003316	Schwarz criterion	13.60126
Log likelihood	-3965.198	Hannan-Quinn criter.	13.59213
F-statistic	741.9507	Durbin-Watson stat	1.988259
Prob(F-statistic)	0.000000		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).

Figure H.2: EGARCH results with a dummy variable

Dependent Variable: DJSE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/29/11 Time: 10:01
Sample (adjusted): 10/14/2009 09:00 2/04/2010 14:00
Included observations: 585 after adjustments
Convergence achieved after 18 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSE	0.233943	0.023819	9.821831	0.0000
DUMMY	-34.83008	19.75365	-0.263342	0.3020
C	29.23079	13.44112	2.174729	0.0297
		Variance Equation		
C(4)	21.36377	0.113894	187.5752	0.0000
C(5)	-0.075317	0.018383	-4.097028	0.0000
C(6)	0.025261	0.010824	2.333874	0.0196
C(7)	-0.993478	0.007604	-130.6545	0.0000

R-squared	0.110177	Mean dependent var	4.594872
Adjusted R-squared	0.107119	S.D. dependent var	228.4562
S.E. of regression	215.8737	Akaike info criterion	13.54922
Sum squared resid	27122045	Schwarz criterion	13.60153
Log likelihood	-3956.148	Hannan-Quinn criter.	13.56961
Durbin-Watson stat	2.254737		

Source: Compiled by author from estimations in Eviews 7 (QMS, 2009).