Stock Market Co-Movement and Volatility Spillover between USA and South Africa

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Abstract

The purpose of this study is twofold. First, I look at the co-movement of the US and South African stock markets. Second, I examine the existence of volatility spillover between them. I estimate unrestricted bivariate GARCH-BEKK representation proposed by Engle and Kroner (1995) and VAR model by using daily total return series. I find evidence of return spillover from NYSE to JSE by analyzing VAR based on two lags. While analyzing the MA-GARCH model, empirical results exhibit that volatility spillover between US and SA is persistence. Uni-directional link regarding transmission of shocks and volatility persistence between NYSE and JSE is revealed, the direction is from NYSE to JSE, as off-diagonal parameters $a_{12}$ and $g_{12}$ are statistically significant. Finally, a strong influence of US market is observed in this paper regarding stock movement in the SA market.

**Key Words:** Financial Globalization, Financial Crisis, Volatility Spillover, MA-GARCH, Unrestricted Bivariate BEKK-GARCH Model.
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1. Introduction

1.1. Background

The substantial increase in global financial flows along with the increasing globalized economic activity has resulted in increased interdependence of major financial markets all over the world (Balios and Xanthakis, 2003 pp 106). The interdependence of stock markets has potential benefits that could boom investment and in turn economic growth (Mishkin, 2005 pp 14). Nevertheless, interdependence is accompanied with greater ease and speedy transmission of volatility shocks in markets. The flow of, almost costless information, reduced the isolation of domestic markets and increased their ability to react promptly to news and shocks originating from the rest of the world (Singh & Kumar, 2008). This enables volatility from global stock market to affect volatility in domestic capital market.

Accordingly, this interdependence between the global financial markets makes investors and portfolio managers to have a close watch on the movement of not only the domestic markets but also the international markets in order to carefully plan their global investment strategy. Besides, policy makers are also interested whether a stock market show signs of co-movement with other global market because the volatility spillover to that market has an impact on the smooth functioning of the financial system and in turn the economic performance (Mishkin 2005 pp 27).

Scholars in the field have been trying the corridor that can express the transmission mechanism and degree of volatility spillover between financial markets. Accordingly, many models and hypothesis has been studied extensively in recent years. Despite the level of severity, many of them has been reached in common consensus that a result of intense volatility somewhere in the global financial market, the dominant one, will spillover through other financial markets (Kim and Rogers, 1995).

There are several studies focusing on the stock market linkage across countries. For instance, Kim and Rogers (1995) found existence of volatility spillover from two well developed financial centers, USA and Japan, to Korea after the announcement of liberalization. The great influence of US market on UK and Japan market through return co-movement was found by the work of Connolly and Wang (2000). Research by Surya (2009) found that there
is significant volatility spillover effect from USA and Japan markets to Indonesia. Sariannidis et al (2010) found that there is positive co-movement between the financial markets of Hong Kong, India and Singapore. They also found the integration of these markets derived from common information which mostly stemmed from the US market. Moreover, the strong impact of high degree shocks in NYSE and RTS on volatility and return of Baltic state stock markets was shown in the thesis of Soultanaeva (2011).

However, considerably, little has been done in volatility spillover and return co-movement between developed markets and emerging African markets. South Africa has the most powerful economy in the continent of Africa and plays a leading role in industrial output, mineral production and supplying a large proportion of Africa’s electricity. According to the KOF index of globalization for 2011, South Africa has the second most economically globalized economy in Africa and which is ranked 55 out of 186 nations around the world. The size of the South African equity market is quite small as compared to that of the US. However, since, a number of South African firms are also listed on the US stock exchanges such as the NYSE; there is a chance of volatility and return spillover among these two markets.

Volatility is a measure of uncertainty about future asset price or return change. Since it is a major measure of risk for modern financial theories, it is a significant input for analyses in risk management, strategic financial planning and policy driving. The motivation for my paper is trying to answer a question of; are there significant volatility interactions in the form of co-movement and spillover between USA and South Africa by focusing on interaction of intraday returns and volatility.

The study considers volatility spillover modeling by using the bivariate BEKK-GARCH model proposed by Engle and Kroner (1995). This BEKK formulation enables us to study the possible transmission of volatility from one market to another, as well as any increased persistence in market volatility (Engle, 1990). Besides, Vector Autoregression (VAR) lags method is applied to capture return spillover and the interdependence of one market on the other.
1.2. Objective

The primary objective of this paper is to study whether there is return co-movement and volatility spillover between USA, which is a proxy for well developed financial market, and African emerging economy; South Africa which is a leading economy in the continent. Therefore, the paper studies the co-movement of the New York Stock Exchange (NYSE) and Johannesburg Stock Exchange (JSE) markets. The paper will give a descriptive statistical analysis of both NYSE and JSE index returns.

1.3. Scope and Limitations

While doing this paper, I faced some constraints which may adversely affect the effectiveness of this study. First and for most, time constraint hindered me to do certain aspects intensively, while they are important and useful for the topic which I studied. Secondly, having the appropriate software package was difficult and then after since, it was a first time to deal with it I faced some difficulties to understand and interpret results. Regarding with the scope of the study, I confined with only two markets while it is better to investigate the topic in broader approach with other additional European markets.

1.4. Data and Methodology

The data used in this paper are daily stock indices of the New York and Johannesburg stock markets, April 1, 2005 to May 31, 2011 i.e. there are 1565 observations from each market place. All data were accessed from Data Stream.

To achieve the objective of this work, different econometric and statistical models and measurements are employed. Vector Autoregression and unrestricted bivariate MA-GARCH BEKK (1, 1) model are employed to capture the return spillover and volatility transmission, between the two markets, respectively. The main advantage of using the BEKK GARCH model is that it has few parameters and ensures positive definiteness of the conditional covariance matrix. This is a requirement needed to ensure non-negative estimated variances.
The paper has employed both the SPSS 18 and EViews 6 software packages. EViews is mainly used to estimate the parameters of the VAR and BEKK models, while SPSS is employed for preliminarily statistical analysis of the data.

1.5. Organization of The Paper

This paper is organized as follows. Chapter 2 reviews both the theoretical and empirical literature related to the topics of this paper. Chapter 3 presents the econometric model specifications which are employed in the paper. Chapter 4 describes data and a preliminary statistical analysis of the data. Chapter 5 reports empirical results and interprets the estimated parameters. Chapter 6 is all about the conclusions.
2. Literature Review

2.1. Theoretical Review

2.1.1. Financial globalization

In most literatures financial globalization is implied as the integration of a country’s local financial system with international financial market. According to Schmukler, integration takes place when liberalized economies experience an increase in cross-country capital movement, including an active participation of local borrowers and lenders in international markets and a widespread use of international financial intermediaries (Schmukler, 2004).

Frenkel describe financial globalization as a historical process with two dimensions. One is the growing volume of cross border financial transactions; the other is the sequence of institutional and legal reforms implemented to liberalize and deregulate international capital movements and national financial systems (Frenkel, 2003).

Financial globalization is not a new phenomenon it was existed for a long time. However, a hundred years ago only a few countries and sectors were participated in the process of capital flow which directed toward supporting trade flows. The appearance of the First World War followed by the Great Depression and Second World War forced governments to impose control on capital flows to regain monetary policy independence (Bordo, 2000).

According to Mundell the 1970s oil price increment let Eurodollar market expand by getting huge fund from the enormous dollar surplus generated by the OPEC countries (Mundell, 2000). The time provides a chance for international banks to invest in developing countries which the largest portion of it was used to finance the deficits of oil importing developing countries. Schmukler in his work stated that Brady Bonds were created to solve the debt crisis which led to the subsequent development of bond markets for emerging economies (Schmukler, 2004). Many literatures argue that, 1980s and 1990s were gave rise to extensive liberalization of domestic financial system, stock markets and international capital transactions by the contemporary world (Isard, 2005).

We observe dramatic changes in information technology during the past two decade which in turn advance the theory of finance and give a room to innovate new financial product and
market design. According to some literatures the new financial landscape enables investors to allocate their risk efficiently. Also, in neoclassical models, financial globalization generates major economic benefits. In particular, it enables investors to diversify risks worldwide, it allows capital to flow where its productivity is highest, and it provides countries an opportunity to collect the benefits of their respective comparative advantages (Stulz, 1999). Generally, the new financial globalization process has a net benefit of facilitated foreign direct investment, enhanced cross-broad trade and implementation of cross-border portfolio investment strategies (Mishkin, 2005). In the other side of the mirror many economists argue that financial globalization beside its benefit, it has a risk. According to Schmukler the most common risk is that globalization can be related to financial crisis (Schmukler, 2004).

### 2.1.2. Financial Crisis

Financial crisis have been a major feature of current globalized high capital mobility. When Schmukler describe the pain of financial globalization he says:

> Financial globalization can also carry some risks. These risks are more likely to appear in the short run, when countries open up. One well-known risk is that globalization can be related to financial crises. The crises in Asia and Russia in 1997–98, Brazil in 1999, Ecuador in 2000, Turkey in 2001, Argentina in 2001, and Uruguay in 2002 are some examples that captured worldwide interest. There are various links between globalization and crises. If the right financial infrastructure is not in place or is not put in place during integration, liberalization followed by capital inflows can debilitate the health of the local financial system (Schmukler, 2004).

He, in his work of “Benefits and Risks of Financial Globalization: Challenges for Developing Countries” discuss different channels through which financial globalization can be related to crisis.

1. The liberalization of countries financial system makes the market subject to market discipline exercised by both domestic and foreign investors. In open economies the weakness in the monetary and fiscal policies and other macroeconomic
fundamentals trigger the chance of generating crisis by the joint force of domestic and foreign investors. According to Schmukler, investors might overreact, being over-optimistic in good times and over-pessimistic in bad ones, not necessarily disciplining countries. Therefore, small changes in fundamentals, or even news, can trigger sharp changes in investors’ appetite for risk.

2. A number of crises were triggered by shifts in market response that did not coincide with any change in underlying economic fundamentals. This is because of imperfectly functioning international financial market. Schmukler says:

   Globalization can also lead to crises if there are imperfections in international financial markets, which can generate bubbles, irrational behavior, herding behavior, speculative attacks, and crashes, among other things. Imperfections in international capital markets can lead to crises even in countries with sound fundamentals. For example, if investors believe that the exchange rate is unsustainable they might speculate against the currency, which can lead to a self-fulfilling balance-of-payments crisis regardless of market fundamentals. Imperfections can also deteriorate fundamentals. For example, moral hazard can lead to over borrowing syndromes when economies are liberalized and implicit government guarantees exist, increasing the likelihood of crises.

3. Schmukler put sudden withdrawal of foreign capital from one country as cause for financial crises and economic downturns. If a country is dependent on foreign capital, even it is associated with sound fundamentals and perfect financial market, the country may direct to crisis due to external factors. According to him, economic cyclical movements in developed economies, a global derive towards diversification of investment in major financial centers, foreign interest rates, and regional effects tend to be important external factors. The 1990s East Asian crisis witnessed the shift of foreign capital flow and intern creates crisis. Initially foreigners were investing in the East Asian economy and then later withdraw their investment, then, ones the countries lacked the operating capital their economy become gloomy.

4. Evidence over the past decade has created a widely held impression that international financial crisis have a tendency to spread from one country to another. The fourth channel through which financial globalization can be related to crisis,
According to him, is through financial contagion, namely by shocks that are transmitted across countries. Literatures have put different channels of contagion. He chose three broad channels while he discussed about contagion: real links, financial links, and herding behavior or “unexplained high correlations”. He discussed those channels like this:

**Real links** have been usually associated with trade links. For example, if two countries trade among themselves or if they compete in the same external markets, a policy change on parameters which is linked with the existing trade in one country will affect the other country’s competitive advantage. As a consequence, both countries will likely end up having similar measures to re-balance their competitive advantage. **Financial links** exist when two economies are connected through the international financial system. This mechanism propagates the shock to other economies. Finally, financial markets might transmit shocks across countries due to herding behavior or panics. He states this herding behavior as asymmetric information. “At the root of this herding behavior is asymmetric information. Information is costly so investors remain uniformed. Therefore, investors try to infer future price changes based on how other markets are reacting”. This asymmetric information implies that what the other market participants are doing might convey information that each uniformed investor does not have. This type of reaction leads to herding behavior, panics, and “irrational exuberance” (Schmukle, 2004).

### 2.1.3. Volatility

Volatility is a measure of uncertainty about future price or return changes on assets. Concerning the factors which drive volatility, there are two arguments. Some scholars say it is exogenously driven by unobservable factor which is correlated with the asset returns. But others concluded that stock market volatility has a very strong pattern of business cycle. According to Jones volatility will be higher during recession than during expansion (Jones P C, 2002).

Economists and policy makers have largely believe financial globalization has the primary impact of reducing domestic barriers to cross-border financial flows. This move towards free and fast capital flow results in all the countries within a global market making closely
related and dependent up on each other, thus, a financial crisis in one country can quickly spread to other countries (Dymski, 2005).

There are many empirical studies that show the existence of co-movements and interdependence between capital markets in the global market. Such co-movement can create interaction between the volatility of different financial market which we can call it volatility spillover. Volatility spillover may exist between the markets of different geographical locations and also between different types of financial markets, such as between the stock markets, the foreign exchange markets and the bond markets (Mulyadi, 2009).

Mulyadi on his work “volatility spillover in Indonesia, USA and Japan capital market” use two terminologies when he explain the nature of volatility spillover, contemporaneous volatility spillover and dynamic volatility spillover. According to him, Contemporaneous volatility spillover is volatility spillover in the very same day which could generally happen on stock markets in a same region having overlapping trading time. So, information between markets could be transmitted on the same day where trading still take place. Based on this information, investor could make a decision that will impact that capital market. Meanwhile, volatility spillover that could happen between capital markets in different region is called dynamic volatility spillover. Time-trading difference is attributed from starting and closing time of trading. One capital market starts trading when the other has been closed or almost in closing time of trading. Therefore, information from one capital market will made an impact to the other on next trading day, so volatility spillover happen on the next day (Mulyadi, 2009).
2.2.  Empirical Literature

2.2.1.  Stylized Facts of Financial Time Series Data

In empirical economic analysis, observations on a variable may be available on once a year or once a quarter and thus come from repeated observations, corresponding to different dates. The sequence of these observations on one variable is called time series (Gourieroux and Monfort, 1990 pp 1). Financial time series is concerned with a sequence of observations on financial data obtained in a fixed period of time. According to Tsay financial time series data analysis is differ from other time series analysis because the financial theory and its empirical time series contain an element of complex dynamic system with a high volatility and a great amount of noise (Tsay, 2005 pp 1). The uncertainty and noise makes the series to exhibit some statistical regularity, which are known as stylized facts. Stylized facts are empirical observations that are so consistence and have been made in so many contexts that they are accepted as truth. Stylized facts are obtained by taking a common denominator among the properties observed in studies of different markets and instruments (Cont R, 2000).

Therefore most financial data exhibits features like:

- **Volatility clustering:** - Volatility does not keep constant. It is quite common that large returns tend to be followed by large returns and small returns tend to be close with low returns.

- **Leptokurtosis effect:** - By viewing the value of kurtosis, we can conclude that the return series can show the feature of fat tails relative to the normal distribution as high kurtosis indicates a larger possibility of extreme movements.

- **Leverage effect:** - Volatility is higher after negative shocks than after positive shocks of same magnitude.

- **Skewness:** - The effect of skewness may be positive or negative, which describes their departure from symmetry.
• **Long-range dependence in the data:** Sample autocorrelations of the data are small whereas the sample autocorrelations of the absolute and squared values are significantly different from zero even for large lags. This behavior suggests that there is some kind of long-range dependence in the data.

• **Long-run memory effect:** The existence of this effect reflects persistence temporal dependence even between distant observations.

### 2.2.2. Empirical Review

Interdependence among world stock markets volatility over time and relationship that exist has naturally represented a privileged field for international financial research. Eun and Shim (1989) analyzed daily stock market returns of Australia, Hong Kong, Japan, France, Canada, Switzerland, Germany, UK and the US markets. They found a substantial interdependence between the national markets with USA. According to their finding the USA market is the most influential market in the world that makes the country the most important producer of information affecting the world stock market.

Kim and Rogers (1995) examine whether there has been any change in the transmission of volatility from Japan and USA to Korea following the liberalization announcement. They use GARCH methodology to inspect the existence of volatility spillover effect on the Korean market from Japan and USA and they found that spillover has increased after the announcement of liberalization especially from Japan. Moreover, they concluded that the spillover effect is on the volatility of returns more than on returns themselves.

Liu and Pan (1997) examine stock return and volatility spillover effects from the U.S. and Japanese markets to four Asian emerging stock markets, including Hong Kong, Singapore, Taiwan, and Thailand. The result of their study declared that the US market is more influential than the Japanese market in transmitting return and volatility to the Asian market.

For the period 1985-1996, Connolly and Wang (2000) examine the co-movement between returns for US, UK and Japan's market, conditional on a representative set of macroeconomic news announcement from these three countries. The result shows that the US market exerts
the greatest influence on both on the UK and Japan's markets, while the UK market has more influence on the US market than the Japan's market has.

The study of volatility spillover across South East Asia Stock markets from USA by Shamiri, and Isa (2009) has found that the USA stock has influential impact on the South East Asia markets mean returns. Using daily and intraday price and stock returns data, they examined volatility spillovers in the context of multivariate Generalized Autoregressive Heteroskedasticity (GARCH), by adopting a bivariate BEKK representation.

By using multivariate BEKK GARCH representation Sariannidis, Konteos and Drimbetas (2010), from the mean return equation, found that India, Singapore and Hong Kong markets are highly integrated and reacting in common information which derives from the largest information producer in the world, USA.

Soultanaeva (2011) examine whether the US and Russian markets has influence on the price and volatility dynamics of the Baltic states' stock markets and they employed an extended AR-asQGARCH model to study the influence of information. The result concludes that news arriving from NYSE has stronger impact on Tallinn and Vilnius market return than Moscow. However, their study showed that Riga market is absolutely independent of shock from abroad which is an interesting result.

To sum up, this empirical literature review advocates the existence of interdependence between most emerging stock markets and those of developed countries. In the era of globalization emerging countries are under market co-movement and volatility spillover pressure which is attributed by information flow from well developed global markets more specifically from USA.
3. Econometric Model

3.1. Conditional Heteroskedasticity

Empirical results declare that there is stochastic volatility in financial time series. Most models for financial time series data have a form of:

$$\xi_t = \delta_t Z_t$$

(1)

where $Z_t$ is a sequence of independent identically distributed random variables and $\delta_t$ is a non-negative stochastic process. $Z_t \sim \text{iid } N(0, 1)$ is independent with $\delta_t$. Let $f_{t-1}$ is domestic information set generated by the observed data up to and including time $t-1$. The distribution of the disturbance conditioned on an information set at time $t$ is assumed to be.

$$E(\xi_t|f_{t-1}) = \delta_t E(Z_t|f_{t-1}) = 0$$

$$\text{Var}(\xi_t|f_{t-1}) = \text{Var}(\delta_t Z_t|f_{t-1}) = \delta_t^2 \text{Var}(Z_t|f_{t-1}) = \delta_t^2$$

Therefore,

$$\xi_t|f_{t-1} \sim N(0, \delta_t^2)$$

A model that can capture the above conditional heteroskedasticity of financial time series was introduced by Engle on 1982 for the first time. The model is called “Autoregressive Conditional Heteroskedasticity” (Engle, 1982).

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \xi_{t-i}^2$$

(2)

The term “Autoregressive” express that the process is depend on its past, the term “Conditional Heteroskedasticity” means the variance is time varying i.e. non constant variance. However, ARCH model is formulated to depict volatility through large shocks of the explanatory variable $\xi_t$. Whereas, it is never be wrong to assume that the conditional variance of the error term is also a function of its own past conditional variance. Bollerslev (1986) has extended the ARCH model in to the generalization of Engle’s ARCH (GARCH) model by adding an autoregressive term to the moving averages of squared errors to capture the impact of lag conditional variance (Bollerslev, 1986).
Then the volatility process becomes
\[
\delta_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \xi_{t-i}^2 + \sum_{j=1}^{q} \beta_i \delta_{t-j}^2
\]  
(3)

where \(\alpha_i\)'s and \(\beta_j\)'s are non-negative parameters and in turn the above model specification ensures a non-negative estimate of the conditional variance. The two models are focused on the volatility process of one time series. Though, to analyze a volatility co-movement in the two markets I estimate a multivariate GARCH model. It helps me to capture the dynamic relationship between NYSE and JSE.

Consider a stochastic vector process \(\{r_t\}\) of daily returns with dimension \(1 \times N\). Let \(f_{t-1}\) denote the information set generated by the observed series \(\{r_t\}\) up to and including time \(t-1\). Since the ARCH models assume that the conditional error is serially uncorrelated, I remove the serial correlation from the stock returns first moment. As Bollerslev (1987) adjust the conditional mean return for a first-order moving average MA (1), the equation of \(r_t\) becomes:

\[
r_t = \mu_t + \xi_t
\]  
(4)

\[
\mu_t = c + \alpha \xi_{t-1}
\]

where \(\mu_t\) is the conditional mean stock return vector with respect to the information \(f_{t-1}\) and the term \(\alpha \xi_{t-1}\) models the conditional mean according to a MA (1) process (Bollerslev, 1987). As Bollerslev and Andersen (1997) suggest, I include the MA (1) term to capture economically minor but statistically significant first-order autocorrelation in the returns (Bollerslev and Andersen, 1997). Besides, \(\xi_t\) accounts for the short term dependence in expected returns and it will have the following form:

\[
\xi_t = H_t^{1/2}Z_t
\]

where \(H_t\) is \(N \times N\) definite positive matrix conditional covariance of vector \(\xi_t\) even also of \(r_t\); and \(Z_t\) is iid vector \(N \times 1\) with mean 0 and variance identity matrix \(I_N\). With these properties of the process, the distribution of the return has the following form:

\[
\text{Var } r_t|f_{t-1} = \text{Var } \xi_t|f_{t-1} = H_t^{1/2}\text{Var } (Z_t|f_{t-1}) H_t^{1/2}
\]

\[
= H_t
\]

\[
r_t|f_{t-1} \sim N(0, H_t)
\]
3.2. BEKK-GARCH Representation

Considering the international literature, MGARCH model is very good choice for modeling volatility transmission among market indices. The following mean equations were estimated for each market’s

\[ r_t = c + \Theta \xi_{t-1} + \xi_t \]  

(6)

where \( r_t \) is an 2x1 vector of daily returns at time \( t \) for each market, \( \xi_t | f_{t-1} \sim N(0, H_t) \) is an 2x1 vector of random errors for each market at time \( t \), \( f_{t-1} \) represents the market information that is available at time \( t-1 \) with its corresponding 2x2 conditional variance-covariance matrix, \( H_t \). \( R_{1,t} \) is an 2x1 vector of daily return for the NYSE and \( R_{2,t} \) is 2x1 vector of daily return for the JSE. The parameters in the conditional variance-covariance matrix can be modeled in several ways. One way is to model it as a bivariate BEKK GARCH process. BEKK formulation enables us to reveal the existence of any transmission of volatility from one market to another (Engel and Kroner, 1995). Then, I start my empirical specification with the model which is based on the bivariate GARCH (1, 1) BEKK representation proposed by Engle and Kroner (1995). One important feature of BEKK model, among the multivariate GARCH models, is that it builds in sufficient generality allowing the conditional variances and covariance of the stock markets to influence each other. Besides, it has few parameters and ensures positive definiteness of the conditional covariance matrix which is a requirement needed to quadratic non-negative estimated conditional variance (Engle and Kroner, 1995).

The conditional variance equation that I used in this paper has the following form:

\[ H_t = C_0 \cdot C_0 + A \cdot \xi_{t-1} \cdot \xi_{t-1}' + G \cdot H_{t-1} \cdot G \]  

(7)

where \( C \) is a 2x2 lower triangular matrix of constants and the purpose of decomposing the constant term into a product of two triangular matrices is to guarantee the positive semi-definiteness of \( H_t \). \( A \) is a 2x2 square matrix which shows how the conditional variances are correlated with past squared errors. The elements of matrix \( A \) measure the effects of shocks or “news” on the conditional variances. The 2x2 square matrix \( G \) shows how past conditional variances affect the current levels of conditional variances, in other words, the degree of volatility persistence in conditional volatility among the markets. The elements of
the covariance matrix $H_t$, depends only on past values of itself and past values of $\xi_t$, which is innovation. The BEKK parameterization for systematic GARCH is:

$$H_t = C_0' C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \xi_{1,t-1}^2 & \xi_{1,t-1} \xi_{2,t-1} \\ \xi_{1,t-1} \xi_{2,t-1} & \xi_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$

where,

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix}$$

The symmetric matrices $A$ captures the ARCH effects, the elements $a_{ij}$ of the symmetric matrix $A$ measure the degree of innovation from market $i$ to market $j$. While the matrix $G$ focus on the GARCH effects, the elements $g_{ij}$ in matrix $G$ represent the persistence in conditional volatility between market $i$ and market $j$. The diagonal parameters in matrices $A$ and $G$ measure the effects of own past shocks and past volatility of market $i$ on its conditional variance. The off-diagonal parameters in matrices $A$ and $G$, $a_{ij}$ and $g_{ij}$, measure the cross-market effects of shock and volatility, also known as volatility spillover.

The above BEKK model has diagonal form by assuming $A$ and $G$ matrices are diagonal. It restricts the off-diagonal elements in $A$ and $G$ to zero. Consequently, each conditional variance only depends on past values of itself and its own lagged squared residuals, whereas the conditional covariance depends on past values of itself and the lagged cross-product of residuals. However, the diagonal BEKK-representation of the above equation will not capture the spillover effect of each market own and cross volatility. So that, the full BEKK representation is choose to analyze the degree of volatility spillover between NYSE and JSE. Therefore, the parameter matrices for the above equation are defined as $C_0$, which is restricted to be lower triangular, and two unrestricted matrices $A$ and $G$. Hence, it can be further expanded by matrix multiplication and presented as follows:

$$h_{11,t} = c_{11}^2 + a_{11}^2 \xi_{1,t-1}^2 + 2a_{11}a_{22} \xi_{1,t-1} \xi_{2,t-1} + a_{21}^2 \xi_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2 g_{11} g_{22} h_{12,t-1} + g_{21}^2 h_{22,t-1}$$

$$h_{22,t} = c_{21}^2 + a_{21}^2 \xi_{1,t-1}^2 + 2a_{12}a_{22} \xi_{1,t-1} \xi_{2,t-1} + a_{22}^2 \xi_{2,t-1}^2 + g_{12}^2 h_{11,t-1} + 2 g_{12} g_{22} h_{12,t-1} + g_{22}^2 h_{22,t-1}$$

$$h_{12,t} = c_{11} c_{21} + a_{11} a_{21} \xi_{1,t-1}^2 + \left( a_{21} a_{22} + a_{11} a_{22} \right) \xi_{1,t-1} \xi_{2,t-1} + a_{21} a_{22} \xi_{2,t-1}^2 + g_{11} g_{12} h_{11,t-1} + g_{12} g_{22} h_{22,t-1} + g_{21} g_{22} h_{22,t-1}$$

where $h_{12,t} = h_{21,t}$. 

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3.3. **Vector Autoregression Model**

The following mean equations were estimated for each market’s own returns and the returns of other markets lagged one period to analyze the existence of return spillover:

\[
R_t = \mu + \Theta R_{t-1} + \xi
\]  

(11)

Vector autoregressive (VAR) models are proposed by Sims (1980) and can be used to capture the dynamics and the interdependency of multivariate time series. It is regarded as a generalization of univariate autoregressive models or a combination between the simultaneous equations models and the univariate time series models. In the bivariate VAR (1) case, with two variables, the model is:

\[
\begin{bmatrix}
r_{1,t} \\
r_{2,t}
\end{bmatrix} = \begin{bmatrix}
u_1 \\
u_2
\end{bmatrix} + \begin{bmatrix}
\Theta_{1,1} & \Theta_{1,2} \\
\Theta_{2,1} & \Theta_{2,2}
\end{bmatrix} \begin{bmatrix}
r_{1,t-1} \\
r_{2,t-1}
\end{bmatrix} + \begin{bmatrix}
\xi_{1,t} \\
\xi_{2,t}
\end{bmatrix}
\]

where \(r_t\) is an 2x1 vector of daily returns at time \(t\) for each market. In the above VAR (1) model, \(r_{1,t}\) represents the daily NYSE market return and \(r_{2,t}\) are JSE market return. The diagonal elements \(\Theta_{ii}\) of matrix \(\Theta\) are the respective market’s own returns lagged one period, while the off-diagonal elements \(\Theta_{ij}\) represent the mean spillover effect across markets. The 2x1 vector \(u_i\) contains constants.

3.4. **Estimation**

Since \(r_t | f_{t-1} \sim N(0, H_t)\), the above BEKK systems can be estimated efficiently and consistently using the full information maximum likelihood method (Engle and Kronor, 1995). The log likelihood function of the joint distribution is the sum of all the log likelihood functions of the conditional distributions, i.e., the sum of the logs of the multivariate-normal distribution. Letting \(\ell_t\) be the log likelihood of observation \(t\), \(n\) be the number of stock markets and \(L\) be the joint log likelihood the function has the following form:

\[
L(\Theta) = \sum_{t=1}^{p} \ell_t(\Theta)
\]

\[
\ell_t(\Theta) = -\frac{n}{2} \log (2\pi) - \frac{1}{2} \log |H_t| - \frac{1}{2} \xi_t' H_t^{-1} \xi_t
\]

where, \(\Theta\) denotes the vector of unknown parameters of the model.
4. Data and Descriptive Statistics

For this study I used daily closing stock index data of NYSE and JSE which are stock markets from USA and SA respectively, for the period Apr 1, 2005 to Mar 31, 2011 and there are 1565 observations for each market. The data are obtained from Data Stream and the daily return series will be generated as follows.

\[ R_t = 100 \times \log \left( \frac{P_t}{P_{t-1}} \right) \]

where, \( P_t \) is the closing value of the stock index on day t. The return series therefore continuously compounded daily returns expressed as a percentage.

Following the discovery of gold in 1886, financial institutions development comes into the picture and in turn led to the born of stock exchange in South Africa. In 1887 Johannesburg stock exchange was established by Benjamin Woollan. As of 2010, the Johannesburg Stock Exchange has almost 480 listed companies on the exchange with a total market capitalization of approximately $580 billion, ranks 18th place in the world.

With USA now a leading financial center in the global market, the New York Stock Exchange (NYSE) has become one of the premier exchanges in the world. The Buttonwood agreement between New York City stockbrokers and merchants led to the birth of New York Stock Exchange in 1792. Today, roughly 1.6 billion shares worth $45 billion are exchanged daily on the floor of the NYSE. As of the end of 2010, there are currently around 2,300 companies listed on the exchange, with a market capitalization of nearly $12 trillion. New York market serves well as a proxy for the global developed markets and is expected to play an influential role in the emerging market of Johannesburg.

Table 1 reports summary statistics for the returns series. During the period under study, the indices have a large difference between their maximum and minimum returns. NYSE has more difference between the two extreme values than JSE. The high values of standard deviation in both markets are indicating a high level of fluctuation of the daily return. During the period under study, the NYSE is the most volatile as measured by the standard deviation of 6.66%, while the JSE index is the least volatile with a standard deviation of 6.63% when compared to NYSE.
Table 1: Sample Statistics of NYSE and JSE

<table>
<thead>
<tr>
<th>ITEM</th>
<th>NYSE</th>
<th>JSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>No.</td>
<td>1565</td>
<td>1565</td>
</tr>
<tr>
<td>Minimum</td>
<td>-4.444</td>
<td>-3.2922</td>
</tr>
<tr>
<td>Maximum</td>
<td>5.006</td>
<td>2.968</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0044</td>
<td>0.0245</td>
</tr>
<tr>
<td>S.D</td>
<td>0.6619</td>
<td>0.6267</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.352</td>
<td>-0.1937</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>9.656</td>
<td>3.1805</td>
</tr>
<tr>
<td>J-B</td>
<td>1.8665 (0,000)</td>
<td>0.0076 (0,000)</td>
</tr>
</tbody>
</table>

The Jarque-Bera statistics reject the null hypothesis that the returns are normally distributed for all cases. The NYSE and JSE indices have a negative skewness, which means that the left tail is particularly extreme and indicating that large negative stock returns are more common than large positive returns. The indices also have higher peaks, as the kurtosis statistics are greater than 3. This coefficient of skewness and kurtosis indicate that the series for both index have asymmetric and leptokurtic distribution.

Figure 1 displays the pattern of estimated return series of the price indices. MA (1) is employed to estimate the return series. The result of estimated model from MA (1) is significant for NYSE but not for JSE. This implies, the return series of NYSE market have characteristics of moving average. This is shown in Table A3 (Appendix).

Figure 1: Fitted Return Series Using MA (1)
There are stretches of time where the volatility is relatively high and relatively low which suggest an apparent volatility clustering in some periods. The two markets have very high volatility during end of 2008 and they enjoy the lower level of volatility during the end of 2006 and beginning of 2007. Statistically, volatility clustering implies a strong autocorrelation in squared return. Residuals ACF and squared returns are confirming the existence of autocorrelation. As we see in figure 3 there is significant autocorrelation in the squared return series. The result implies, since squared return measure the second order moment, the time series NYSE and JSE exhibit time varying conditional heteroskedasticity and volatility clustering.

Figure 2: Residual ACF and PACF plot for NYSE and JSE

Figure 3: Squared Return Autocorelation Plot for NYSE and JSE
5. Empirical Results

5.1. VAR Estimation

The results are presented in Table 2. I apply two lag VAR model in order to estimate the parameters for mean return model (equation 11) which I exploit to analyze the existence of return spillover and information transformation between NYSE and JSE.

Table 2: Vector Autoregression Estimates

<table>
<thead>
<tr>
<th></th>
<th>DRNYSE</th>
<th>DRJSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRNYSE(-1)</td>
<td>-0.142600</td>
<td>0.381099</td>
</tr>
<tr>
<td>(0.02905)</td>
<td>(0.02602)</td>
<td></td>
</tr>
<tr>
<td>[-4.90888]</td>
<td>[ 14.6472]</td>
<td></td>
</tr>
<tr>
<td>DRNYSE(-2)</td>
<td>-0.120938</td>
<td>0.074170</td>
</tr>
<tr>
<td>(0.03091)</td>
<td>(0.02769)</td>
<td></td>
</tr>
<tr>
<td>[-3.91196]</td>
<td>[ 2.67861]</td>
<td></td>
</tr>
<tr>
<td>DRJSE(-1)</td>
<td>0.075922</td>
<td>-0.172133</td>
</tr>
<tr>
<td>(0.03253)</td>
<td>(0.02913)</td>
<td></td>
</tr>
<tr>
<td>[ 2.33405]</td>
<td>[-5.90830]</td>
<td></td>
</tr>
<tr>
<td>DRJSE(-2)</td>
<td>0.019117</td>
<td>-0.040130</td>
</tr>
<tr>
<td>(0.02973)</td>
<td>(0.02663)</td>
<td></td>
</tr>
<tr>
<td>[ 0.64309]</td>
<td>[-1.50717]</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.003396</td>
<td>0.027731</td>
</tr>
<tr>
<td>(0.01663)</td>
<td>(0.01489)</td>
<td></td>
</tr>
<tr>
<td>[ 0.20422]</td>
<td>[ 1.86192]</td>
<td></td>
</tr>
</tbody>
</table>

F-statistic 8.319832 54.82702
Log likelihood -1556.671 -1384.457
Akaike AIC 1.998299 1.777936
Schwarz SC 2.015427 1.795065

I use the conventional level of significance of 5% in the discussion. The Akaike and Schwarz information values for the model are 1.9983 and 2.0154 respectively; which is lower than the corresponding value of lag one and four. This implies, since the lower the value of Akaike and Schwarz information is the better the model, lag 2 model is preferable. Beside, the F value, at 5 percent \( F_{0.5} (4, 1563) =2.37 \), is statistically significant; the \( p \) values are actually 8.3198 and 54.8270 in NYSE and JSE regression respectively. Therefore, there is no
reason to accept the null hypothesis that state lag value of its own return and cross market return has no impact on its current return.

The serial correlation value of about 0.43 between the NYSE and JSE return series reveals the co-movement of their returns. This is also exposed in the stock indices movement through the period which the study undertakes (see figure Appendix 1). Almost non-overlapping trading hour between them implies the existence of one period lag correlation. However, it does not mean that there is return spillover between these two markets. VAR analysis solves the question regarding the existence of return spillover.

In order to see the relationship in terms of return across the two indices I firstly look at matrix $\Theta$ in the mean equation, equation (11). As the diagonal parameters for own market shows, both 1-period and 2-period lag of $\Theta_{11}$, and 1-period-lag of $\Theta_{22}$, are statistically significant which indicate that these parameters have non zero value. This demonstrate that, even if it is weak, the return of NYSE index is depend on its first and second lags whereas JSE index is only depend on its first lag. In contrast, off diagonal estimators for cross-market return linkages show the significant of $\Theta_{12}$ (1-period lag) and the insignificant of $\Theta_{21}$ both 1-period and 2-period lags. The VAR model discloses a large and significant value of about 0.3811 for the dependence of JSE return on 1-period lagged NYSE return. It implies the existence of uni-directional return spillover from the NYSE to JSE; i.e. emerging market. The question is how and why this spillover occur between this two markets.

The cross-market returns linkage reveal that the U.S market has influence to transmit news towards South Africa market. As table 3, JSE will open after ten hours that the NYSE market closed. During the regular trading hours of the JSE, NYSE has already done their trading day. Therefore, Information concerning price change in USA affects next trading day of JSE´s stock price movement.

Table 3: Market Opening Times in GMT Time Zone

<table>
<thead>
<tr>
<th>Exchange Name</th>
<th>Opening Time (GMT)</th>
<th>Closing Time (GMT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NYSE</td>
<td>14:30</td>
<td>21:00</td>
</tr>
<tr>
<td>JSE</td>
<td>7:00</td>
<td>15:00</td>
</tr>
</tbody>
</table>
The above results, in general, put in the picture that information from the US market is transmitted into the pricing process of the stock exchange in SA. As a result, there is a unidirectional return spillover from NYSE to JSE.

### 5.2. MA-GARCH BEKK Estimation

The conditional variance covariance equations presented in bivariate MA-GARCH model effectively captures the volatility and cross volatility spillover among the stock markets. Table 4 presents the estimated coefficients in the variance–covariance matrix of bivariate MA-GARCH-BEKK model employed for analyzing volatility relationship between the NYSE and JSE.

**Table 4: MA-GARCH estimated coefficients for variance covariance equations**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>MU(1)</td>
<td>0.026945</td>
<td>0.008136</td>
<td>3.312081</td>
</tr>
<tr>
<td>MU(2)</td>
<td>0.039351</td>
<td>0.011619</td>
<td>3.386832</td>
</tr>
<tr>
<td>TETA(1)</td>
<td>-0.243372</td>
<td>0.021930</td>
<td>-11.09786</td>
</tr>
<tr>
<td>TETA(2)</td>
<td>-0.011246</td>
<td>0.024343</td>
<td>-0.461993</td>
</tr>
<tr>
<td>OMEGA(1) c</td>
<td>-0.049163</td>
<td>0.006274</td>
<td>-7.835631</td>
</tr>
<tr>
<td>BETA(1) g</td>
<td>0.958416</td>
<td>0.005025</td>
<td>190.7134</td>
</tr>
<tr>
<td>BETA(3) g</td>
<td>7.32E-05</td>
<td>0.011985</td>
<td>0.006108</td>
</tr>
<tr>
<td>ALPHA(1) a</td>
<td>-0.295548</td>
<td>0.022820</td>
<td>-12.95111</td>
</tr>
<tr>
<td>ALPHA(3) a</td>
<td>0.043499</td>
<td>0.024240</td>
<td>1.794543</td>
</tr>
<tr>
<td>OMEGA(3) c</td>
<td>0.084485</td>
<td>0.014256</td>
<td>5.926251</td>
</tr>
<tr>
<td>OMEGA(2) c</td>
<td>-0.062655</td>
<td>0.023220</td>
<td>-2.698270</td>
</tr>
<tr>
<td>BETA(4) g</td>
<td>0.894998</td>
<td>0.012098</td>
<td>74.34840</td>
</tr>
<tr>
<td>BETA(2) g</td>
<td>0.022000</td>
<td>0.008962</td>
<td>2.454783</td>
</tr>
<tr>
<td>ALPHA(4) a</td>
<td>0.383423</td>
<td>0.025239</td>
<td>15.19144</td>
</tr>
<tr>
<td>ALPHA(2) a</td>
<td>-0.384320</td>
<td>0.027156</td>
<td>-14.15224</td>
</tr>
</tbody>
</table>

| Log likelihood   | -2093.875  | Akaike info criterion | 2.696771 |
| Avg. log likelihood | -1.338795 | Schwarz criterion | 2.748130 |
| Number of Coefs.  | 15         | Hannan-Quinn criter.  | 2.715864 |

Considering the set of parameters, the diagonal values in matrix A indicates own market innovations and diagonal G matrix represent the persistence in own stock market conditional volatility. As shown in table 4, the own past shocks and past volatility of all markets are significant. From the result that $|a_{ii}| < |g_{ii}|$, suggesting that the behavior of
current variance and covariance is not so much affected by the magnitude of past innovations as by the value of lagged variances and covariances. Moreover, the statistical significance of GARCH parameters $g_{ii}$ is revealing the extent of volatility clustering.

The off-diagonal elements of matrices A and G capture the cross-market effects of shocks and volatility spillovers among the markets. I found uni-directional link regarding transmission of shocks between NYSE and JSE as off-diagonal parameter $a_{12}$ is statistically significant. This suggests volatility spillover from NYSE to JSE, since innovations initiating in one country affect volatility in the other; this is because innovation, $\xi_{1,2}t-1$, does affect the behavior of $h_{22}$ whereas $\xi_{2,2}t-1$ does not affect the dynamics of $h_{11}$ significantly. Finally, there is also strong evidence of uni-directional volatility persistence linkages between NYSE and JSE, the direction is from NYSE to JSE, as only $g_{12}$ is statistically significant. In this case, lagged volatility persistence in NYSE has a positive effect on current volatility in JSE over time.

$$h_{11,t} = 0.002 + 0.09\xi_{1,2}t-1 - 0.23\xi_{1,t-1} + 0.002\xi_{2,2}t-1 + 0.92h_{11,t-1} + 1.72h_{12,t-1} \quad \text{eq}(8)$$

$$h_{22,t} = 0.01 + 0.15\xi_{1,2}t-1 - 0.3\xi_{1,t-1} + 0.15\xi_{2,2}t-1 + 0.001h_{11,t-1} + 0.04h_{12,t-1} + 0.81h_{22,t-1} \quad \text{eq}(9)$$

$$h_{12,t} = 0.003 + 0.11\xi_{1,2}t-1 - 0.1\xi_{1,t-1} + 0.02\xi_{2,2}t-1 + 0.02h_{11,t-1} + 0.86h_{12,t-1}$$

From equation 8 and 9, compared with that of NYSE market, JSE market’s own shock effect on current volatility is higher than NYSE market own shock effect. Whereas, NYSE market is affected more by its own lagged volatility when it is compared with JSE market. Besides the own shock effect, past shocks in NYSE have a positive effect on current volatility in JSE market. Surprisingly, compared own and cross shocks, shock transmission to JSE have equal impact like past shocks has on its own current volatility. However, lagged own volatility persistence in JSE has a large effect on its own current volatility than cross volatility persistence. The volatility persistence from NYSE to JSE is weak but significant. As we see from equation 9, therefore, there is a significant uni-directional volatility spillover from NYSE to JSE. It reveals strong impact of the USA markets on SA stock return movement which is consistence to the arguments that developed stock markets have significant influence in transmitting return and volatility to emerging stock markets (Liu and Pan, 1997).

Generally, the above estimated parameters for the sample period support the existence of uni-directional volatility spillover between USA and SA and the direction is from USA to SA.
We see that the SA return variation of present day is depend on the return variation of the previous day of USA and SA markets which is a component of weak ARCH effect and strong GARCH. Similarly, covariance equation indicates that there is a statistically significant co-variation in returns. This significant conditional covariance together with the spillover effect noticeably implies that both markets are influenced by common information. Since their time trading is different, information from the US market has an impact on next trading day of the SA market. In the same token, volatility spillover will happen in the next day; which we call it dynamic volatility spillover.

Figure 3 presents the fact that unrestricted bivariate BEKK MA-GARCH model is well capture the volatility spillover.

![Figure 3: Estimated Conditional Variance-Covariance by Unrestricted BEKK MA-GARCH](image)

Finally, the overall variance-covariance equations are significant under log likelihood test. In conventional 5% significance level, the value of log likelihood about 2093.875 gives room to reject the null hypothesis. This proclaims the suitability of the unrestricted bivariate BEKK model and it fits significantly analyze the persistence of volatility spillover among the stock markets.
6. Conclusion and Further Studies

The substantial increase in global capital flow along with the globalized economy is attributed for the existence of interdependence between financial markets which is more apparent than before. In the other side of the mirror, financial crisis was frequently happened and adversely affect the global economy. This thesis investigates weather there is stock market co-movement and volatility spillover between the USA and South Africa markets. I employed daily stock return indices from Apr 1, 2005 to May 31, 2011.

First, by applying VAR representation approach based on two lag period, I found evidence of uni-directional return spillover, which is from the NYSE to JSE. In this circumstance, information from the US market has made impact on the SA market. According to the assessment of trading time of both markets, the South Africa market is strongly affected on what happened in the US market one period lag stock movement. Finally, the unrestricted bivariate MA-GARCH – BEKK model is built to capture the existence of volatility spillover between returns of the NYSE and JSE stock indices. I found significant own past shocks and past volatility persistence impact on the current return fluctuation of both markets. Though the dynamics of the conditional volatilities differ, there is uni-directional volatility transmission between these two markets. This is due to the existence of significant and positive shocks and volatility spillovers from USA to SA. Based on this, I conclude that USA has influential impact on the South Africa stock return movement.

In summary, I consider my result support the finding in established literature on stock return co-movement and volatility spillover between developed and emerging markets. Hence, stakeholders on the investment activity, including government, should pay attention on the behavior of volatility transmission. Policy makers and private as well as institutional investors should modify their investment strategy and asset allocation decisions accordingly to the spillover effects so that they can protect their investment from default and/or make profit by hedging their investment.

Last but not least, however, this thesis could also be improved in the following ways. Firstly, beside USA, one strong European market could be included to examine the effect from which South Africa is strongly affected. Secondly, the study can be done by dividing the sample in to two sub-samples: pre-reformation and post-reformation of South African market.
Reference

"Eviews 6 User Guide II."


Appendix

Table 1: Estimated parameters for the mean return model
Vector Autoregression Estimates
Date: 05/30/11   Time: 00:11
Sample (adjusted): 4/05/2005 3/31/2011
Included observations: 1563 after adjustments
Standard errors in ( ) & t-statistics in [ ]

<table>
<thead>
<tr>
<th></th>
<th>DRNYSE</th>
<th>DRJSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRNYSE(-1)</td>
<td>-0.142600</td>
<td>0.381099</td>
</tr>
<tr>
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<td>(0.02602)</td>
</tr>
<tr>
<td></td>
<td>[-4.90888]</td>
<td>[ 14.6472]</td>
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<td>0.074170</td>
</tr>
<tr>
<td></td>
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<td>(0.02769)</td>
</tr>
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<td></td>
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<td></td>
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<td>(0.02913)</td>
</tr>
<tr>
<td></td>
<td>[ 2.33405]</td>
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<tr>
<td>DRJSE(-2)</td>
<td>0.019117</td>
<td>-0.040130</td>
</tr>
<tr>
<td></td>
<td>(0.02973)</td>
<td>(0.02663)</td>
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<tr>
<td></td>
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<td>[-1.50717]</td>
</tr>
<tr>
<td>C</td>
<td>0.003396</td>
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</tr>
<tr>
<td></td>
<td>(0.01663)</td>
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<tr>
<td></td>
<td>[ 0.20422]</td>
<td>[ 1.86192]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>DRNYSE</th>
<th>DRJSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-squared</td>
<td>0.020914</td>
<td>0.123393</td>
</tr>
<tr>
<td>Adj. R-squared</td>
<td>0.018400</td>
<td>0.121143</td>
</tr>
<tr>
<td>Sum sq. resid</td>
<td>670.7431</td>
<td>538.0888</td>
</tr>
<tr>
<td>S.E. equation</td>
<td>0.656137</td>
<td>0.587683</td>
</tr>
<tr>
<td>F-statistic</td>
<td>8.319832</td>
<td>54.82702</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1556.671</td>
<td>-1384.457</td>
</tr>
<tr>
<td>Akaike AIC</td>
<td>1.998299</td>
<td>1.777936</td>
</tr>
<tr>
<td>Schwarz SC</td>
<td>2.015427</td>
<td>1.795065</td>
</tr>
<tr>
<td>Mean dependent</td>
<td>0.004542</td>
<td>0.024630</td>
</tr>
<tr>
<td>S.D. dependent</td>
<td>0.662258</td>
<td>0.626880</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>DRNYSE</th>
<th>DRJSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Determinant resid covariance (dof adj.)</td>
<td>0.110329</td>
<td></td>
</tr>
<tr>
<td>Determinant resid covariance</td>
<td>0.109624</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2707.942</td>
<td></td>
</tr>
<tr>
<td>Akaike information criterion</td>
<td>3.477852</td>
<td></td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>3.512109</td>
<td></td>
</tr>
</tbody>
</table>
Table A2: Estimated parameters for full BEKK MA-GARCH presentation

LogL: BVGARCH  
Method: Maximum Likelihood (Marquardt)

Included observations: 1564  
Evaluation order: By observation  
Estimation settings: tol= 1.0e-05, derivs=accurate numeric

Initial Values: MU(1)=0.15761, MU(2)=0.21396, TETA(1)=0.10000,  
TETA(2)=0.10000, OMEGA(1)=0.05270, BETA(1)=0.50000,  
BETA(3)=0.50000, ALPHA(1)=0.50000, ALPHA(3)=0.50000,  
OMEGA(3)=0.07695, OMEGA(2)=0.00000, BETA(4)=0.50000,  
BETA(2)=0.50000, ALPHA(4)=0.50000, ALPHA(2)=0.50000

Convergence achieved after 97 iterations

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>MU(1)</td>
<td>0.026945</td>
<td>0.008136</td>
<td>3.312081</td>
</tr>
<tr>
<td>MU(2)</td>
<td>0.039351</td>
<td>0.011619</td>
<td>3.386832</td>
</tr>
<tr>
<td>TETA(1)</td>
<td>-0.243372</td>
<td>0.021930</td>
<td>-11.09786</td>
</tr>
<tr>
<td>TETA(2)</td>
<td>-0.011246</td>
<td>0.024343</td>
<td>-0.461993</td>
</tr>
<tr>
<td>OMEGA(1)</td>
<td>-0.049163</td>
<td>0.006274</td>
<td>-7.835631</td>
</tr>
<tr>
<td>BETA(1)</td>
<td>0.958416</td>
<td>0.005025</td>
<td>190.7134</td>
</tr>
<tr>
<td>BETA(3)</td>
<td>7.32E-05</td>
<td>0.011985</td>
<td>0.006108</td>
</tr>
<tr>
<td>ALPHA(1)</td>
<td>-0.295548</td>
<td>0.022820</td>
<td>-12.95111</td>
</tr>
<tr>
<td>ALPHA(3)</td>
<td>0.043499</td>
<td>0.024240</td>
<td>1.794543</td>
</tr>
<tr>
<td>OMEGA(3)</td>
<td>0.084485</td>
<td>0.014256</td>
<td>5.926251</td>
</tr>
<tr>
<td>OMEGA(2)</td>
<td>-0.062655</td>
<td>0.023220</td>
<td>-2.698270</td>
</tr>
<tr>
<td>BETA(4)</td>
<td>0.899498</td>
<td>0.012098</td>
<td>74.34840</td>
</tr>
<tr>
<td>BETA(2)</td>
<td>0.022000</td>
<td>0.008962</td>
<td>2.454783</td>
</tr>
<tr>
<td>ALPHA(4)</td>
<td>0.383423</td>
<td>0.025239</td>
<td>15.19144</td>
</tr>
<tr>
<td>ALPHA(2)</td>
<td>-0.384320</td>
<td>0.027156</td>
<td>-14.15224</td>
</tr>
</tbody>
</table>

Log likelihood: -2093.875  
Avg. log likelihood: -1.338795  
Number of Coefs.: 15

Akaike info criterion: 2.696771  
Schwarz criterion: 2.748130  
Hannan-Quinn criter.: 2.715864
Table A3: Estimated Parameters for MA (1)

<table>
<thead>
<tr>
<th>MA Model Parameters</th>
<th>Estimate</th>
<th>SE</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNYSE-Model_1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNYSE</td>
<td>Constant</td>
<td>,004</td>
<td>,015</td>
<td>,302</td>
</tr>
<tr>
<td>No Transformation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA Lag 1</td>
<td>,117</td>
<td>,025</td>
<td>4,657</td>
<td>,000</td>
</tr>
<tr>
<td>RJSE-Model_2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RJSE</td>
<td>Constant</td>
<td>,025</td>
<td>,016</td>
<td>1,511</td>
</tr>
<tr>
<td>No Transformation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA Lag 1</td>
<td>-.026</td>
<td>,025</td>
<td>-1,022</td>
<td>.307</td>
</tr>
</tbody>
</table>

Table A4: Correlations

<table>
<thead>
<tr>
<th></th>
<th>RNYSE</th>
<th>RJSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNYSE Pearson Correlation</td>
<td>1</td>
<td>.430**</td>
</tr>
<tr>
<td>Sig. (2-tailed)</td>
<td></td>
<td>.000</td>
</tr>
<tr>
<td>N</td>
<td>1565</td>
<td>1565</td>
</tr>
<tr>
<td>RJSE Pearson Correlation</td>
<td>.430**</td>
<td>1</td>
</tr>
<tr>
<td>Sig. (2-tailed)</td>
<td></td>
<td>.000</td>
</tr>
<tr>
<td>N</td>
<td>1565</td>
<td>1565</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
Figure A1: Stock indices
Figure 2A: Frequency distribution of NYSE and JSE daily return series

Mean = .024543
Std. Dev. = .0267157
N = 1565

Mean = .004442
Std. Dev. = .0618523
N = 1565
Figure 3A: Estimated Conditional Variance of NYSE and JSE by Full BEKK Model
Unrestricted Version of bi-variate MA-GARCH BEKK PRG (28/12/2011)

BV_MA_GARCH.PRG (02/21/2012)
  ' unrestricted version of
  '  y = µ + res
  '  µ= c+Θres(-1)
  '  res ~ N(0,H)
  '  H = omega*omega' + beta H(-1) beta' + alpha res(-1) res(-1)' alpha'
  'where
  '  y = 2 x 1
  '  µ = 2 x 1
  '  H = 2 x 2 (symmetric)
  '  H(1,1) = variance of y1  (saved as var_y1)
  '  H(1,2) = cov of y1 and y2 (saved as var_y2)
  '  H(2,2) = variance of y2  (saved as cov_y1y2)
  '  omega = 2 x 2 low triangular
  '  beta = 2 x 2
  '  alpha = 2 x 2

' change path to program path
%path = @runpath
  cd %path

' dependent variables of both series must be continues
smpl @all
  series y1 = DRNYSE
  series y2 = DRJSE

' set sample
' first observation of s1 need to be one or two periods after
' the first observation of s0
sample s0 4/1/2005 3/31/2011
sample s1 4/2/2005 3/31/2011

' initialization of parameters and starting values
' change below only to change the specification of model
smpl s0

' get starting values from univariate GARCH
  equation eq1.arch(m=100,c=1e-5) y1 c ma(1)
  equation eq2.arch(m=100,c=1e-5) y2 c ma(1)

' declare coef vectors to use in bi-variate GARCH model
' see above for details
  coef(2) mu
    mu(1)= eq1.c(1)^.5
    mu(2)= eq2.c(1)^.5

  coef(3) teta
    teta(1) = .1
    teta(2) = .1

  coef(4) omega
    omega(1)=eq1.c(3)^.5
    omega(2)=0
\[
\omega(3) = \text{eq2.c}(3)^{.5}
\]

\text{coef(5) alpha}

\[
\alpha(1) = 0.5 \\
\alpha(2) = 0.5 \\
\alpha(3) = 0.5 \\
\alpha(4) = 0.5
\]

\text{coef(5) beta}

\[
\beta(1) = 0.5 \\
\beta(2) = 0.5 \\
\beta(3) = 0.5 \\
\beta(4) = 0.5
\]

\text{' constant adjustment for log likelihood}

\text{!mlog2pi = 2*log(2*@acos(-1))}

\text{' use var-cov of sample in "s1" as starting value of variance-covariance matrix}

\text{series cov_y1y2 = @cov(y1-mu(1), y2-mu(2))}
\text{series var_y1 = @var(y1)}
\text{series var_y2 = @var(y2)}

\text{series sqres1 = (y1-mu(1))^2}
\text{series sqres2 = (y2-mu(2))^2}
\text{series res1res2 = (y1-mu(1))*(y2-mu(2))}

\text{smpl 4/1/2005 4/2/2005}

\text{series res1=y1-mu(1)}
\text{series res2=y2-mu(2)}

\text{smpl 4/2/2005 3/31/2011}

\text{series res1=y1-mu(1)-teta(1)*res1(-1)}
\text{series res2=y2-mu(2)-teta(2)*res2(-1)}

\text{series cov_y1y2 = @cov(y1-mu(1)-teta(1)*res1(-1), y2-mu(2)-teta(2)*res2(-1))}
\text{series var_y1 = @var(y1-teta(1)*res1(-1))}
\text{series var_y2 = @var(y2-teta(2)*res2(-1))}

\text{series sqres1=y1-mu(1)-teta(1)*res1(-1)^2}
\text{series sqres2=y2-mu(2)-teta(2)*res2(-1)^2}
\text{series res1res2=(y1-mu(1)-teta(1)*res1(-1))*(y2-mu(2)-teta(2)*res2(-1))}

\text{' ...........................................................}
\text{' LOG LIKELIHOOD}
\text{' set up the likelihood}
\text{' 1) open a new blank likelihood object (L.O.) name bvgarch}
\text{' 2) specify the log likelihood model by append}
\text{' ...........................................................}

\text{logl bvgarch}
\text{bvgarch.append @logl logl}

\text{smpl 4/1/2005 4/2/2005}

\text{bvgarch.append res1=y1-mu(1)}
\text{bvgarch.append res2=y2-mu(2)}
```
smpl 4/1/2005 4/2/2005
bvgarch.append sqres1=(y1-mu(1))^2
bvgarch.append sqres2=(y2-mu(2))^2
bvgarch.append res1res2= (y1-mu(1))*(y2-mu(2))

bvgarch.append res1=y1-mu(1)-teta(1)*res1(-1)
bvgarch.append res2=y2-mu(2)-teta(2)*res2(-1)

bvgarch.append sqres1 = (y1-mu(1)-teta(1)*res1(-1))^2
bvgarch.append sqres2 = (y2-mu(2)-teta(2)*res2(-1))^2
bvgarch.append res1res2 = (y1-mu(1)-teta(1)*res1(-1))*(y2-mu(2)-teta(2)*res2(-1))

' calculate the variance and covariance series
bvgarch.append var_y1  =  omega(1)^2 + beta(1)^2*var_y1(-1)+beta(1)*beta(3)*cov_y1y2(-1)+beta(1)*beta(3)*cov_y1y2(-1)+beta(3)^2*var_y2(-1)+ alpha(1)^2*sqres1(-1)+alpha(1)*alpha(3)*res1res2(-1)+alpha(1)*alpha(3)*res1res2(-1)+alpha(3)^2*sqres2(-1)

bvgarch.append var_y2  = omega(3)^2+omega(2)^2 +beta(4)^2*var_y2(-1)+beta(4)*beta(2)*cov_y1y2(-1)+beta(4)*beta(2)*cov_y1y2(-1)+beta(4)*beta(2)*cov_y1y2(-1)+alpha(4)^2*sqres2(-1)+alpha(4)*alpha(2)*res1res2(-1)+alpha(4)*alpha(2)*res1res2(-1)+alpha(4)^2*sqres2(-1)

bvgarch.append cov_y1y2 = omega(1)*omega(2) + beta(2)^2*var_y1(-1) + beta(3)*beta(2)*cov_y1y2(-1) + beta(4)*beta(2)*cov_y1y2(-1) + alpha(2)^2*var_y2(-1) + alpha(4)*alpha(2)*res1res2(-1) + alpha(4)*alpha(2)*res1res2(-1) + alpha(4)^2*sqres2(-1)

' determinant of the variance-covariance matrix
bvgarch.append deth = var_y1*var_y2 - cov_y1y2^2

' inverse elements of the variance-covariance matrix
bvgarch.append invh1 = var_y2/deth
bvgarch.append invh3 = var_y1/deth
bvgarch.append invh2 = -cov_y1y2/deth

' log-likelihood series
bvgarch.append logl =-0.5*(!mlog2pi + (invh1*sqres1+2*invh2*res1res2+invh3*sqres2) + log(deth))

' remove some of the intermediary series
' bvgarch.append @temp invh1 invh2 invh3 sqres1 sqres2 res1res2 deth

' estimate the model
smpl s1
bvgarch.ml(showopts, m=100, c=1e-5)

' change below to display different output
show bvgarch.output
graph varcov.line var_y1 var_y2 cov_y1y2
show varcov

' LR statistic for univariate versus bivariate model
scalar lr = -2*( eq1.@logl + eq2.@logl - bvgarch.@logl )
scalar lr_pval = 1 - @cchisq(lr,1)
```