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Dynamic Returns Linkages and Volatility Transmission Between South African and World Major Stock Markets*

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Abstract

This paper analyses returns and volatility linkages between the South African (SA) equity market and the world major equity markets using daily data for the period 199-2007. Also analysed is the nature of volatility, the long term trend of volatility and the risk-premium hypothesis. The univariate GARCH and multivariate Vector Autoregressive models are used. Results show that both returns and volatility linkages exist between the SA and the major world stock markets, with Australia, China and the US showing most influence on SA returns and volatility. Volatility was found to be inherently asymmetric but reasonably stable over time in all the stock markets studied, and no significant evidence was found in support of the risk-premium hypothesis.

JEL Classification: C32, F3, G15

Keywords: Reruns and volatility linkages; exponential GARCH; GARCH-in-mean; Vector Autoregressive; Portfolio Diversification; Financial Stability

1 Introduction

The linkage of international stock markets has attracted considerable attention since Grubel's (1968) work which suggested the possibility of gains from international portfolio diversification. Early studies (c.f. Granger and Morgenstern, 1970; Ripley, 1973; Lessard, 1974) overwhelmingly documented the existence of low correlations among equity markets and the domination of return generating processes in equity markets by domestic factors. As a result international portfolio diversification was considered worthwhile. Recent studies document increasing comovement among stock markets (c.f. Lee, 2001; Cifarelli and Paladino, 2005; Tastan, 2005).

Apart from portfolio diversification, there are at least three more reasons why understanding the linkage of international stock markets is important. These are stock market efficiency, financial stability and monetary policy. For instance, due to increased globalisation, financial and exchange rate liberalisation, and financial innovation, it has become imperative that the informational efficiency of stock markets is not only inferred from its reaction to domestic factors, but also to international factors. In this regard, events in the international macroeconomic environment and stock market become a very important ingredient in pricing of domestic securities. Likewise, strong linkages of stock markets could be detrimental to global financial stability through contagion effect. Finally, Tobin's (1969) $\boldsymbol{q}$ theory demonstrates the existence of an important connection between equity prices and interest rate. Given this link, it becomes essential that monetary authorities understand issues

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regarding the linkages between international equity markets if they hope to effectively formulate and implement monetary policy.

Empirical study of the linkages of among international stock markets has gained momentum since the 1987 global equity markets crash and the 1997 Asian crisis. Despite using different methodologies, studies on returns and volatility linkages have generally concluded that significant linkages exist between most developed markets. For instance, a study by Koch and Koch (1991) used simultaneous equations to establish that both contemporaneous and lead-lag relationships exist among the US, UK, Japan, Hong Kong and Singapore stock markets and that geographical proximity positively influences interdependence among stock markets. Earlier, Eun and Shim (1989) used the Vector Autoregressive model to establish cross-country linkages among Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, UK and the US, with the US market showing dominance over all the other markets. Similarly, Lee (2001) used the discrete Walvet Decomposition[1] analysis with daily stock market indices for the period 1998-2001 to provide evidence in support of unidirectional transmission of volatility from developed markets of the US, Japan and Germany to emerging markets of the Middle East and North Africa (MENA) region (i.e. Turkey and Egypt). However, using both univariate and multivariate GARCH, and VAR, Bala and Premaratne (2004) document evidence of bidirectional volatility transmission between the US, UK, Japanese and Chinese markets and the Singapore emerging market.

Some studies have looked at how the announcement of news impacts on returns and volatility linkages among stock markets. The hypothesis here is that good news and bad news have different impacts on returns and volatility and their transmission – a hypothesis normally referred to as the leverage/asymmetric effect. Using the multivariate EGARCH model with both opening and closing stock prices, Koutmos and Booth (1995) test this hypothesis for the US, UK and Japanese stock markets for the period 1986–1993. Simultaneously, the authors also tested the contagion hypothesis in volatility transmission by dividing the sample of study into pre- and post-1987 stock market crash. The findings of the study support both hypotheses. Koutmos (1996) also used the same methodology together with VAR to establish quite similar results for UK, France, Germany and Italy for the period 1986-1991. In a study employing similar methodology, Cifarelli and Paladino (2005) utilised the daily exuberance index[2] rather than the usual stock markets index for the US, UK and German stock markets and employed a dummy variable for the 1997 Asian crisis. The authors' findings were in line with the former studies, except that the stock market exuberance index was found to be better and more accurate as an alternative to stock returns.

A recent study by Tastan (2005) employed a dynamic conditional correlation multivariate GARCH model to test whether countries with close trading and investment ties also have closely linked financial markets by examining Turkey before and after joining the European Union. By dividing the period of study into pre- and post-custom union the author found that correlation between the Turkish and all the other stock markets was stronger for post-union than the pre-union period.

Due to the poor level of development of equity markets in Africa very little attention has been paid to these markets. The few existing studies have produced mixed findings. Lamba and Otchere (2001) used VAR to provide evidence that weekly returns of South Africa and Namibia are influenced by the US and UK equity markets. A further finding by the authors was that Ghanaian, Namibian and SA markets were linked to the resource-based stock markets like Australia and Canada. Collins and Biekpe (2003) used the adjusted Pearson's correlation coefficient to establish that except for Egypt and South Africa, the African stock markets were not vulnerable to contagion effect from the 1997 Asian stock market crisis. The authors also document limited evidence of causal relationship among African stock markets except among regional blocks. Piesse and Hearn (2002:1711) provide further evidence in support of integration among African regional blocks. Using the Johansen cointegration

[1] For a description of this methodology see Lee, 2001.

[2] The stock market exuberance index is derived from the standard portfolio arbitrage relationship. For a comprehensive discussion, derivation and computation of stock market exuberance index see Cifarelli and Paladino (2005:416-417).

and Granger Causality test, they found that monthly stock indices of the Southern African Customs Union (SACU) equity markets are cointegrated. However, surprisingly they found that causality runs from the Namibian to the South African stock market. They attributed this to the presence of common regional factors that tend to affect Namibia more than SA, which then spill over to the more open South Africa equity market (Piesse and Hearn, 2002:1721).

Ogum (2002) used a time-varying asymmetric moving average threshold GARCH (asymmetric-MA-TGARCH) model and daily stock indices for SA, Nigeria and Kenya for the period 1985-1998, to establish evidence that both conditional mean and conditional variance respond asymmetrically to past innovations. A recent study by Samouilhan (2006) shows evidence of both broad market and sectoral returns and volatility linkages between UK and SA stock markets.

The current study contributes to the scant literature on African stock markets by analysing returns and volatility linkages between SA and the following equity markets: Australia, China, German, Japan, the UK and the US, using daily data for the period 1995 to 2007. Apart from providing new evidence in this area, our study also addresses issues which have not been addressed by existing studies for SA. Firstly, we evaluate the performance of various GARCH models in capturing volatility in the seven stock markets under review. Secondly, we analyse risk-return relationship in each of the stock markets using the GARCH-in-mean. Thirdly, following Frömmel and Menkhoff (2003), we examine the long term trend of volatility of each of the stock markets.

The remainder of the paper is organised as follows: Section 2 describes the methodology, Section 3 looks at sources, issues and properties of data, Section 4 reports and analyses the empirical results and finally Section 5 concludes the paper.

2 Methodology

2.1 Examining returns linkages: Vector Autoregressive (VAR)

In order to understand the returns and volatility comovement, it is important to analyse the market dynamics, transmission and propagation mechanism driving these markets. A model that clearly shows how returns and volatility are transmitted from one market to another in a recognised fashion, as well as ensuring that multilateral interactions are simultaneously analysed, is necessary. The Vector Autoregressive (VAR) model is one of the most appropriate models.

Developed by Sims (1980), the VAR model can estimate a dynamic simultaneous equation system without putting any prior restrictions on the structure of the relationships. Because it does not have any structural restrictions, the VAR system can enable the estimation of a reduced form of correctly specified equations whose actual economic structure may be unknown. This is an important feature in empirical analysis of data since structural models are normally mis-specified.

Our study will express the VAR model as follows:

$$X_t = C + \sum_{s=1}^{m} A_s X_{t-s} + \varepsilon_t \tag{1}$$

where $X_t$is a 7 x 1 column vector of equity market returns for the seven stock markets under consideration, C is a 7x1 deterministic component comprised of a constant, A_s are 7 x 7 matrices of coefficients, m is the lag length and $\varepsilon_t$is the 7 x1 innovation vector which is uncorrelated with all the past X_s.

The VAR analysis is a useful tool to test for and examine spillovers and linkages between stock markets. However, the fact that there are so many coefficients raises problems regarding interpretation. Of particular concern here is that the signs of the coefficients of some of the lagged variables may change across lags. This could make it difficult to see how a given change in a variable would impact on the future values of the variables in the VAR system (Brooks, 2002:338), hence the VAR model is normally analysed using block exogeneity, impulse responses and variance decomposition functions. These are discussed below.

2.1.1 *Block exogeneity test*

The block exogeneity test follows an F-distribution, and is analogous to testing for Granger causality. This test is based on testing the validity of a set of zero restrictions on some of the parameters in the VAR equation [1]. In this study we use the block exogeneity test to determine which of the stock markets has an influence on SA returns and volatility. Block exogeneity will also be used to identify which of the stock markets are the most exogenous and endogenous in returns and volatility linkages. Finally, this test will allow us to determine whether the SA equity market also influences volatility and returns of other stock markets.

2.1.2 *Impulse response analysis*

This traces out the responsiveness of a dependent variable to shocks to each of the other variables in the VAR framework. In the context of this study, the impulse response function answers questions with regard to the response of the SA equity market to a one standard error unit shock in any of the developed and emerging equity markets being studied. In this analysis, the sign, magnitude and persistence of responses of one market to shocks in another stock market are captured. Since our study utilises daily data, the finding of 'contemporaneous' response could be interpreted as a measure of the degree of informational efficiency of the SA equity markets (Bala and Premaratne, 2004).

As noted by Lutkepohl and Saikkonen (1997:130) and Aziakpono (2007:7), if the process [1] is white noise, then the estimated VAR can be inverted into a moving average representation whose coefficients are forecast error impulse responses. The moving average takes the following form:

$$X_t = C + \sum_{s=0}^{k} B_s \varepsilon_{t-s} \tag{2}$$

where $X_t$denotes a linear combination of current and past one step ahead forecast error orinnovations. In the context of this study, the coefficient B_s can be interpreted as the response of one stock market returns to a one standard error shock of any of the markets under study s periods ago. As in equation [1], the ε_t'sare also serially uncorrelated although they may be contemporaneously correlated.

As noted by Aziakpono (2007:8), the impulse responses in equation [2] are commonly estimated using the generalised impulse response proposed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), and the Cholesky decomposition proposed by Sims (1980). Whilst the former has the advantage over the latter in that it does not require orthogonalisation of innovations and does not vary with the ordering of variables in the VAR (Pesaran and Shin, 1998:17 and Aziakpono, 2006:8), results from the two methods coincide if the shocks are uncorrelated. This study uses the Cholesky decomposition estimation criterion and the markets will be orthogonalised according to their trading sequence.

2.1.3 *Variance decomposition analysis*

The Variance Decomposition analysis can also be utilised in analysing the returns and volatility linkages between the equity markets. Unlike the impulse response, which traces the effects of a shock to one endogenous variable on other variables in the VAR framework, variance decomposition splits the variations in one stock market into component shocks in the VAR. By so doing this analysis gives information about the relative importance of error/innovation of each stock market in explaining other stock markets included in the VAR system. Stated differently, variance decompositions show the proportion of the movements in the explained stock market that are due to its 'own' innovations, against those from other stock markets. Empirical literature widely documents that own series innovations tend to explain most of the forecast error variance of the series in the VAR (see Brooks, 2002:342; Lamba and Otchere, 2001:18).

In this study, we use variance decomposition to measure and explain the proportion of the movements in any of the stock markets that are explained by other markets. Of particular concern is how much of the variations in SA's stock market returns and volatility can be explained by innovations of world stock markets. This will help us determine which of the world stock markets has the greatest influence on the returns and/or volatility of the SA market. Variance decomposition will also help us determine whether the SA market is either largely exogenous or endogenous. This will be inferred from the extent to which own-innovations explain variations in SA stock market returns and volatility.

2.2 Analysis of volatility and volatility linkages

Financial data is characterised by excess volatility, volatility clustering and leverage effects. These properties cannot be properly captured by time series models and thus volatility models have been suggested as the most appropriate alternative. The Autoregressive Conditional Heteroscedasticity (ARCH) of Engle (1982) and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) of Bollerslev (1986) and different extensions to these models have been extensively used in recent empirical studies. The application of the ARCH methodology on a single return series involves modelling the variance in the return series with its lags as well as past errors that are derived from the regression of the mean return series on lagged versions of itself. Maximum Likelihood Estimations are then used to estimate the coefficients of the model. As documented by Hurditt (2004:6) normal ARCH and GARCH models have been found to be generally good in estimation of in-sample parameters and, when the appropriate volatility measure is used, reliable out-of-sample volatility forecasts can be obtained. However, there are a number of problems with the symmetric ARCH and GARCH models. Firstly, they cannot guarantee non-negativity of conditional variance, in which case it becomes necessary to place restrictions on the parameters. Secondly, under certain circumstances these models fail to account for volatility clustering and excess kurtosis in financial series. This is the case if the series' volatility is more persistent than that captured by the standard GARCH and ARCH models (Tse, 1998:49). Thirdly, the model fails to allow any direct feedback between the mean and conditional variance (Brooks, 2002:469). Lastly, the models cannot capture asymmetry in volatility.

Because of these weaknesses, different extensions have been suggested to the basic models. Some of the extensions to these models include the GARCH-in-mean (GARCH-M), Exponential GARCH (EGARCH), and Glosten, Jaganathan and Runkle GARCH (GJR GARCH)[3]. Whilst the GARCH-M was developed to account for the issue of lack of direct feedback between the conditional variance and the mean, the latter two were developed to deal with the volatility asymmetry. A number of empirical studies have used the asymmetric models to establish that volatility in financial markets is asymmetry (see for example Koutmas and Booth, 1995 and Piesse and Hearn, 2002).

In order to address the issue of volatility transmission among the equity markets, we first analyse the volatility of each of the stock markets using the GARCH, EGARCH and GJR GARCH models. We then generate conditional variance series using the most appropriate of these three models. These conditional variance series then serve as a proxy for volatility for each of the stock markets. Partly in line with an approach followed by Brooks and Ragunathan (2003:750-752), the conditional variance series are then analysed using the VAR model based on impulse response and variance decomposition to examine the transmission of volatility among the stock markets.

Below is a discussion of the models and the procedures that will be used to determine volatility in each of the stock markets and their transmission among the stock markets.

[3] Note that the GJR GARCH can also be referred to as the TARCH model.

2.2.1 *The mean equation and the GARCH-in-mean extension*

The starting point of modelling volatility is to specify an appropriate mean equation. The mean equation can be a standard structural model, an autoregressive (AR) model or a combination of these. Since our aim is to generate conditional variance series for each of the stock markets, it is inappropriate to use a structural model. A number of studies on volatility employ a mean model that regresses the depended variable on a constant (see for example Takaendesa *et al.*, 2006). An important feature for an appropriate mean equation is that it should be 'white noisy' i.e. its error terms should be serially uncorrelated. Following previous studies (e.g.Takaendesa *et al.*, 2006), this study begins with the following mean equation:

$$y_t = \mu + \varepsilon_t \tag{3}$$

where y_t is returns for each of the stock markets and μ is a constant and ε_t is the white noise error term. The estimated model will then be tested for autocorrelation using the Durbin Watson (DW) test and the LM autocorrelation test. If there is evidence of autocorrelation, lagged values of the dependent variable will be added to the right hand side of equation [3] until serial correlation is eliminated. The appropriate mean equation will also be tested for ARCH effect to ensure that it is necessary to proceed to estimating volatility models.

An important hypothesis that has prevailed in financial markets is that more risky markets have higher returns than less risky ones (see Brooks, 2002), because risk-loving investors want to be rewarded for taking higher risk. The GARCH-M model provides a practical way of modelling risk and return in such a manner that this hypothesis can be empirically investigated. Proposed by Engle, Lilien and Robins (1987), the GARCH-M model is modelled by augmenting the relevant mean equation with lagged conditional variance term. Thus, for instance, equation [1] above becomes:

$$y_t = \mu + \delta\sigma_{t-1}^2 + \varepsilon_t \quad , \quad \varepsilon_t \sim N(0, \sigma_t^2) \tag{4}$$

where y_t denotes mean returns, σ_{t-1}^2 is a lagged conditional variance term and ε_t is the residual term. A conditional variance equation (in the form of GARCH, EGARCH or TARCH) is then entered into the equation [4] and the parameters are estimated. The parameter δ is interpreted as risk premium, and if it is positive and statistically significant, then increased risk, given by an increase in the conditional variance, leads to a rise in the mean return.

2.2.2 *Univariate GARCH models*

The GARCH model was developed independently by Bollerslev (1986) and Taylor (1986). The GARCH model, which employs the maximum likelihood procedure, allows the conditional variance to be dependent upon previous own lags, so that the conditional variance equation is as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad , \quad \alpha + \beta < 1 \tag{5}$$

This is a GARCH (1, 1) model where σ_t^2 is the conditional variance, ω is a constant, α is the coefficient of lagged squared residuals, ε_{t-1}^2 is the lagged squared residual from the mean equation and β is the coefficient for the lagged GARCH component which is the lagged conditional variance. The condition given in [5] i.e. $\alpha+\beta < 1$ is necessary for stationarity of the GARCH model. As Brooks (2002) notes, there is no theoretical justification for a model in which the summation of parameters of the lagged residual term and the lagged conditional variance term is more than one. The GARCH (1, 1) model is parsimonious and avoids over-fitting. As a result it is less likely to breach non-negativity constraints (Brooks 2002:453). Brooks (2002:453) further argues that a GARCH (1,1) model is usually sufficient to capture volatility clustering in the data, hence any higher order model of GARCH is typically not estimated in the academic finance literature.

If, after estimating the GARCH model, further tests suggest the presence of ARCH effect, then we explore the E-GARCH model. E-GARCH is an asymmetric model. Brooks (2002:469) suggests that equity returns exhibit asymmetric responses of volatility to positive and negative shocks which are attributed to leverage effects. Leverage effects is a situation whereby a fall in the value of a firm's stock causes the firm's debt to equity ratio to rise, which leads ordinary shareholders to perceive their future cash flow stream as being relatively more risky. The Exponential GARCH method proposed by Nelson (1991) is specified with the following conditional variance equation:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \gamma \left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{6}$$

$\alpha + \beta < 1$; and $\gamma < 0$ if volatility is asymmetric. Where α and β are still interpreted as they are in the GARCH (1, 1) model and γ is the asymmetry coefficient. As evident from the conditions given under the equation, if $\gamma \neq 0$and significant, then negative shocks imply a higher next period conditional variance than positive shocks of the same magnitude (i.e. asymmetric impacts). A leverage effect, which is a special case of asymmetric impacts, would exist if $\gamma < 0$.

The EGARCH model provides a number of advantages over the pure GARCH. Firstly, since the Log (h_t)is modelled, then even if the parameters are negative, h_t will be positive thus there is no need to artificially impose non-negativity constraints on the parameters. Secondly, asymmetries are allowed for since if the relationship between volatility and returns is negative, δ will be negative (Brooks, 2002:469).

The GJR GARCH will also be explored. Like the EGARCH model, this model captures asymmetry. However, the specification and interpretation of the model differ from the EGARCH. The GJR GARCH was proposed by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993). This model is simply a re-specification of the GARCH (1, 1) model with an additional term to account for asymmetry as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_t^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \tag{7}$$

$$\textit{where } I_{t-1} = \textit{ 1 if } \varepsilon_{t-1} < 0 = 0 \;= \textit{0 if otherwise}$$

I is the asymmetry component and γ is the asymmetry coefficient. If leverage effects exist, then the coefficient of asymmetry coefficient will be positive and significant (i.e.$\gamma > 0$). The idea behind this is: good news ($\varepsilon_t > 0$)and bad news ($\varepsilon_t < 0$)will have different impacts on volatility of the stock returns. While good news will have an impact of α_1, bad news will have an impact of $\alpha_1 + \gamma$. Thus, if γ is significantly different from zero, then clearly the impact of good news is different from the impact of bad news on current volatility. If $\gamma > 0$ leverage effect exists in stock markets and if $\gamma \neq 0$[4] then the impact of news is asymmetric (Eviews 5, 2004:587). The theoretical argument for the existence of leverage lies in the source and cost of capital. Bad news normally causes a decline in stock prices and this increases the firm's debt to equity ratio. As a result the risk of equity investments will increase, and as investors react to this increased risk, the volatility of stock prices will increase.

2.2.3 *Examining trends in volatility*

Since volatility in stock markets can affect financial stability, it is worth investigating its long term trend. Following Frömmel and Menkhoff (2003), we regressed each of the conditional variance series against a constant and a time variable to analyse the trend of volatility over time.

$$h_t = \beta_1 + \beta_2 T \tag{8}$$

[4]The difference between $\gamma > 0$ and$\gamma \neq 0$ is that in the former case the parameterγ only takes a positive value and such an instance would imply that there is evidence for both leverage and asymmetric effects. In the latter caseγcan take both positive and negative values. Should it take a positive value, then only evidence of asymmetric effects and not leverage effects exist in the data (Eviews 5, 2004:597).

where h_t is the conditional variance in each market generated from the appropriate volatility model and T is the time in days. If β_2 is positive and significant then it implies that volatility increases over time, while a negative and significant β_2 implies that volatility decreases over time.

3 Data Sources, Issues and Properties

3.1 Data and its Sources

The dataset used in this analysis comprises the daily closing stock market capital indices (P_{it}) for the seven markets for the period 30/12/1995 to 28/02/2007, totalling 3 125 observations. Following existing empirical studies, the indices used are in their domestic currencies (see Koutmos, 1996; Darrat and Benkato, 2003; Tastan, 2005). Berben and Jansen (2005:835) argue that expressing returns in domestic currencies will ensure that true price developments as they are perceived in the financial press and by policy makers are reflected. The following indices were used for the respective stock markets: All Ordinaries index for Australia, Heng Teng index for the Chinese stock market, DAX index for Germany, Nikkei 225 index for Japan, FSTE index for South Africa, FTSE 100 index for United Kingdom and Standard and Pool (S&P 500) for United States of America. The choice of these indices has been motivated by the fact that they are the best representative indices for their respective stock markets as well as being the most recurring in empirical studies. All the indices were obtained from the Thompson DataStream. The index of each market is converted into compounded daily returns as follows:$y_t = (InP_t - InP_{t-1}) \times 100$; where y_t is current continuous compounded returns, P_t is the current closing stock price index and $P_{t-1}$is the previous day closing stock market index. Figure 1 plots the computed returns for each of the markets.

3.2 Data Issues

There are a number of issues with regard to the choice of data frequency for financial markets research. Daily data is preferred to lower frequency data as it captures the dynamic interactions that occur within a day, a property that cannot be captured by low frequency data. Financial markets in general, and the stock market in particular, react promptly to new information. Thus, lower frequency data distorts such reactions. Korolyi and Stulz (1996:3) argue that "the daily data horizon is important for risk management purposes and for portfolio management whenever dynamic hedging strategies are used." Moreover, from the point of view of policy makers concerned with financial stability, correlations and comovements at a high frequency are more relevant than correlations and comovements over lower frequency (Berben and Jansen, 2005:835).

However, there are also problems with daily data. One concern is that distortions may arise due to non-trading during holidays and noise trading. Glezakos *et al.* (2007:28) suggest that a possible way to resolve the problem of non-trading is to calculate the relevant index by simulation for that particular day. Another possible way to resolve this problem is to eliminate all the non-traded days of each market across all markets (c.f. Chowdhury, 1994; Chang *et al.*, 2006). For this study, we preferred the latter since there is no guarantee that simulation will provide the index that could have resulted had the market been opened. Since our sample size is very large, this is not expected to have any major effects on the empirical findings.

Another important concern that arises from the use of daily data is that financial markets in different continents operate at different times. Such lack of coincidence among international stock markets has important implications for interpretation of our results and model specification. For instance, the Japanese stock market trades before the JSE Securities Exchange opens, while the US stock exchange trades after the JSE. As noted by Isakov and Perignon (2000:6), this has two implications for this analysis. Firstly, an overlapping period will exist between the returns of the contemporaneous US (r_{USt}) and the lagged South African returns (r_{SAt-1}). Secondly, there is also an overlapping period between contemporaneous SA returns (r_{SAt}) and the lagged Japanese returns

(r_{JPt-1}). This overlapping might result in the Granger causality[5] between r_{SAt-1} and r_{USt} on one side and between $r_{SAt}$and r_{JPt-1}on the other side to be upward biased. A possible solution to limit this problem as suggested by Hamao *et al.* (1990) and Koutmas and Booth (1995) is to compute *open to close* returns. However, Isakov and Perignon (2000:7) express doubts that this could fully solve the problem of non-synchronicity of trading hours as it neglects significant periods of time when the market is closed, when information may arrive. They further argue that the opening prices are "subject to frequent microstructure problems". Nevertheless, a comparison of the results obtained from utilising *close to close* and *open to close* returns by Hamao *et al.* (1990) revealed that they give very close empirical results. For this reason our study uses the *close to close* data. In this study, the trading sequence of the markets will be used for orthogonalising/ordering of the markets for impulse response and variance decomposition analyses.

3.3 Descriptive statistics and simple correlation test

Table 1 provides the summary statistics, namely, sample means, maximums, minimums, medians, standard deviations, skewness, kurtosis and the Jarque-Bera tests with their p-values for the return series. Whilst it is clear that all the statistics show the characteristics common with most financial data, for instance non-normality in the form of fat tails, there are a number of noticeable differences, especially between developed and emerging stock markets. Firstly, returns in emerging stock markets are more than those of their developed counterparts. More specifically, the smallest of the emerging stock markets (SA) has the highest unconditional average daily stock market return of around 0.026%. The returns for SA fluctuate between the minimum of -5.48% and a maximum of 4.38%. Among the emerging markets, Australia has the second highest average returns and China the third with unconditional mean returns of 0.017% and 0.012% respectively. Of the developed stock markets Germany has the highest unconditional average returns of around 0.020% with Japan having the lowest unconditional mean returns of around 0.003%. The US, which is the world's largest stock market, has unconditional mean returns of about 0.016% and its returns fluctuate between -3.08% and 2.42%. A common observation is that the emerging stock markets (China and SA) have more extreme values (i.e. the difference between the maximum and the minimum) for the daily returns compared to the developed stock markets. This could be an indication that volatility is much higher in emerging stock markets than in developed stock markets, which is well in line with most theoretical and empirical literature.

Surprisingly, contrary to the common findings that the unconditional standard deviation for emerging markets tends to be higher than in developed markets, indicating the existence of more risk in the former markets (see Tastan, 2005:6), the picture seems to be mixed in our case. As evident from the table, China, an emerging market, has the highest unconditional standard deviation of around 0.75%, whilst Australia has the lowest of about 0.36%. Quite surprisingly, the smallest emerging market of the sample, SA, has a standard deviation which is well below some of the world's largest stock markets, i.e. Japan and Germany. This could be due to the fact that there has been a gradual improvement in investors' optimism since the 1994 democratisation. Returns of most of the stock markets under consideration are negatively skewed except for the Asian stock markets (China and Japan). All the stock markets under consideration have distributions with positive excess kurtosis and show evidence of fat tails. A distribution with a kurtosis value of more than 3 is described as leptokurtic relative to normal (Bala and Premaratne, 2004:5). This implies that the distribution of stock returns in all the stock markets tends to contain extreme values. Lastly, the Jarque-Bera (JB) statistic tests whether the series are normally distributed. As can be seen from the table, the JB indicates that the hypothesis of normality is rejected for all return series. This non-normality is also evident from the fatter tails of the kurtosis and negative and positive skewness.

[5] The term Granger causality is used to distinguish between statistical causality, which will be investigated here using the VAR, and real causality.

Table 2 shows the pairwise correlation matrix, and there is evidence of contemporaneous correlation among the markets. Correlation between all the markets is positive, which tends to indicate that there is a common trend/factor that is driving the markets in the same direction. This is adverse for international diversification since one condition for international diversification is that correlation between returns should be negative to ensure that some markets will go up if some go down (Narayan and Smyth, 2005:232). However, the other condition for international portfolio diversification (i.e. correlation among stock markets should be low (see Glezakos *et al.*, 2007:25) is satisfied. As is evident from Table 2, correlation between most of the stock markets returns (except for the case of the Chinese with the Australian stock markets, the German with the US stock markets and the UK and German markets) is low (i.e. less than 50%). The SA stock returns are mostly correlated with the UK, Chinese, Australian, German, Japanese, and US stock markets in descending order. In what follows we explore more rigorously the nature of the relationship between South African and the other stock markets.

4 Empirical Results

4.1 Returns Linkages

To explore the returns linkages among the stock markets we used a VAR model. An important issue before estimating a VAR model is to determine the lag length. In this study we use the Akaike, Hannan-Quinn and Schwarz Information Criteria which are widely employed in empirical studies. The three information criteria suggested a lag order of 2. However, lag order produced residuals that are serially correlated. Therefore, following Gallagher and Taylor (2002) we started the estimation with a VAR lag length of 2 and the lag length was subsequently increased until serial correlation was eliminated. Serial correlation only disappears at lag 5. Thus we estimated our VAR using a lag order of 5 and based on this block exogeneity, impulse responses and variance decomposition functions were estimated to examine the dynamic links between the markets and the transmission of the returns shocks. The results for the block exogeneity, impulse responses and variance decomposition are reported in Table 3, Figure 2 and Table 4 respectively.

As shown in Table 3, except for the Japanese and the UK equity markets, all the markets significantly influence the SA market returns at 1% level. The UK case is surprising given the dual listing agreement between the LSE and the JSE. As would be expected, the SA equity is the most endogenous since it does not significantly influence any of the stock market returns. On the other hand, the US stock market is the most exogenous. While it significantly influences returns of all the other markets, none of the stock markets influence its returns significantly. This later result is in line with, amongst others, Arshanapalli *et al.* (1995), Hassan and Naka (1996) and Masih and Masih (2001).

The impulse response function was estimated using the Cholesky approach and the results are reported in Figure 2. The orthogonalisation was based on the trading sequence of the stock markets as follows: AUS; JPN; CH; SA; GR; UK; UK. Figure 2 shows that the response of SA returns to both own and to foreign markets innovations is generally positive. As would be expected, the response of SA returns to own innovations is the highest. It starts positive and high and it quickly declines to zero within the third day, after which it becomes insignificantly negative and finally dies off within the seventh day. With regard to response from cross innovation, the SA returns seem to respond quickest to innovations in the Chinese, Japanese and the US stock markets, although response to innovations from the Asian markets is insignificant. Response of SA to US innovations starts at zero in the first day, picks up sharply and then sharply declines by the third day. This pattern of response to US market innovations is peculiar to all the markets. The response of the SA market to innovations from the European stock markets is also very insignificant. The response of SA to the Australian innovations also starts significantly positive, sharply declines and almost dies off in day two, and it insignificantly continues and finally dies off within the sixth day. The response of other stock markets to SA innovations is also positive and fast although it seems insignificant for the case of the US and the Asian markets. Overall, consistent to informational efficiency, the response of all stock market returns to both own and cross innovations is quick, i.e. it takes less than a week.

With regard to the variance decomposition analysis we seek to address the question regarding the proportion of the movements in the stock market returns that are due to its 'own' innovations, against those that are due to shocks to other stock markets. The returns are ordered by trading sequence of the markets. Brooks and Tsolacos (1999) and Mills and Mills (1991) stress the importance of ordering variables in the decomposition, arguing that it is as good as putting restrictions on the primitive form of the VAR. As in the case of impulse response, our ordering of the stock markets according to trading sequence. Given that all the seven stock markets tend to respond to innovations within a week (impulse response results), only the variance decomposition results for the 5, 10 steps ahead are reported in Table 4.

The main focus is to examine which of the markets mostly influence SA returns. As evident from Table 4, SA own past returns tend to explain most of the variation in current returns (approximately 69%). With regard to influence from other markets, Australia followed by US and China in that order tend to have the greatest influence on SA returns. The Australian influence may be due to the fact that like the SA stock, the former is a resource-based stock market. US influence is not surprising given the fact that it is the largest stock market in the world. In our view, the influence of China can be explained by the fact that it is an emerging market like SA and it is increasingly emerging as one of the most powerful economies in the world with growing trade relations with SA. Once again we are astounded that despite the dual listing of JSE companies in the London Stock Exchange, UK innovations do not significantly explain variations in SA returns.

4.2 Volatility and volatility transmission across the markets

Having established returns linkages between SA and some of the major world markets, we now investigate if this is also the case with volatility. This is done by first generating volatility (conditional variance) series of each stock using an appropriate volatility model and then analysing the volatility series using a VAR framework based on the impulse response and variance decomposition. In analysing the volatility models to select the most appropriate one, we simultaneously tested the risk-premium hypothesis by including the GARCH-in-mean component in each of the volatility models.

4.2.1 *Determining the appropriate GARCH model, testing for the risk-premium hypothesis and examining trends in volatility*

The mean equation [i.e. Equation 3] was estimated and tested for autocorrelation for each of the stock markets. The results are reported in Table 5. No evidence of significant autocorrelation was found in the mean equation. Consequently, we estimated the GARCH models based on this mean equation.

The univariate GARCH (1, 1), EGARCH (1, 1, 1) and GJR GARCH (1, 1, 1) models were estimated with a variance-GARCH-M. In the case of Germany, we estimated the models with a residual component of order 2 i.e. GARCH (2, 1), EGARCH (2, 1, 1) and GJR GARCH (2, 1, 1) because the standard models could not adequately capture the volatility. The results for the three models are reported in Table 6.

For all the stock markets and in all models, the risk-premium coefficient (δ) was not statistically significant. This implies that for all the stock markets, there is no significant risk-premium in returns. This is in contrast with the behavioural finance suggestion that more risky stock markets are more rewarding than less risky ones. One would expect this coefficient to be significant, especially for emerging equity markets where risk is more pronounced.

For all the stock markets, all the coefficients for the three GARCH models were significant at 1%, except in the case of Germany where the coefficient for the squared residual was insignificant. Furthermore, the summation of the residual squared coefficient and the variance squared coefficient was very high for all the markets. This implies that volatility in all the seven markets is persistent. In the EGARCH and the GJR GARCH models, the coefficient of asymmetry,γ, was negative and very significant, and positive and very significant respectively. This implies volatility is inherently asymmetric and there is evidence of leverage effects in all the seven stock markets.

In selecting our most appropriate model to model volatility, we considered the stationarity condition (i.e. $\alpha+\beta<1$), and the ability of a model to best capture ARCH effect as well as whether there is any leverage/asymmetry effect in volatility. Since there is evidence of asymmetry which cannot be captured by the GARCH (1, 1) model, the choice was between the EGARCH (1, 1, 1) and the GJR GARCH (1, 1, 1). For the EGARCH model, $\alpha+\beta>1$ for all the stock markets. Furthermore, this model could not adequately capture ARCH effects for Germany. Thus, we dropped the EGARCH model and chose the GJR GARCH. Based on the GRJ GARCH model, conditional variance series (proxy volatility) were generated for each of the stock markets.

Before we examined the extent to which the equity markets volatilities are linked, we analysed the behaviour of volatility over time in each of the stock markets. Figure 3 is a graphical plot of volatility of each stock market returns. As is evident from Figure 3, all the stock markets show evidence of excess volatility. Generally volatility for most of the stock markets except for the Japanese market seems to have decreased in recent years. Volatility for the Chinese and Australian equity markets seem to have significantly decreased since 2000 and volatility in the US seems to have decreased since late 2001. For the SA equity market, volatility seems to have decreased during the period 2001-2003, before suddenly increasing for the period 2003-2004, since when it has stabilised. An important issue to consider is the behaviour of volatility during/after the 1997 Asian crisis and the September 11, 2001 US attacks. Volatility in SA, Japan, Germany, China, US, and UK seems to have increased during the Asian crisis. While reactions of emerging markets like China and SA can be attributed to emerging market contagion effects, the reaction of developed markets could be due to the fact that investors shift their funds into developed markets when there is a crisis in emerging markets.

Volatility for the US, Germany and UK seem to have increased just after the September 11 attacks. The fact that only developed markets react could be an indication that only companies whose stocks were listed in US were affected and thus the non-reaction of emerging markets is reasonable since only a limited number of firms from emerging markets are listed on the US stock markets.

To formally investigate the long-term behaviour of volatility, equation [8] was estimated. The results for the estimation are reported in Table 7. As is evident from Table 7, volatility in four stock markets – Australia, China, Japan and the US – is decreasing although not significantly so. On the other hand volatility is insignificantly increasing over time for the SA, German and UK equity markets. Overall the results show that volatility in all the stock markets is relatively stable over time. This implies that these world stock markets have been relatively stable since mid-1995. This could be attributed to the fact that investors are becoming more confident in investing in equity markets and are not very responsive to crisis. This explanation is also confirmed by the fact that most of the markets under study, except China and Japan, did not seem to have significantly responded very much to the Asian and Latin American crises.

4.2.2 *Volatility transmission across the markets*

In order to examine volatility transmission across stock markets, a VAR model was estimated for all the conditional variance series. As with the returns linkages, the lag length was determined by first taking the smallest lag selected by the AIC, Hannan-Quinn and SIC information criteria and then increasing the lag length until the VAR residuals were serially uncorrelated. The three information criteria selected the second lag but the results were serially correlated. Only after increasing the VAR order to 25 was serial correlation eliminated. Thus, the VAR model was estimated using 25 lags and, based on the VAR, block exogeneity, impulse response and variance decomposition functions were estimated. As with returns, the volatility series were orthogonalised based on the trading sequence of the markets. The results for the block exogeneity, impulse response and variance decomposition are reported in Table 8, Figure 4 and Table 4 respectively.

Except for the Japanese and the Australian equity markets, volatility from all the other equity markets influences volatility in the SA equity market. As in the case of returns linkages, the US stock market is still the most exogenous of all, although in this case most of the stock markets, except for Australia and Japan, also influence volatility in the US stock market. The German market seems to be the most endogenous, since its volatility is explained by all the other markets, yet it does not explain some of the other markets. Of importance to note is that volatility transmission between emerging markets (SA and China) is very significant, raising the possibility of contagion effects during financial crises.

From Figure 4, it is clear that volatility in the SA equity market shows positive, significant and persistent response to own, Australian, Chinese, German, and US innovations. The response to innovations from the US sharply increased in the first two days, before slowly decreasing continuously. The response of volatility of the SA to own and Australian innovations starts high and gradually decreases continuously. Response to the Chinese market innovations starts low in the first three days, then picks up and becomes relatively constant. Finally, response to innovations from Germany, Japan and UK seems to be insignificant. On the other hand, the extent to which other stock markets react to SA equity market innovations is also quite insignificant.

From the variance decomposition (see Table 5), it is evident that Chinese and Australian innovations seem to be the most important in explaining SA volatility. They explain about 30% and 26% of the variations in SA volatility respectively. While the Australian case could be due to resource-based similarity of the stock market with SA, the Chinese case can be explained by emerging markets contagion effect. US innovations explain less than 10% of the variation in SA volatility. Surprisingly, the UK only explains less than 5% of the variations in SA volatility. Also noteworthy from the results is that while the European stock markets (German and UK) seem to explain each other's volatility quite well, the situation is exactly opposite for the Asian stock markets (China and Japan).

5 Conclusion

This study set out to examine return and volatility linkages between the SA and world equity markets using VAR and univariate GARCH models. The risk-premium hypothesis and the long-term trend of volatility were also analysed.

Our results show the existence of both returns and volatility linkages between SA and some of the markets studied. Australia followed by US and China respectively are three markets that significantly explain the variations in SA returns. The case is similar for SA volatility, although the order of importance changes to China, Australia and US respectively. Our explanations for the results are that the Australian stock market is largely resource-based like SA, the Chinese stock market is an emerging market as the SA, and the US stock market is the largest in the world. Despite the fact that some of the SA companies are cross-listed on the LSE, the UK stock market does not seem to significantly explain variations in either returns or volatility of the SA market. With regard to the nature of volatility, we found significant evidence of leverage effects and asymmetry in volatility for all the stock markets. Finally, no significant evidence of risk-premium was found for any of the stock markets studied.

The findings of this study have important implications for policy and portfolio diversification. Firstly, the existence of close returns and volatility linkages between SA with Australia, China, and the US could be an indication of limited potential benefits from international equity diversification in these markets for SA investors, while Japan, Germany and the UK provide good opportunities for diversification.

Secondly, the fact that volatility from China, Australia and the US stock markets is quickly transmitted into the SA stock market should be of concern for policy makers as volatility affects financial stability. Volatility transmission from the world stock markets to the SA market could be harmful during times of crises. This situation is referred to as the 'contagion effect' and it was widely established in many emerging markets during the Latin American and Asian crises in the late 1990s. If such harmful volatility is transmitted into the SA equity, it could, in turn, be transmitted into other domestic markets (e.g. the money market and bond market) since it has been established that volatility linkages may also exist among domestic financial markets (see Hurditt, 2004). This could threaten the stability of the domestic financial markets. Therefore, there is a need for policy makers to keep a 'watchful eye' on the behaviour of volatility, especially in emerging markets such as China, and the developed markets, in particular the US and Australia. The high volatility transmission from China to the South African market highlights the often negative investors' sentiment that plague emerging markets when there is a crisis in one. While it is often difficult to prevent such contagious effects, one way of minimising the effect is to ensure a stable macroeconomic and political environment. With regard to Australia, which is also a resource-based economy like South Africa, one would expect any adverse developments that affect the resource sector would easily be transmitted to the South African market. One way of mitigating the contagion effects from being resource-based economies is for South Africa to diversify its economy to be less dependent on the natural resource sector.

While this study has focused on one financial market, it is important to note that other financial markets, such as the money, bond and foreign exchange markets, also offer potential for diversification and are also important for financial stability and monetary policy. Thus, we recommend that similar studies be undertaken for these financial markets so as to complement the current study in the quest for ways to improve financial stability and investment strategies.

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TABLES

Table 1: Descriptive statistics

	AUS	CH	GR	JPN	SA	UK	US
Mean	0.017	0.013	0.019	0.003	0.026	0.011	0.016
Median	0.027	0.022	0.047	0.006	0.036	0.028	0.030
Maximum	2.634	7.491	3.801	3.325	4.383	3.366	2.421
Minimum	-4.119	-6.399	-4.498	-3.142	-5.484	-3.72	-3.089
Std. Dev.	0.358	0.750	0.704	0.641	0.589	0.502	0.499
Skewness	-0.967	0.235	-0.151	0.018	-0.496	-0.117	-0.048
Kurtosis	15.19	16.198	6.676	4.801	10.89	7.370	5.991
Jarque-Bera	1626.1	1860.500	1451.100	346.3000	6750.000	2043.000	955.100

Source: Authors' estimates
Note: AUS, CH, GR, JPN, SA, UK, US denotes the stock market returns for Australia, China, Germany, Japan, South Africa, United Kingdom and United States respectively.

Table 2: Correlation matrix for returns

	SA	US	UK	CH	AUS	JPN	GR
SA							
US	0.281						
UK	0.482	0.482					
CH	0.473	0.189	0.392				
AUS	0.469	0.17	0.348	0.526			
JPN	0.326	0.15	0.307	0.439	0.448		
GR	0.457	0.555	0.748	0.37	0.326	0.282	

Source: Authors' estimates

Table 3: Block exogeneity for returns linkages

	Dependent Variables						
Excluded Variables	AUS	JPN	CH	SA	GR	UK	US
AUS		16.55[0.01]	11.96[0.04]	19.32[[0.01]	14.68[0.01]	18.96[0.00]	6.52[0.26]
JPN	12.82[0.03]		18.42[0.01]	5.64[0.34]	5.75[0.33]	13.81[0.02]	1.49[0.91]
CH	15.62[0.01]	5.32[0.38]		21.81[0.00]	3.67[0.59]	8.01[0.15]	5.66[0.34]
SA	7.90[0.16]	5.57[0.35]	4.91[0.43]		6.43[0.27]	4.68[0.46]	10.83[0.06]
GR	3.86[0.56]	6.38[0.27]	7.44[0.19]	23.16[0.00]		12.12[0.03]	3.24[0.66]
UK	12.18[0.03]	0.48[0.99]	16.24[0.01]	7.03[0.21]	7.06[0.22]		5.13[0.40]
US	422.5[0.00]	168.0[0.00]	268.1[0.00]	282.6[0.00]	185.4[0.00]	294.6[0.00]	
All	846.4[0.00]	345.9[0.00]	442.2[0.00]	392.5[0.00]	236.3[0.00]	373.9[0.00]	42.77[0.06]

Source: Authors' estimates.
Note: Parentheses [ ] are used to denote the probability values. The lag-order is initially based on the Akaike, Schwarz and Hannan-Quinn information criteria and the lag was subsequently increased until diagnostically robust results were found.

Table 4: Variance decomposition for returns and volatility

Variance Decomposition of AUS														
Period	AUS	AUS1	JPN	JPN1	CH	CH1	SA	SA1	GR	GR1	UK	UK1	US	US1
5	75.29	81.24	0.45	0.09	0.75	3.66	2.66	0.55	7.21	1.17	1.32	1.8	12.32	11.49
10	75.13	75.45	0.47	0.07	0.76	8.22	2.68	0.47	7.26	1.91	1.34	2.58	12.36	11.3
Variance Decomposition of JPN														
Period	AUS	AUS1	JPN	JPN1	CH	CH1	SA	SA1	GR	GR1	UK	UK1	US	US1
5	10.79	16.55	77.8	71.48	0.32	0.04	1.23	0.93	4.06	2.24	0.19	3	5.64	5.77
10	10.77	14.43	77.5	67.74	0.37	0.4	1.26	1.11	4.09	2.84	0.21	5.74	5.79	7.73
Variance Decomposition of CH														
Period	AUS	AUS1	JPN	JPN1	CH	CH1	SA	SA1	GR	GR1	UK	UK1	US	US1
5	15.77	23.93	0.48	0.06	65.45	59.62	0.4	0.78	3.18	0.57	1.38	2.13	8.86	12.91
10	15.75	18.29	0.49	0.28	65.33	67.46	0.46	0.42	3.18	1.15	1.39	2.48	8.86	9.91
Variance Decomposition of SA														
Period	AUS	AUS1	JPN	JPN1	CH	CH1	SA	SA1	GR	GR1	UK	UK1	US	US1
5	10.9	29.3	4.97	0.01	5.46	13.75	68.8	42.81	1.7	0.36	0.34	1.93	9.41	11.82
10	9.96	27	5.03	0.21	5.69	25.01	68.4	32.72	1.7	1.19	0.41	3.25	9.38	10.62
Variance Decomposition of GR														
Period	AUS	AUS1	JPN	JPN1	CH	CH1	SA	SA1	GR	GR1	UK	UK1	US	US1
5	7.32	17.09	1.43	0.65	2.61	0.34	3.02	0.49	72.65	74.1	0.15	4.79	6.74	2.52
10	7.43	15.98	1.45	0.87	2.56	0.99	3.03	0.45	72.29	70.7	0.22	8.24	6.82	2.83
Variance Decomposition of UK														
Period	AUS	AUS1	JPN	JPN1	CH	CH1	SA	SA1	GR	GR1	UK	UK1	US	US1
5	7.39	3.27	2.51	0.35	4	0.51	7.27	0.91	29.32	27.7	68.3	63.56	10.24	3.72
10	7.63	3.28	2.52	0.22	4.07	0.4	7.24	0.65	29.13	27.3	67.41	64.2	10.31	3.9
Variance Decomposition of US														
Period	AUS	AUS1	JPN	JPN1	CH	CH1	SA	SA1	GR	GR1	UK	UK1	US	US1
5	4.04	9.01	2.77	0.05	1.36	1.74	4.6	0.96	23.65	9.8	1.66	8.43	63.69	70.01
10	4.16	8.4	2.91	0.16	1.5	2.81	4.6	0.62	23.62	10.6	1.73	13.3	63.38	64.11

Source: Authors' estimates.
Note: AUS, JPN, CH, SA, GR UK, US denotes the stock market returns for Australia, China, Germany, Japan, South Africa, United Kingdom and United States respectively, AUS1, JPN1, CH1, SA1, GR1, UK1, US1 denotes the stock market volatilities for Australia, China, Germany, Japan, South Africa, United Kingdom and United States. The series were orthogonalised based on the trading sequence of the stock markets.

Table 5: Results for the mean equation

STOCK MARKET	DW STATISTIC	LM TEST	ARCH LM
AUS1	2.04	0.857 [0.425]	98.969[a]
CH1	2.002	1.183 [0.307]	241.200[a]
GR1	2.023	0.229 [0.795]	38.998[a]
JPN1	2.024	0.423 [0.515]	30.923[a]
SA1	1.993	0.649 [0.523]	200.930[a]
UK 1	2.047	1.853[0.157]	105.542[a]
US1	1.999	1.245 [0.288]	78.562[a]

Source: Authors' estimates.
Note: Parentheses [ ] are used to denote the probability values. Both the Durbin Watson (DW) and the LM Test for Autocorrelation were performed on the mean equation. The ARCH LM statistic measures whether volatility has been captured by the mean equation, and as is evident it has not been captured.

TABLE 6: COMPARISON OF THE GARCH MODELS

	GARCH (1,1)							EGARCH							GJR GARCH						
PARAMETER	AUS1	CH1	GR1	JPN1	SA1	UK 1	US1	AUS1	CH1	GR1	JPN1	SA1	UK1	US1	AUS1	CH1	GR1	JPN1	SA1	UK1	US1
δ	0.11	0.03	0.03	-0.02	0.06	0.07	0.12[c]	0.04	-0.02	0.03	-0.03	-0.01	0.06	0.09[c]	-0.01	0.02	0.01	-0.03	-0.01	0.03	0.04[c]
ϖ	0.01[a]	0.01[a]	0.01[a]	0.01[a]	0.01[a]	0.01[a]	0.01[a]	-0.20[a]	-0.13[a]	-0.17[a]	-0.16[a]	-0.22[a]	-0.12[a]	-0.14[a]	0.01[a]	0.01[a]	0.01[a]	0.01[a]	0.01[a]	0.01[a]	0.01[a]
α_1	0.12[a]	0.08[a]	0.02	0.08[a]	0.12[a]	0.09[a]	0.07[a]	0.12[a]	0.15[a]	0.04	0.16[a]	0.23[a]	0.13[a]	0.12[a]	-0.01[a]	0.03[a]	-0.01	0.03[a]	0.06[a]	0.01[a]	-0.01[a]
β	0.86[a]	0.92[a]	0.88[a]	0.91[a]	0.88[a]	0.91[a]	0.92[a]	0.95[a]	0.98[a]	0.97[a]	0.97[a]	0.97[a]	0.98[a]	0.97[a]	0.87[a]	0.92[a]	0.88[a]	0.90[a]	0.88[a]	0.93[a]	0.92[a]
α_2	N/A	N/A	0.09[a]	N/A	N/A	N/A	N/A	N/A	N/A	0.15[a]	N/A	N/A	N/A	N/A	N/A	N/A	0.06[a]	N/A	N/A	N/A	N/A
$\alpha_1 + \alpha_2 + \beta$	0.98	1.0	0.99	0.99	1.00	1.00	0.99	1.07	1.13	1.16	1.13	1.20	1.11	1.09	0.86	0.95	0.93	0.93	0.94	0.94	0.91
γ	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-0.14[a]	-0.06[a]	-0.07[a]	-0.07[a]	-0.08[a]	-0.10[a]	-0.12[a]	0.20[a]	0.10[a]	0.09[a]	0.09[a]	0.11[a]	0.12[a]	0.15[a]
F-LM	0.05	0.37	0.36	1.69	0.001	0.03	1.062	0.263	0.80	4.54[a]	1.18	0.01	0.07	1.03	0.03	1.21	0.95	1.956	0.464	0.09	4.64[a]
SIC	0.66	1.89	1.81	1.85	1.541	1.15	1.243	0.622	1.868	1.81	1.84	1.52	1.12	1.2	0.64	1.87	1.8	1.843	1.529	1.13	1.206
AIC	0.68	1.88	1.79	1.84	1.53	1.138	1.231	0.608	1.854	1.79	1.83	1.51	1.11	1.18	0.63	1.86	1.79	1.829	1.516	1.12	1.193

Source: Authors' estimates

[a, b,] *implies the coefficient is significant at 1%, 5% respectively.*

δ *- GARCH-in-mean coefficient,* ϖ *- The constant term for the various GARCH model,* α *1 – The coefficient of the squared residual term,* α *2 – The coefficient for the second squared residual term. This coefficient is only applicable in the case of Germany.* $\alpha_1 + \alpha_2 + \beta$ *- Condition for stationarity of the GARCH model. Note that this is only the case for Germany, for the other markets, the condition is* $\alpha_1 + \beta$.

Table 7: Trends in volatility

STOCK MARKET	β_1	β_2
VOLAUS	0.155(0.000)[a]	-0.000025(0.17)
VOLCH	0.817(0.000)[a]	-0.000009(0.94)
VOLGR	0.435(0.000)[a]	0.000016(0.89)
VOLJPN	0.448(0.000)[a]	-0.000089(0.57)
VOLSA	0.325(0.000)[a]	0.000004(0.96)
VOLUK	0.448(0.000)[a]	0.000010(0.85)
VOLUS	0.239(0.000)[a]	-0.000013(0.80)

Source: Authors' estimates.
Note: p-values are in parenthesis. [a] denotes significance at 1%.

Table 8: Block exogeneity for volatility linkages

	Dependent Variables						
Excluded Variables	VOLAUS	VOLJPN	VOLCH	VOLSA	VOLGR	VOLUK	VOLUS
VOLAUS		52.91[0.00]	64.62[0.00]	27.44[0.33]	63.51[0.00]	117.6[0.00]	35.20[0.08]
VOLJPN	36.05[0.07]		32.21[0.15]	28.33[0.29]	46.39[0.01]	73.16[0.00]	32.07[0.16]
VOLCH	109.6[0.00]	75.41[0.00]		258.3[0.00]	121.1[0.00]	200.2[0.00]	121.9[0.00]
VOLSA	36.32[0.07]	46.82[0.01]	88.20[0.00]		142.7[0.00]	155.1[0.00]	64.27[0.00]
VOLGR	32.91[0.13]	28.72[0.28]	68.44[0.00]	83.67[0.00]		105.6[0.00]	58.97[0.00]
VOLUK	25.11[0.46]	65.17[0.00]	41.41[0.02]	39.02[0.04]	116.5[0.00]		76.48[0.00]
VOLUS	420.9[0.00]	192.1[0.00]	600.9[0.00]	668.1[0.00]	165.9[0.00]	266.4[0.00]	

Source: Authors' estimates
Note: Note: Parentheses [ ] are used to denote the probability values. The lag-order is initially based on the Akaike, Schwarz and Hannan-Quinn information and the lag was subsequently increased until diagnostically robust results were found.

FIGURES

Figure 1: Graphical plots of returns series

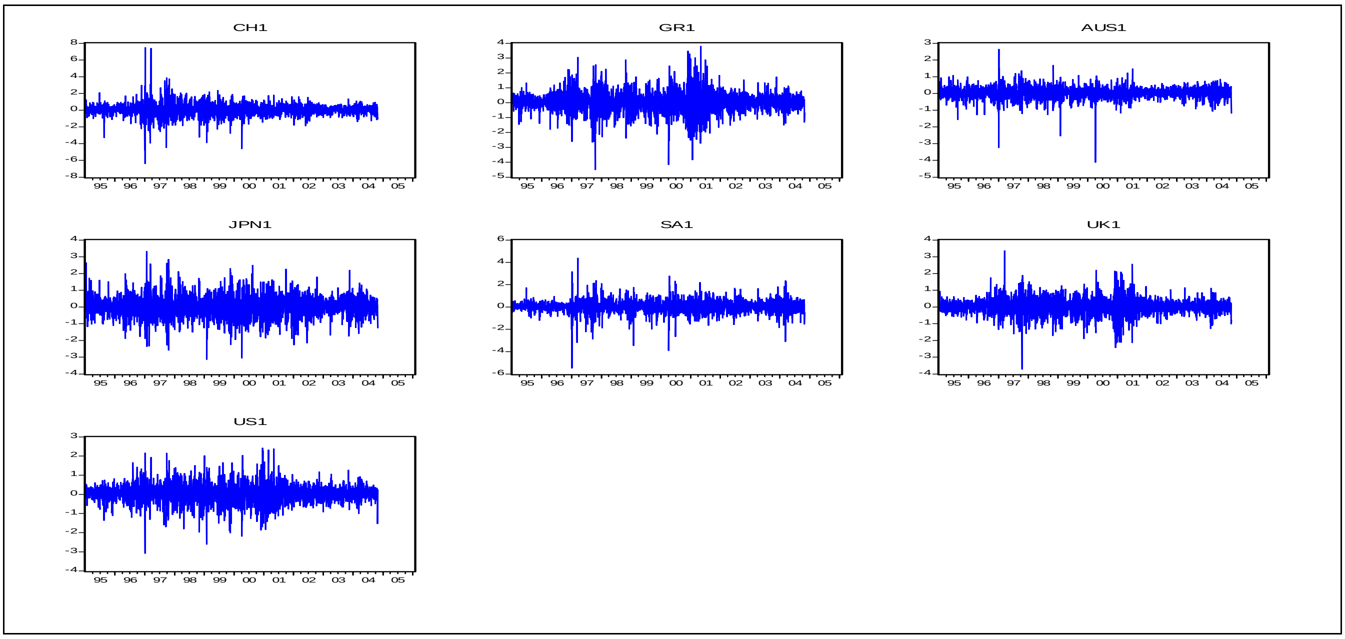

Figure 2: Impulse response function for returns linkages

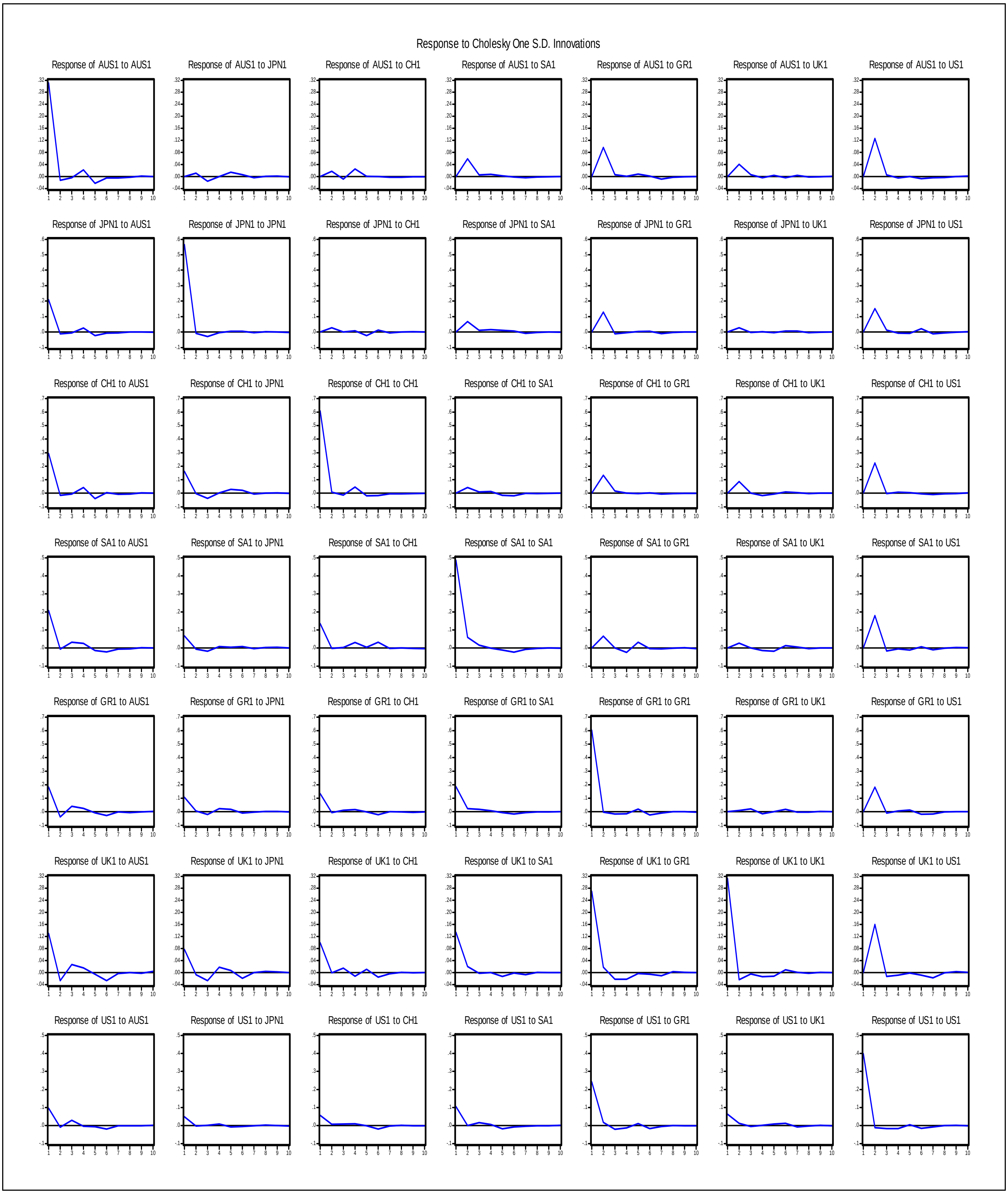

Figure 2: Graphical plots of volatility series

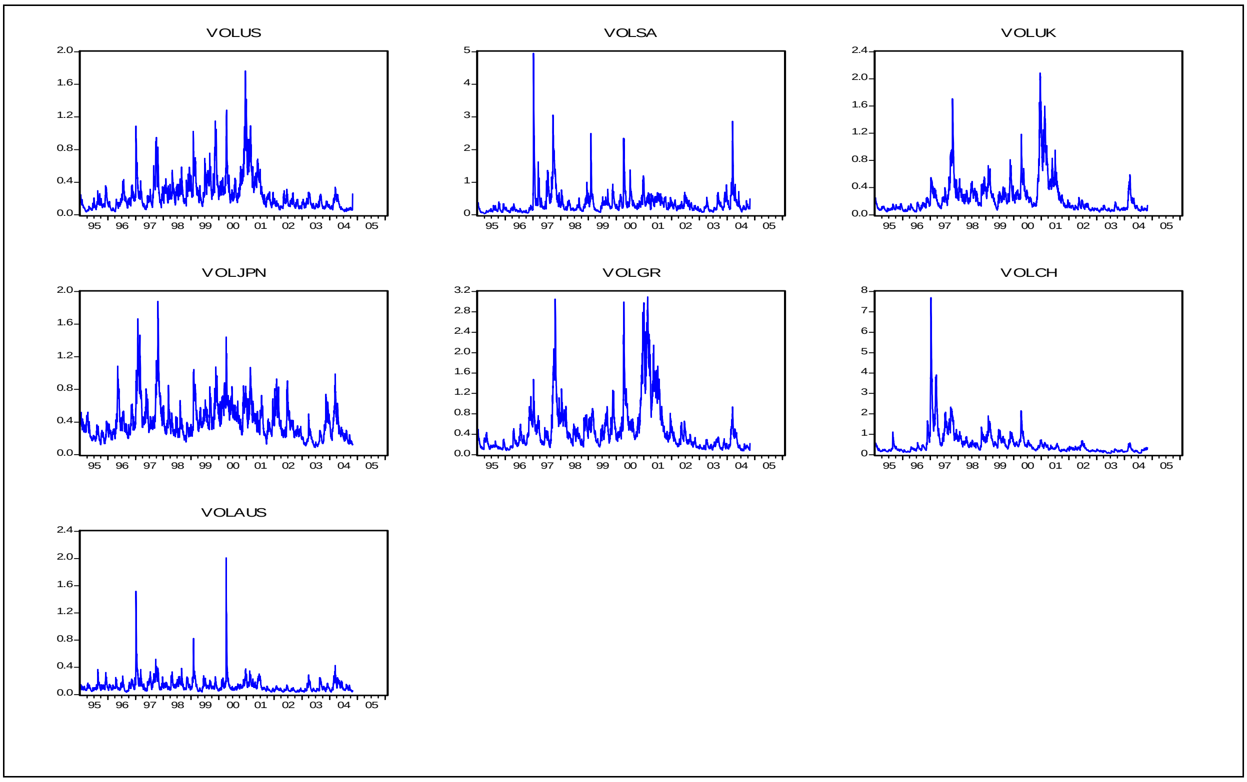

Figure 4: Impulse response functions for volatility linkages