THE EXCHANGE RATE AS AN ABSOBER OF COMMODITY PRICE VOLATILITY ON STOCK RETURNS OF COMMODITY PRODUCING FIRMS

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Abstract

This paper provides an empirical analysis of the effect of commodity price volatility on the volatility of the South African exchange rate and subsequently the returns on the equity of commodity producing firms listed on the JSE. GARCH and VAR models evaluate South African exchange rate and stock market data between the years 1995 and 2015. Results show that there exists a spill over and bidirectional relationships between the equity returns volatility and the volatility of the exchange rate. Findings also indicated that international commodity price shocks transmitted into the South African Rand.

1. Introduction

The commodity price bubble has resulted in peaked interest in the sector. This spurred debates on whether the trading of commodity futures and stocks led to the unsustainable price surges. According to research, large investor participation in the commodity futures market is a possible driver to the commodity price boom that took place in 2008 (Cheng & Xiong, 2013). The large price volatility that started at this time is still prevalent in certain commodities and is under the limelight as policy makers as and investors question whether the regulatory framework around this sector is airtight. Following this discourse, both policy makers as well as equity investors have an additional concern: The impacts on commodity price volatility on producers and exporters.

Volatility affects the cash flows generated from commodity exports as well as the firm's performance on the domestic markets for commodity producing firms (Austin, 1984). Bulk of the volatility in commodities arises from them being attractive to investors who are hedging against price changes in stocks[1]. This includes passive investors such as pension funds who keep commodity futures in their portfolios for extended periods and hedge funds who actively trade the derivatives of commodity futures (Silvennoinen & Thorp, 2013). This has resulted in more commodities

[1] PriceWaterhouseCoopers (2009). Managing commodity risk through market uncertainty

exposed to risk. The combined effect of globalisation, financial market liberalization and the financialising of commodities has led to a tighter link between global markets and any weakness in policies or investment strategies can result in rapid spill over of risk in markets. (Olson, Vivian, & Wohar, 2014) and (Jones, Leiby, & Paik, 2004) showed that oil shocks affect the stock market by changing firms' present and future cash flows, which results in stock prices being valued at lower or higher prices. The US Dollar is believed to be a part of the shocks for crude oil price volatility as it is used to invoice transactions (Zhang, Fan, Tsai, & Wei, 2008). (Bartram S. , 2005) argued that commodity price exposure relates to firms more than interest and exchange rates because the core assets of the business are the commodities. According to the research, the most exposed firms will be those that have not hedged against this risk. This is because one of the largest risks in mining companies is commodity prices and operating cost changes amongst other factors (Zhang, Nieto, & Kliet, 2015).

For South African producers and exporters, there exists the South African monetary system, which is structured to absorb shocks to import and export prices by having a floating exchange rate (Edwards & Yeyati, 2005). The disadvantage of this regime, however, is that should the shocks cause an increase in the exchange rate's volatility, there is limited control available to minimize it. The currency fluctuations lead to investor uncertainty. This uncertainty on the performance of the exchange rate filters into the financial market in a number of ways. Firstly, as variance of the profits increases, future returns become hard to estimate and investors require a higher return on equity to hedge the downside risk associated with assets. Secondly, international investors limit their financial position and resort to 'safe havens'. Findings show that the presence of uncertainty around an exchange rate negatively effects a country's investments (Choi, Fang, & Fu, 2010).

For primarily exporting firms, with a constant consumption of the trading partner, the net profit margin appreciates with the depreciating Rand because of US dollar denominated commodities that will generate increased cash flows (Liang & Yu, 2014). The presence and extent of the profit appreciation depends on a company's business practices such as timing of export sales and import purchases to capitalize on the exchange rates performance (Khoo, 1994).

For commodity currencies[2], an appreciation results when commodity prices increase or when there is a significant increase in the terms of trade (Clements & Fry, 2008). The purchasing of more equity in a country also appreciates its currency (Chaban, 2009). Inclusion of precious metals in portfolios to reduce systematic risk is an extensively researched topic. The inclusion is especially beneficial to investors when equity markets are volatile and safe assets are needed (Antonakakis & Kizys, 2015).

Financial instruments of different countries have large portions of accumulated savings that have been invested due globalisation of cash flows (Kargbo, 2009). This pool of private investors is critical to the growth of an emerging market but the movement of their capital will largely depend on the exchange rate (Rjoub, Tursoy, & Gunsel, 2009). In order to formulate and present opportunities for return generation and possible arbitrage, there needs to be a laying of empirical groundwork on the emergence of shocks to the system, their distribution and their dissipation. This research aims to define the shocks and sources of shocks present in the commodities sector and the extent to which the exchange rate absorbs these shocks to prevent the erosion of investor returns. Commodity assets contribute significantly toward equity markets with a large and broad investor base. With the knowledge of the dampening effect that the exchange rate plays on the market, these investors can make informed decisions on which assets to hold and forecasting timelines on how long they will do so.

Government policy makers also need to know the extent of volatility impact as the commodities sector still accounts for close to 8% of the GDP and its supporting activities accounting for close to 7%. Any changes in policies made should be conducive to economic growth but not diminish the earnings of the commodities sector. The magnitude and duration of spillovers can be used to develop of tools such as stabilization funds in anticipation of long-term spillovers.

Background of the problem

Global demand determines commodity prices. Countries may buy gold based on production needs, to expand their foreign reserves or to shift from holding currencies that may be depreciating. Due to these factors, the prices of commodities may become volatile based on global growth, investor prospects and the reserve

[2] Commodity currencies: Currencies of countries whose primary commodities constitute a sizeable share of exports. (Chaban, 2009)

regulations of different countries. Commodity prices have been historically found to be one of the most volatile of international asset prices (Kroner, Kneafsey, & Claessens, 1995).

Mining sector exports form a large part of South Africa's GDP[3]. The prices of these exported commodities are mostly denominated in US dollars whereas the assets of some firms that mine and process the commodities are denominated in South African Rands. For a commodity exporting country, a decrease in commodity prices will result in the depreciation of its currency. This will result in lower dollar revenue for firms; however, the depreciated currency will increase the cash flows when they are converted to the local currency. This causes an increase in mining firm asset values, which in turn increases equity prices of the firms. If the decrease in commodity prices is wholly reflected in the depreciation of the currency, then there exists a 1:1 relationship between the volatility of commodity prices and the volatility of currency. Similarly, if the extent of currency appreciation is equivalent to the equity price changes, there also exists a 1:1 relationship between the exchange rate and the equity price.

This research will add to the knowledge of the nexus between commodities, exchange rate and commodity equity returns as a whole. This relationship is important to policy makers to understand the impact of different macroeconomic variables on the performance and growth of the commodities sector and equity markets. Domestic and international fund managers also benefit from the establishment of this relationship in order to allocate assets accordingly in portfolios. An understanding of the structure of volatility will provide more information regarding the asset price.

1.1 Statement of the problem

There is currently no clear relationship between commodity price volatility and its transmission into the Rand (ZAR) and equity returns of commodity producing firms in South Africa. This relationship is important for investors looking to optimize their portfolio, economists seeking to explain or predict macroeconomic factors and policy makers looking to regulate markets and support producers.

[3] In 2015 Q1, mining was contributing to the GDP by 85% (StatsSA, 2015)

1.2 Objectives of research

The objective of the research is to

- Test and verify whether there are relationships in the volatilities of the South Africa Rand exchange rate, South African commodity producing firms and the international prices of commodity stocks.
- quantify any measured spill overs between the markets and
- Present the long-term behaviour of the spillovers.

Research scope

The research focuses on the exchange rate between the South African Rand and the US dollar only. The scope will also include mining resource producers and the international commodity prices will be specific to mining resources as well.

1.3 Hypothesis

Hypothesis 1: Commodity price volatility causes exchange rate volatility

Hypothesis 2: Exchange rate volatility is negatively related to the equity price volatility of mining firms.

Hypothesis 3: Exchange rate volatility influences equity price volatility of manufacturing firms will act as a shock absorber for commodity price appreciation/depreciation.

1.4 Significance of study

The study adds on to the discourse of commodity price volatility by quantifying its impact on producers of mining resource commodities. Factors such as the persistence of shocks are tools that can be useful for long term planning, pricing of instruments as well as managing performance expectations. The research also presents additional information on the behaviour of the commodity prices by using a larger data sample that starts before the 2008 financial crisis where the behaviour of the markets could have changed.

Previous similar studies (specific to South Africa) considered the effects on the stock market as a whole (using the JSE top 40 index as a proxy) whereas this study will focus only on commodity producers.

1.5 Structure of thesis

Below is the structure of the rest of the thesis:

The second chapter will be a literature review of academic studies in the subject matter. The third chapter will comprise of research methodology, data description and empirical models. The fourth chapter will include research findings and analysis. Chapter 5 will be the conclusion of the research.

1.6 Conclusion

This chapter introduced the research. A background of current affairs, regulatory framework issues, and dynamics of commodity exporting businesses were presented to contextualise the problem. Initial hypotheses and objectives which will drive the research are stated.

2. Chapter 2: Literature review and theoretical framework

The nature of the mining industry and the quantity of resources that it exports has led to hypothesis that the sector is very sensitive to the exchange rate. This hypothesis was proved to be factual by (Khoo, 1994) for Australian commodities but the actual effect of the exchange rate was not very large.

(Hausmann, Panizza, & Rigobon, 2006) found that the exchange rates of developing countries are three times more volatile than developed countries. This is an indication that primary commodities are a prevalent source of this volatility as they contribute significantly to the GDP in developing countries (Al-Abri, 2013). It has been shown in research that gold has an ability to predict the movement of the nominal exchange rate at daily frequencies however, there is minimal to no predictive ability at a monthly or quarterly level (Ferraro, Rogoff, & Ro, 2015). When using gold prices to predict out of sample data, the predictive ability only works by using lagged price values and the frequency still needs to remain daily as the models break down for quarterly and monthly data. The inverse relationship between commodities and exchange rates also does hold when investigating whether the real exchange rate predict commodity prices at a quarterly frequency (Chen, Rogoff, & Rossi, 2010).

Countries such as China, India and the USA which have been growing in the past decade contributed significantly in increasing the prices of commodities (Frenkel & Rose, 2010). This is a result of these economies growing and building infrastructure, which drives up the demand and price for commodities used in the building processes.

Another demand for commodities stems from the need for investors to diversify portfolios using commodity minerals. Diversifying with commodity minerals reduces systematic risk leading to the reduction of the overall portfolio risk (Antonakakis & Kizys, 2015)(Chen, Rogoff, & Rossi, 2010). This effect has resulted in 48% of the demand of precious metals being for non-industrial investment uses. This 48% of the total gold demand is geared towards non-industrial investment uses though 12% of this value is geared towards official reserves (Antonakakis & Kizys, 2015). This expresses the impact of governments, their policies and trade relationships in the commodity market. Further, the level of interest rates used in different economies propels commodity prices as producers find incentive to hold on to inventories (high interest rates) or sell them (low interest rates) depending on the expected cash benefits (Frenkel & Rose, 2010).

Both producers and investors can potentially use commodity futures to try and predict the price of a commodity. This predictive ability of commodity futures as price indicators is limited since commodity financial markets are not as extensive and developed as foreign exchange markets (Chen, Rogoff, & Rossi, 2010). Commodities such as natural gas have better forecasting power of the future prices compared to all other commodities. When used individually, this means that this commodity can be used for monetary decision making for countries that export it. Little predictive ability of futures prices has been found for metal futures. Globally, exchanges have the same metal futures. The JSE has futures markets for gold, silver, platinum and copper which makes it difficult for policy makers to use this information in decision making as it represents only a fraction of the mining sector production.

At a global aggregate level, commodity prices were not found to be able to predict exchange rates for commodity currency countries. This picture changed when commodity futures indices for each specific country were used to predict exchange rates (Chen, Rogoff, & Rossi, 2010).

For commodity exporting countries that are not largely diversified, the volatility of commodities has largely impacted exchange rates as well as inflation volatility (Abounoori, Elmi, & Nademi, 2016).

Research has been conducted to test for the correlation between stock prices and exchange rates where (Granger, 1981) argued that a change in exchange rate will impact the value of a multinational company and consequently result in a change of the stock price. (Schwert, 1989) Looked into stock prices and found that volatility in the stocks was caused by a number of factors but exchange rate was not one of them. The research also deduced that volatility was higher in stocks after there was a drop in prices. This effect was observed for recessions and during financial crisis.

The value of equity for both domestic and international firms can be influenced by the exchange rates. This change is observable faster for a multinational firm as the balance sheet will immediately reflect the change in the value of its international assets. The extent of the balance sheet change will depend on the types of translation procedures used. The downstream gains or losses due to this will impact the firm's stock prices (Aggarwal, 1981).

Analysis of Commodity prices & it's determinants

Large fluctuations in commodity exporting result in big changes in the terms of trade which directly impacts the exchange rate for commodity exporting countries and may cause volatility (Arezki, Dumitrescu, Freytag, & Quityn, 2014) (Chen, Rogoff, & Rossi, 2010). For countries that trade goods, a positive shock in the output would result in the terms of trade strengthening. Countries with pricing power, where commodity prices are more flexible, prices will absorb some of the impact that may result from decreased terms of trade due to an output shock. This limits the need for investors to remove equity from the country experiencing the shock (Chaban, 2009) (Clements & Fry, 2008).

As economies grow and build infrastructure, the demand for commodities used in the building process increases. This in turn drives up the prices of different commodities. Countries such as China, India and the USA which have been growing in the past decade contributed significantly in increasing the prices of commodities (Frenkel & Rose, 2010). If these demand change significantly, the reaction of policy makers will depend on whether the drops/increases in demand are temporary changes that can be waited out or permanent changes that need to be resolved using policies. (Reinhart & Wickham, 1994) investigated whether the decrease in commodity prices in the 1980s and early '90s was temporary or a long term trend. The findings from the research gathered included the long apparent increase in production costs and decrease in commodity prices. Factors such as the increase in supply have also contributed to the downward trend of the prices as technological developments improved and new companies emerged in the sector in that decade. With numerous factors considered, it was found that the real prices of commodities remained relatively constant whereas nominal prices were mainly a permanent trend.

The increased access into commodity futures by investors increase decreases the liquidity of these assets which results in the decrease of possible premiums earned for holding risky assets. The decrease in this premium leads to a decrease in the prices of the assets according to (Silvennoinen & Thorp, 2013).

Cost of carry is an important factor in driving the supply of commodities which impacts the prices. Cost of carry can be described as the finance burden carried by a firm for storing its commodity product instead of selling it in the market with low prices. These costs may vary depending on the specific product but will be considered by commodity exporting firms under market conditions where demand needs to be minimized (Chinn & Coibion, 2013). Avoidance of this cost is also a small but present factor in the pricing of commodities and derivative traders will aim for futures contracts that are longer than 1 month to avoid carrying physical commodities and incurring these costs (Tang & Xiong, 2012).

Commodity financial markets are not as extensive and developed as foreign exchange market, this limits the predictive ability of commodity futures as price indicators (Chen, Rogoff, & Rossi, 2010). However, commodities such as natural gas have better forecasting power of the future price compared to other commodities.

Little predictive ability of futures prices has been found for metal futures. This does not suggest that there is no value in analysing this source of information. Globally, exchanges have the same metal futures, whilst the JSE has futures markets for gold, silver, platinum, copper. When combined with energy futures, the predictive ability of metal futures strengthens. The combination of different commodity properties and pricing methods leads to the futures of specific commodities being constructed and used differently in the hedging and speculation process (Antonakakis & Kizys, 2015).

The cost of spill overs:

Emerging market economies are generally destabilized by exchange rate volatility. Commodity exports result in a county accumulating more foreign reserves. A reduction in exports results in the destabilization of the balance of payments as less reserves are accumulated (Hegerty, 2016). For small commodity exporting economies, commodity prices Granger-cause the exchange rates (Chen, Rogoff, & Rossi, 2010). This relationship and its inverse are given the following terms in research:

Commodity currency: Countries where GDP largely relies on the production of commodities for exportation will have currencies that are sensitive to any changes relating to commodity prices. These currencies are named commodity currencies. (Chen, Rogoff, & Rossi, 2010). Domestic goods produced by these countries are typically small fractions of the economy and can be used to replace imported goods (Clements & Fry, 2008). Due to the nature of their movements, commodity currencies lessen the impact of price increases in the global market. The causal relationship of commodity prices on currency prices. This is common for countries that heavily rely on the exportation of commodities (Clements & Fry, 2008). For commodity exporting countries that are not largely diversified, the volatility of commodities has largely impacted exchange rates as well as inflation volatility (Abounoori, Elmi, & Nademi, 2016).

Currency commodity: Countries that produce large portions of the total supply of a specific commodity can be classified as currency commodities since they have enough power in the market to influence the price (Clements & Fry, 2008). This power allows for producers to factor in through any domestic price increases into the global prices.

The exchange rate & Macroeconomic factors

The monetary approach is found to be one of the most important factors in explaining exchange rate volatility. This is based on the condition that domestic interest rates balance out with global rates via the uncovered interest parity condition. An increase in interest rate is followed by a reduced the demand for money both domestically and internationally resulting in a currency depreciation (Akpan, Inyang, & Simeon, 2009). Also, the increase in inflation or the forecasted increase in inflation has shown to lead investors towards using precious metals to protect their investments from the risks (Sari, Hammoudeh, & Soytas, 2010).

A change in domestic currency reserves and international currency reserves affects the overall money supply and thus influences the volatility of the domestic currency (Kindleberger, 1965). This change in reserves may be caused by activities that demand foreign currencies such as payments for the country's imports, payment of debt, capital investments that are long term and the lending of money by the government.

Doing research on developing countries (Akpan, Inyang, & Simeon, 2009) presented that volatility in exchange rates can be explained by implications such as uncertainties around macroeconomic planning and growth. They found that this instability results in efficient industries struggling to price their products due to unpredictable surges in imported input prices.

Exchange rate

Post the publishing of the work by Mckinnon and Shaw (1973), many countries embarked on a path to liberalize their economies. The research presented detailed analysis on how the presence of certain macroeconomic regulations, with emphasis on interest rates, limited the natural growth of economies. Recommendations were made to change economic policies, liberalize financial markets and finally the liberalizing the current account using the exchange rate.

(Frenkel, 1989) hypothesized and proved that there is a negative relationship that exists between interest rate changes and exchange rate fluctuations[4]. This relationship was shown to be positive for the inflation rate changes.

“Increasingly, emerging markets have adopted more flexible exchange rate regimes that enabled countries cushion external shocks and accumulate an impressive amount of foreign reserves” (Fama & French, 2016). Financial liberalization has been adopted by both developing and developed economies as vehicle to stimulate growth in the economy. It is one method that is used by different countries to integrate their economies with the global market as well as to stimulate growth domestically by promoting the participation of private investors in businesses. The globalisation of financial markets has promoted and increased portfolio investments The minimal correlation between international markets (compared to domestic markets) indicates the available gap for investors to diversify which has promoted growth of emerging market investment portfolios and foreign direct investment (FDI).

[4] Frenkel followed the Keynesian theory in his theory formulation, stating that a higher interest rate leads to higher capital being invested in a country, causing the exchange rate to appreciate.

Stock market
It takes time for large international firms to adjust to changes in exchange rates. This operational exposure is sometimes hedged but a certain impact is still realized by the firm (Can Inci & Soo Lee, 2014). Under volatile Rand conditions, fund managers may sell their South African assets to buy into stocks that are safer and maintain portfolios with larger proportions of commodities like gold. In doing this, the Rand will depreciate while equities of commodity producing firms will appreciate (Schaling, Ndlovu, & Alagedede, 2014). As the currency becomes more volatile, the current cash flows and future cash flows of firms change. Exchange rate movements have been found to have asymmetric effects on the performance of stock returns (Can Inci & Soo Lee, 2014).

Multifactor models

Macroeconomic models use observable economic time series, such as inflation and interest rates, as measures of the pervasive shocks to security returns. The models are limited by their need for the specification of all the factors before they can be used. (Connor, 1995). Variables such as term structure of interest rate, industrial production, risk premium, inflation, market return, consumption and oil prices were tested for an ability to explain stock returns (Rjoub, Tursoy, & Gunsel, 2009).

Fundamental (use the returns to portfolios associated with observed security attributes such as dividend yield, the book-to-market ratio, and industry identifiers). This models focuses on the firm in question to analyse returns by using its characteristic (dividend yield) as betas.

Statistical (derive their pervasive factors from factor analysis of the panel dataset of security returns). Statistical models analyse factors using time series regression. This may render them weaker than fundamental models as returns data may not be stable for the definition of a stable model.

Inflation: The impact of inflation on the discount rate of firms leads to changes in revenue and borrowing ability. This change in revenue largely impacts the market value of the stock which results in diminished stock returns (Rjoub, Tursoy, & Gunsel, 2009).

CAPM

The capital asset pricing model is a tool that is used to estimate the expected returns based on the risk that an asset has. The model is called a mean variance model in that it minimises the variance in returns and maximises that returns over one investment period (Fama & French, 2004).

The model shows how an asset that has no relation to the market returns will have a return equal to the risk free rate where as an asset whose returns are related to the market will have a returns that contains a proportion of the market returns. This proportion is called beta (β) (Fama & French, 2004).

A weakness of the CAPM is that asset returns are computed the same way for portfolios that have different sizes. Mixed results have been obtained on the validity of CAPM (Ericsson & Karlsson, 2004).

Since these establishments, different econometric models and effects have been used to investigate different relationships between the stock market and exchange rate. It has been previously mentioned that exchange rate volatility enters the market in various ways however stock prices can also effect exchange if they significantly drop. The decreased returns can result in capital outflows to countries of different currency denomination or to portfolio that include 'safe haven' commodities. This causes the demand for the host countries currency to lower resulting in a depreciation. This feedback loop was explained by (Granger, Huang, & Yang, 2000) where it was found that for some emerging Asian economies such as Hong Kong, stock prices do lead the exchange rate but the reverse relationship is generally observed for the rest of the economies.

Empirical Literature Review

Assuming no changes in discount rates, (Schwert W. G., 1989) presented eq.1 which describes changes in stock prices as characterized by changes in the expected future cash flows.

$$E_{t-1}P_t = E_{t-1}\sum_{k=1}^{\infty}\frac{D_{t+k}}{1+i_{t+k}} \tag{1}$$

Where P, D and i represent the stock price, cash flows gained (dividends and capital) and discount rate respectively. From eq.1, it can be deduced that a change in the expected cash flows will change the stock price and the variance of the cash flows will lead to the variance of the stock price.

Several monetary models have been developed for the purposes of determining the exchange rate. Key models include the flexible price, sticky price and sticky asset monetary models that were developed by Frenkel-Bilson, Dornbusch-Frenkel and Hooper-Morton respectively (Meese & Rogoff, 1983). The Frenkel-Bilson model (flexible price) is based on the assumptions of purchasing power parity, no capital inflow limitations and exchange rate depreciation that is equivalent to the current and spot rate difference. (Frenkel, 1989).

Dornbusch-Frenkel model considers the long run price adjustments and therefore also factors in short term interest rates to allow for short term deviations from purchasing power parity. The sticky asset model allows for any long run change to the real exchange rate by including the trade balance as one of the explanatory variables for exchange rate and is expressed in the following way:

$$s = a0 + a1(m - m^*) + a2(y - y^*) + a3(r - r^*) + a4(pi - pi^*) + a5TB + a6TB^* + u \qquad (2)$$

where s is the log of the price of the foreign currency, m-m* is the difference in logs of the US money supply and that of the foreign country, y-y* is the difference in logs of the real income, r-r* is the difference in short term interest rates, pi-pi* is the difference in the long term inflation, TB and TB*are the US and foreign trade balances respectively and u is the disturbance term. As previously discussed, the main difference between the three models is the base assumptions used in modelling the exchange rate and this leads to different variables being omitted from the models.

Meese and Rogoff compared the performance of the structural model to that of a univariate time series model to observe which model will give superior performance in the long run. The time series model involved lags of the exchange rate and lags of explanatory variables. This model is based on the spot rate being an indicator of the future spot rate, that is, the exchange rate follows a random walk. Although the structural model factors in the critical variables for the regression, time series models consider any correlation that may be present in the data.

The testing for causality between commodities and exchange rates for commodity currencies (i.e South Africa, Australia, Canada, New Zealand and Chilli) by (Chen, Rogoff, & Rossi, 2010) resulted in small weak results. They used the Granger causality method which showed that there is more robust evidence advocating for exchange rates causing commodity prices compared to the reverse causality. This may be explained by the extent of development in commodities financial markets (Chen, Rogoff, & Rossi, 2010).

(Chaban, 2009) Tested for the relationship between commodities, equities and exchange rates for countries where commodities are a significant part of exports.

VAR models are used to understand the relationship between and independent variable with its own lags and lags of other explanatory variables. An extension of the VAR models is the vector error correction model which was used by (Arezki, Dumitrescu, Freytag, & Quityn, 2014) when investigating the long and short run relationship between volatility of gold prices and the volatility of the Rand's real exchange rate. The real effective exchange rate was computed using the nominal exchange rate and consumer price index data from the IMF. Monthly data was sampled from 1979-2010 with variation measured over a 12month window. They found a significant coefficient of the error term which meant that there exists a long run relationship between commodity price volatility and real effective exchange rate. The short run relationship conversely not observed as the coefficient of the lags was not significant. They also found that gold price volatility explained Rand volatility more after the currency was liberalized.

Previous specifications for measuring exchange rate volatility's impact on the stock market have done so using standard deviation (Gambovas, 2003). This method is flawed in several ways, namely: The model assumes the exchange rate changes are normally distributed whereas this may not be the case. Second, it ignores the distinction between predictable and unpredictable elements in exchange rate process.

The assumption of normality of exchange rate returns has been brought to question by different researchers who found that returns have a large leptokurtosis. The

Student-t distribution is recommended for returns as it does not impose this assumption on the data (Mlambo, Maredza, & Sibanda, 2013).

Stock market returns

The Fama French three factor model was modified to include two extra factors: investment and profitability, in order to explain deviations that are not explained by the three factor model. The three factor model included market, size and growth which failed to address issues such as net share issues, momentum and volatility. (Fama & French, 2016).

GARCH and ARCH models

When choosing the correct model for investigating exchange rate volatility, (Choi, Fang, & Yong Fu, 2009) compare the ability of different modifications of the GARCH model to capture the leverage effect. They conclude that in order to exclusively model and analyse volatility, the EGARCH model is the best since it will be able to filter out the leverage effect.

(Bekaert, Wei, & Xing, 2007) showed that most GARCH models struggle to fit highly volatile data. The use of an asymmetric (with focus on the sign of the disturbance term) GARCH models has aided in increasing the fit of the data. These models include the EGARCH (exponential GARCH) and the TARCH (threshold GARCH) or GJR GARCH models that factor in the asymmetry component (i.e negative news adds more to volatility than positive news of the same magnitude and the model uses squared returns which are positive) (Chinzara, 2010). The EGARCH is also advantageous in its use for modelling because it does not make the assumption that independent variables are always positive.

Using the New Open Economy Macroeconomics model (Mpofu, 2016) selected exchange rate variables hypothesized influence of volatility. The variables added in the model were: Output, money supply, openness, foreign reserves, commodity prices. Terms of trade was left out of the model. Data was collected from the IMF and was adjusted for seasonality because of the tendency of low frequency data to show this property. Exchange rate volatility was measured using a GARCH model but also adopts the EGARCH model to accommodate the asymmetry of the data. The results show that gold prices effect the volatility of the exchange rate.

For a large open economy with a significant terms of trade and produces one major commodity, an increase in commodity price will result in the exchange rate increasing as a result of higher wages received. This is caused by the increase in demand for goods by the workforce receiving higher wages as found by (Schaling, Ndlovu, & Alagedede, 2014). They used VAR models as these models allowed for stationarity, cointergration and causality tests. Monthly nominal exchange rate data was used for testing. For commodity prices, IMF data for all commodities except for fuel were used. The research finds that there is a relationship between commodity prices and exchange rates. This relationship was weaker than that of other exporting countries which, they explain, could've have been a result of the Commodity Terms of Trade. (Gaurav, 2010) Found a similar unidirectional causality from Indian market returns and the exchange rate.

Multivariate GARCH models: Covariance and correlation modelling

Studies on volatility transmission using the multivariate GARCH models began predominantly with Engle and Kroner (1995) who proposed the use of an BEKK GARCH for modelling of the spillover of volatility from one time series the other. These models have been found to be very useful in investigating the volatility spill over between stock markets (Sadorsky, 2010). The model has been used in the energy sector for the analysis such as the transmission of spot electricity prices inspired by the observed shocks to prices in localized regions. The influences of present volatility resulting from innovation and previous volatility and innovation from other markets and transmission of volatility from other markets can be adequately modelled using the BEKK GARCH making it a suitable empirical tool for understanding volatility (Worthington 2005).

The models are characterized by assumptions such as the error terms being uncorrelated and have a zero mean with a variance that dependents on the previous lags and any new available information (Bala Lakshimi). It improves on the original VECH GARCH by having less terms and allowing for the modelling of volatility spill overs (Manex Yonis 2010)

The ability of multivariate GARCH models to model correlation between different series is a significant property when attempting to find value at risks, hedge ratios and betas of different assets. Due to the possible presence of structural changes in over extended period of time, the covariance of certain times series may change over time and the common GARCH may not be able to capture and forecast this efficiently (Ji-Chun Liu, A family of Markov switching GARCH models.)

(Oberholzer & von Boetticher, 2015) Investigate the presence of a bi-directional spill over volatility between the ZAR and the JSE/FTSE Indices. The data was first test for normality and cointergration using the Jarque-Bera and Augmented Dickey Fuller (ADF) tests. A GARCH model was fitted on the data and then on the CCC-GARCH. The mean lag variance results of the models were compared to determine the volatility spill over. The direction and extent of the volatility spill over was found to be from the Rand volatility to the JSE/FTSE indices.

The distribution of financial returns is understood to be changing depending on whether and economy is growing or is going through a recession. Also, the volatility of these returns is essential in establishing the portfolios that maximize returns for managers and guiding decisions for traders (Abounoori, Elmi, & Nademi, 2016). The subject of volatility has been widely researched in the field of financial markets to enable market participants to meet the goal of maximising returns. Different variables and relationships have been studied under the subject matter of financial markets. Models for these relationships differ extensively based on the property to be tested.

Focusing on only four precious metals (gold, silver, platinum and palladium) individually, (Batten, Ciner, & Lucey, 2010) investigate the volatility of commodities. They use macroeconomic determinants of this volatilities, namely; Annual dividend yields (S&P 500), Term structure spread (US 10 year bonds and 3-month treasury bills), Business cycle and growth (Annual change in production), Inflation (change in JSE MINING INDEXI), Monetary aggregate and the consumer confidence index for the US. They use VAR models to examine the volatility and find that monetary and financial determinants can be used to forecast the volatility of the commodities except for silver (whose volatility is explained by the volatility of other metals).

(Bartram & Bodnar, 2012) Showed that the returns to exposure on the exchange rate depend on the quantity and sign of the exposure. They test for exposure by building a set of regression models.

Switching models

Markov Process

A possible approach to modelling structural changes over time is the Markov switching model. The differentiating characteristic of this model from a normal GARCH is the fact that it changes according to different states or conditions over time, the model is therefore able to capture any structural changes that may arise in the series over time (Ji-Chun Liu, A family of Markov switching GARCH models.).

3. Chapter 3: Methodology

The relationship between the commodity price, South African exchange rate and equity prices will be investigated in the following section using GARCH models (GARCH(1,1) and Multivariate GARCH) and VAR models for detailed analysis of the volatilities. This is because GARCH models use minimal lags when fitting the data compared to ARCH models and VAR models give an indication of the duration of the interaction of volatilities as a result of spill overs.

3.1 Research Design: Structural models

The commodity price, exchange rate and equity returns volatility will be generated using the GARCH(1,1) model as done by (Mlambo, Maredza, & Sibanda, 2013) and (Subair, 2009). The spillover is then measured using the VAR and multivariate GARCH models as stated in the previous section.

<u>Model Specification</u>

To understand the effect of exchange rates (ER) and commodity prices (IMF index) on the returns of commodity producing firms (JSE Mining), three regression models were formulated in line with the work conducted by (Mlambo, Maredza, & Sibanda, 2013). The models hypothesized that there is significant impact of the dollar on stock prices as most international transactions are in this currency (Choi, Fang, & Fu, 2010). It also considers interest rates as this is a measure for the level of borrowing and investment in a country (Mlambo, Maredza, & Sibanda, 2013). The effect of South Africa being an open economy and the impact of investors looking to maximise returns in emerging markets has led to increased foreign investor participation (Mlambo, Maredza, & Sibanda, 2013).

The model looks at the coefficients of explanatory variables (mainly commodity prices and exchange rate) and their individual and combined explanation of the stock returns.

$$SP = \beta_0 + \beta_1 ER + \beta_2 Int + \beta_3 M3 + \beta_4 USInt + \varepsilon \quad (3)$$

$$SP = \beta_0 + \beta_1 Cp + \beta_2 Int + \beta_3 M3 + \beta_4 USInt + \varepsilon \quad (4)$$

$$SP = \beta_0 + \beta_1 ER + \beta_2 Cp + \beta_3 Int + \beta_4 M3 + \beta_5 USInt + \varepsilon \quad (5)$$

Where SP is the stock price returns, ER is the exchange rate, Int is the real interest rate, M3 is the money supplied by the government, USint is the US interest rate and JSE mining index is the commodity prices.

$$h^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_0 h_{t-1}^2 \quad (6)$$

Where *h* is the volatility of the independent variables Commodity price, Exchange rate or Share prices.

For unconditional volatility

$$Var(u_t) = \frac{\alpha_0}{1-(\alpha_1 + \beta_0)} \quad (7)$$

In order for the above condition to yield a stable GARCH, $\alpha + \beta < 1$

The multivariate GARCH model was specified in the following way.

$$H_t = C'_0 C_0 \begin{bmatrix} a11 & a12 \\ a21 & a22 \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a11 & a12 \\ a21 & a22 \end{bmatrix} + \begin{bmatrix} g11 & g12 \\ g21 & g22 \end{bmatrix}' H_{t-1} \begin{bmatrix} g11 & g12 \\ g21 & g22 \end{bmatrix} \quad (8)$$

Where H is a matrix of covariance, C is a matrix of constants. Matrix A is a representation of the ARCH effects of the model. Where the non-diagonal terms measure the effect of market innovation that transmit to the second market being modelled. Matrix G is a representation of the variance terms that are present in the series.

An important aspect of the BEKK model is the conditional covariance matrix that informs the spillover terms. General simplifications of the BEKK model do not include the non-diagonal terms, which results in conditional variance estimations where variables are only related to their own residuals and past variances.

3.2 VAR specification

To quantify the persistence of the volatility spill overs between the different variables, VAR models will be used. The analysis of this persistence will follow the method adopted by Mensi (2013).

$$\begin{bmatrix} rcom \\ rexchange\ rate \\ requity \end{bmatrix} = \begin{bmatrix} u \\ u \end{bmatrix} + \begin{bmatrix} com \\ exchange\ rate \\ equity \end{bmatrix} + [\varepsilon] \qquad (9)$$

3.3 Descriptive statistics

The normality of the data will be tested using the JB statistic which assumes the null hypothesis of the returns being normally distributed. The extent that the data deviates from the normality condition will be observed from the skewness and kurtosis values where a skewness below or above 0 indicates positively and negatively skewed data respectively and the access kurtosis needs to be zero for normally distributed data (Medel, Camilleri, Hsu, Kania, & Touloumtzoglou, 2015).

3.4 Stationarity tests: ADF

Data will be then tested for unit root to estimate the order of integration of the time series. Stationarity indicates that the data has a constant mean and variance over time and the covariance between periods depends on the distance between the lags and not the time used for analysis. This condition needs to be met to ensure that the effects of the error term do not persist and increase over time. This will be done using the Augmented Dickey Fuller test (Dickey and Fuller 1981). Where the null hypothesis is that, the series has a unit root, (i.e. the series is non-stationary). Failure to reject this null hypothesis would mean that the series indeed has a unit root which must be corrected for.

3.5 ARCH testing

To verify whether the GARCH model is the right fit for the data, an ARCH test can be applied on the data. This test establishes whether there exists a relationship between the residuals at time=t and the previous lags of the residuals. This done by estimating the coefficients of the residuals with a null hypothesis that they are equal to zero.

This test has a null hypothesis of no heteroscedasticity in the data which will need to be rejected before commencing to the GARCH modelling. The results of the test can be supported using a correlogram of squared residuals.

To measure the effect of previous lags of returns on the present returns, correlation functions are used. Autocorrelation and partial correlation functions measure the impacts of different lags of data on the observed result at time t. The autocorrelation function will measure the correlation of a specified number of lags with the value at time=t whereas the partial correlation function will measure the correlation of a specific lag of data with the value at time=t. The major difference between the two functions is the autocorrelation function does not fully consider the correlation between the lags and so it may continuously carry over a single correlation over to subsequent lags. For the stock market, this may mean inefficiencies and financial losses due to giving relevance and effort to lags/data that does not actually drive the returns at time=t. This carry over of autocorrelation may eventually decay. The partial correlation function addresses this by focusing upon a specific lag but ensuring all correlations between previous lags and specific lag are eliminated or accounted for.

3.6 Controls

Sample data

The frequency of data collection was limited to the availability of information such as the money supply which is published monthly. This lead to the collection of data at this frequency in order to align time series. The source for the data is Bloomberg © and IMF, it will be comprised of commodity Prices (using and index), Rand/Dollar exchange rate, Industrial indices: Market index of South African Mining companies, Interest rate, Broad money supply, Inflation rate

Data collected over a 20-year period (1995 to 2015) is used. It is possible that certain data will not be available over the whole sample period as some firms may have not been established until the later years, however the index will be used as it will reflect the condition of the available data at that time.

4. Chapter 4: Findings and analysis

4.1 Introduction

This section presents the results from modelling and analyses them whilst drawing attention to the objectives of the research and the hypotheses that the researcher formulated in chapter 1 and any key findings that were presented by literature over the course of the research report.

4.2 Time series properties

Table 1 shows the diagnostic properties of the time series of variables used in the research. Samples for the exchange rate (ER), SA interest rate (Int) and money supply (M3) are positively skewed, showing that there's high number of occurrences where the values were higher than the mean beyond the normal distribution ranges. Variables having a kurtosis higher than 3 indicate that the series is highly peaked which is typical of data that would be modelled using non-linear models. The combined effects of the skewness and kurtosis results in a JB statistics that are significant indicating that the null hypothesis of normally distributed series can be rejected.

Table 1Moments of the data around the origin

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev**	**Skewness**	**Kurtosis**	**JB**	**p-value**
Panel A: Spot prices									
ER	7.7007	7.3300	15.5450	3.8600	2.1488	0.8328	3.6629	31.8747	0.0000
Int	9.4486	8.8500	21.4750	4.8650	3.4682	0.7152	2.7384	21.0540	0.0000

USInt	2.6451	1.7500	6.5000	0.2500	2.2754	0.2505	1.3595	29.7896	0.0000
JSE	14356.75	11552.31	58666.96	1176.28	12331.4	0.8276	3.1679	28.0218	0.0000
JSE mining index	119.5308	105.0600	256.2400	49.5500	60.0331	0.3906	1.7077	23.0899	0.0000

Stationarity tests

From visual analysis of the graphs in Figure 1, it can be deduced that the trends do not frequently cross the mean. This is both a property of a non-stationary series and a common behaviour of financial time series. Stationarity tests were therefore executed to statistically deduce the behaviour of the data. The Augmented Dickey Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test results presented in Table 2. At level values, the null hypothesis of non-stationarity cannot be rejected for all variables. Tests for stationarity of the differenced data all show significance of less than 1% resulting the failure to reject the null hypothesis. The first differences of these series are presented in Figure 1 and table 2.

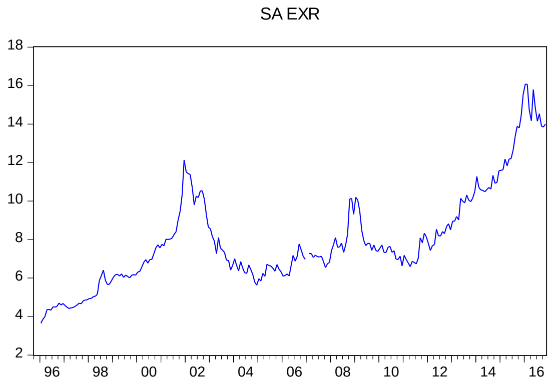
Table 2 Stationarity tests

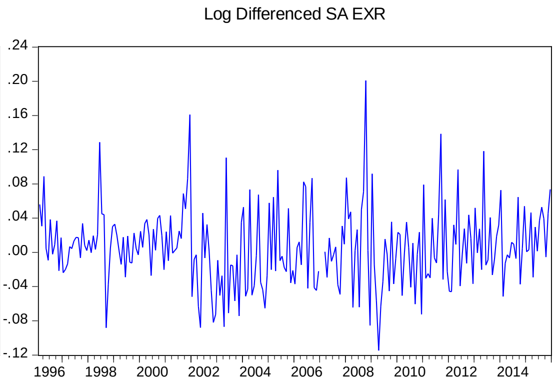
ADF At Level						
	SA_EXR	SA_INT	SA_M3	US_INT	JSE	PX_LAST
t-Statistic	0.5818	-2.4013	-2.2065	-1.8352	-1.6319	-1.5807
Prob.	***0.9890***	***0.1425***	***0.2046***	***0.3628***	***0.4646***	***0.4905***
ADF At First Difference						
	d(SA_EXR)	d(SA_INT)	d(SA_M3)	d(US_INT)	d(JSE)	d(PX_LAST)
t-Statistic	-14.1146	-10.7628	-4.2503	-4.5180	-11.7445	-11.9531
Prob.	***0.0000***	***0.0000***	***0.0007***	***0.0002***	***0.0000***	***0.0000***

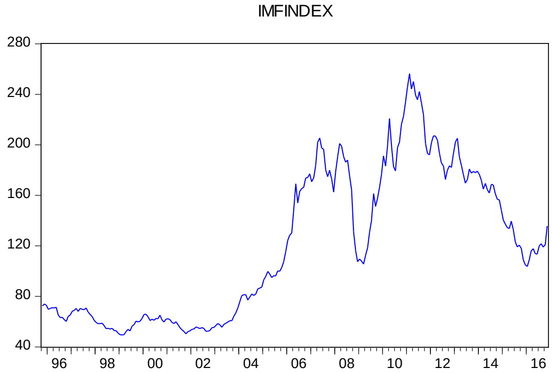
PP At Level						
	SA_EXR	SA_INT	SA_M3	US_INT	JSE	PX_LAST
t-Statistic	0.3194	-2.2134	-2.0741	-1.4464	-1.6780	-1.7938
Prob.	***0.9789***	***0.2022***	***0.2555***	***0.5590***	***0.4411***	***0.3828***
PP At First Difference						
	d(SA_EXR)	d(SA_INT)	d(SA_M3)	d(US_INT)	d(JSE)	d(PX_LAST)
t-Statistic	-14.1890	-10.5879	-17.3645	-13.1081	-11.9582	-12.0462
Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***

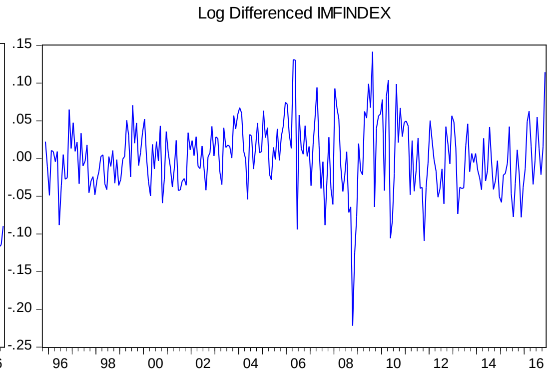
KPSS At Level						
	SA_EXR	SA_INT	SA_M3	US_INT	JSE	PX_LAST
t-Statistic	0.9134	1.4758	0.5434	1.2465	1.3191	0.9221
KPSS At First Difference						

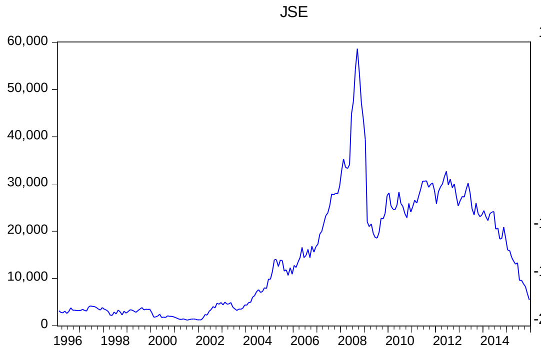
	d(SA_EXR)	d(SA_INT)	d(SA_M3)	d(US_INT)	d(JSE)	d(PX_LAST)
t-Statistic	0.2593	0.1041	0.0753	0.0662	0.1612	0.1392

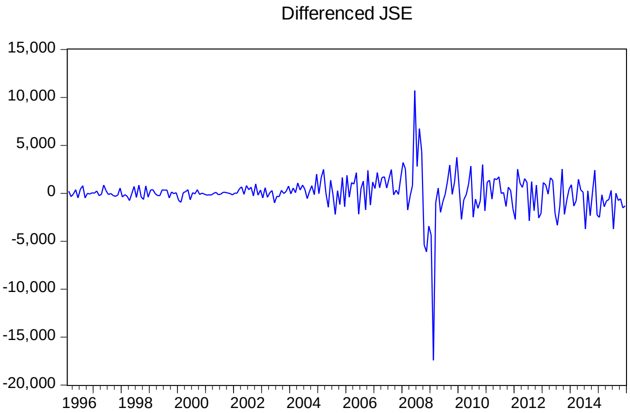


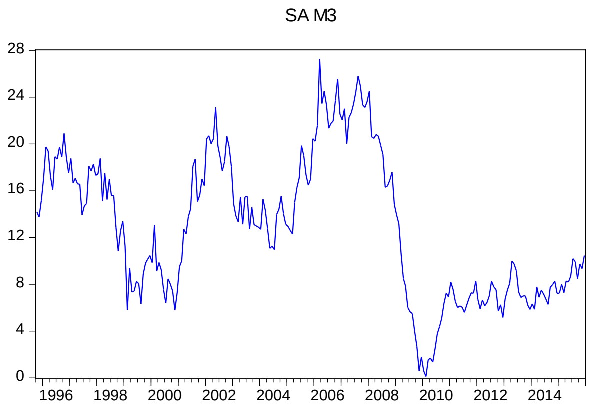


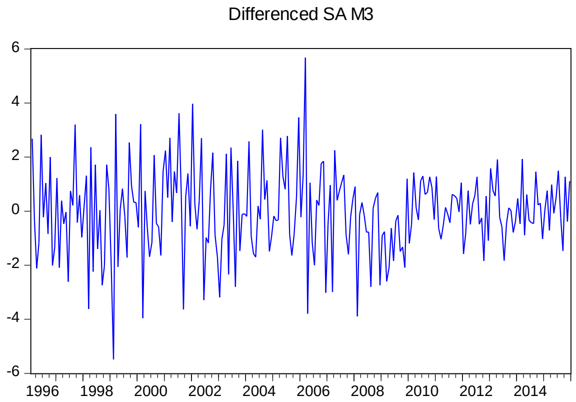


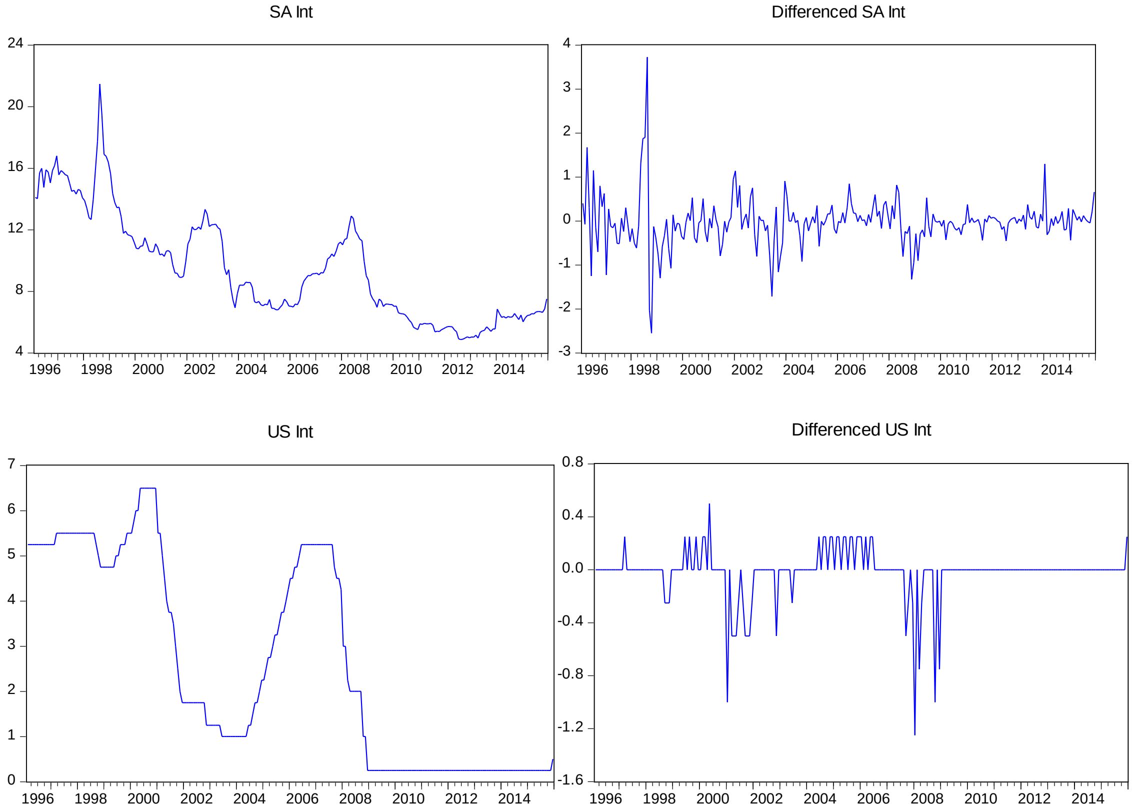












Collinearity

A high correlation (>0.8) coefficient exists between the JSE mining index and the IMF index. This may impact the interpretation of the model results.

Table 3 Correlation Matrix

	SA_EXR	SA_INT	SA_M3	US_INT	JSE	IMFINDEX
SA_EXR	1.0000	-0.4877	-0.2621	-0.623	0.2517	0.2306
SA_INT	-0.4877	1.0000	0.4766	0.7089	-0.5165	-0.6615
SA_M3	-0.2621	0.4766	1.0000	0.5295	-0.1986	-0.2875
US_INT	-0.623	0.7089	0.5295	1.0000	-0.5308	-0.5159
JSE	0.2517	-0.5165	-0.1986	-0.5308	1.0000	**0.8446**
IMFINDEX	0.2306	-0.6615	-0.2875	-0.5159	**0.8446**	1.0000

4.3 Testing for ARCH effects

A mean equation of each variable was specified to generate residuals for testing. Information criterions were used as a best indicator of the fit of the mean equation. The lowest information criteria resulted in an ARMA(0,0) for the exchange rate, an

ARMA (1,0) for the IMF commodity prices, and eq(7) for the JSE mining index security prices[5].

Although the kurtosis of the data indicates the possible requirement for fitting non-linear models on the data sets, a good test for the appropriateness of the GARCH models is the ARCH test conducted in this section. The ARCH test results presented in Table 4 show a significant p-value meaning that the null hypothesis of no heteroscedasticity in the residuals can be rejected. This points out the existence of ARCH effects in the residuals and qualifies the use of GARCH models to estimate the volatility of the variables. Additional to this test, a correlogram of squared residuals is presented to show the past lag relationships with the present value. All the lags presented are not significant indicating the presence of serial correlation.

Table 4 ARCH Test results

Heteroscedasticity Test: ARCH RSAEXR (10 lags)			
F-statistic	3.046972	Prob. F(6,226)	0.0012
Obs*R-squared	28.08216	Prob. Chi Square(6)	0.0018
Heteroscedasticity Test: ARCH IMFINDEX			
F-statistic	5.331139	Prob. F(2,237)	0.0054
Obs*R-squared	10.32836	Prob. Chi Square(2)	0.0057
Heteroscedasticity Test: ARCH JSE (ARMA) (4 lags)			
F-statistic	1.968596	Prob. F(4,230)	0.1001
Obs*R-squared	7.779235	Prob. Chi-Square(4)	0.1000
Heteroscedasticity Test: ARCH JSE (4 lags)			
F-statistic	5.609805	Prob. F(4,241)	0.0002
Obs*R-squared	20.95378	Prob. Chi-Square(4)	0.0003

Table 5 Correlogram of squared residuals SAEXR

	Sample: 1999M02 2015M12				*Sample: 1999M02 2015M12*				*Sample: 1995M10 2016M12*			
				SAEXR	IMF INDEX				JSE MEAN			
Lag	AC	PAC	Q-Stat	Prob*	AC	PAC	Q-Stat	Prob*	AC	PAC	Q-Stat	Prob*
1	0.051	0.051	0.5372	0.464	0.144	0.144	5.0434	0.025	0.051	0.051	0.6518	0.419
2	-0.040	-0.043	0.8754	0.646	0.170	0.153	12.086	0.002	0.139	0.136	5.5405	0.063
3	0.049	0.054	1.3761	0.711	0.072	0.030	13.346	0.004	0.215	0.206	17.292	0.001
4	-0.058	-0.066	2.0815	0.721	-0.018	-0.059	13.427	0.009	0.154	0.130	23.339	0.000
5	-0.027	-0.015	2.2319	0.816	0.061	0.057	14.355	0.014	0.022	-0.038	23.462	0.000
6	0.061	0.056	3.0293	0.805	0.042	0.041	14.799	0.022	0.068	-0.011	24.671	0.000
7	-0.069	-0.072	4.0362	0.776	0.063	0.041	15.775	0.027	0.063	0.007	25.698	0.001

[5] Mean equations were selected using Automatic ARIMA selection add-in - Eviews 8 ©

8	0.005	0.017	4.0411	0.853	0.099	0.070	18.205	0.020	0.050	0.029	26.340	0.001
9	0.072	0.057	5.1649	0.820	0.196	0.172	27.836	0.001	-0.022	-0.042	26.461	0.002
10	-0.152	-0.149	10.123	0.430	0.187	0.128	36.645	0.000	-0.010	-0.045	26.489	0.003
11	-0.034	-0.015	10.373	0.497	0.167	0.083	43.659	0.000	0.075	0.065	27.966	0.003
12	0.102	0.085	12.631	0.396	0.086	0.007	45.519	0.000	-0.026	-0.015	28.147	0.005
13	-0.067	-0.058	13.628	0.401	-0.029	-0.083	45.733	0.000	-0.004	-0.001	28.152	0.009
14	-0.062	-0.066	14.466	0.416	0.104	0.096	48.493	0.000	-0.005	-0.026	28.159	0.014
15	-0.059	-0.080	15.245	0.434	-0.008	-0.029	48.508	0.000	0.016	0.008	28.225	0.020

4.4 GARCH

Although all variables present non-normal behaviour, the normally distributed GARCH model was first utilised for modelling the variance of the exchange rate and subsequently contrasted with other GARCH(1,1) model extensions in order to choose the best fitting model that will generate volatility.

RIMFINDEX	GARCH (1,1)	p-value	EGARCH	p-value	Student t GARCH (1,1)	p-value
C	-0.0006	0.8601	0.0020	0.2466	0.0002	0.9548
AR(1)	0.2942	0.0000	0.3352	0.0000	0.3129	0.0000
w	4.77E-05	0.2000	-0.0392	0.3329	5.06E-05	0.2917
Alpha	0.0739	0.0590	-0.0479	0.0838	0.0662	0.0959
Beta	0.9026	0.0000	0.0903	0.0010	0.9080	0.0000
gamma			0.98801	0.0000		
AIC	-1.3042		-1.3259		-1.3984	
SIC	-1.1756		-1.183		-1.2555	

RSAEXR	GARCH (1,1)	p-value	EGARCH	p-value	Student t GARCH (1,1)	p-value
C	0.0073	0.0244	0.0073	0.0259	0.0068	0.0086
AR(1)	0.0266	0.7385	0.03	0.7034	-0.0233	0.7432
w	0.0004	0.0317	-1.7065	0.0517	0.0002	0.1629
Alpha	0.2053	0.0087	0.3442	0.0184	0.2048	0.0291
Beta	0.6275	0.0000	0.0778	0.2727	0.7444	0.0000
gamma			0.7690	0.0000		
AIC	-3.3588		-3.3586		-3.392	
SIC	-3.2858		-3.2711		-3.3044	

JSE	GARCH (1,1)	p-value	EGARCH	p-value	Student t GARCH (1,1)	p-value
C	0.0127	0.0782	0.0085	0.2579	0.0072	0.2849
RSAEXR	-0.1311	0.5115	0.0528	0.7258	-0.0808	0.6175
RSAINT	0.4683	0.0108	0.4097	0.0104	0.3583	0.0197

RSAM3	0.004	0.9202	0.0005	0.9888	0.0039	0.8943
RUSINT	-0.1098	0.0001	0.0377	0.5959	0.0410	0.5872
RIMFINDEX	0.2153	0.2230	0.1995	0.2421	0.2218	0.1353
w	0.0013	0.1262	-1.048	0.0004	0.0011	0.3268
Alpha	0.2107	0.0057	0.3191	0.0010	0.1528	0.0649
Beta	0.749	0.0000	-0.2113	0.0020	0.8052	0.0000
gamma			0.8102	0.0000		
AIC	-1.3042		-1.3259		-1.3984	
SIC	-1.1756		-1.183		-1.2555	

The AIC and SIC values point towards the GARCH (1,1) with a student's t distribution being the best fit for the data from the three models. IMF metal prices have a volatility that is highly persistent as the sum of alpha and beta coefficients are very close to unity (0.975) when using the GARCH (1,1). The JSE mining index has the highest alpha value of the three series which means that past innovations persist for a longer period of time compared to the other variables. The high significance level of all the GARCH terms in the models points toward possible volatility clustering.

The mean equation results indicate that the US interest rate is negative and not significant. Possible causes for the insignificance of the US interest is the very limited number of changes made by the Federal Reserve System over the duration of the timeline. The negative sign of the coefficient is an indication that as the US interest rate increases, the Rand loses value which verifies the findings of (Mlambo, Maredza, & Sibanda, 2013).

4.5 Granger causality

Causality in all directions is significant in all variables when the test is conducted using low lags lengths. This gives possibility to a short run relationship between the variables and the spillover effects. It is an indication of the links that exists between different countries' financial systems and shows why crisis effects from one market will be seen on another, albeit smaller. A lag structure was generated using information criteria on the VAR output. The structure indicated that the tenth lag must be used for Granger causality testing.

Results show that the hypothesis that the JSE index returns do not Granger causes the IMF index or the ZAR exchange rate cannot be rejected. The IMF index was found to Granger cause the JSE index with a very high significance level and was found not to Granger cause the ZAR exchange rate. The ZAR exchange rate causes the LME index and JSE mining index. This supports both the hypothesis that equity returns are impacted by the performance of the exchange rate. Furthermore, the exchange rate was found to also Granger cause commodity prices which is in agreement with previous research the findings (Chen, Rogoff, & Rossi, 2010).

Pairwise Granger Causality Tests		
	F-Statistic	Prob.
RJSE does not Granger Cause RIMFINDEX	0.6993	0.5533
RIMFINDEX does not Granger Cause RJSE	7.0001	0.0002
RSAEXR does not Granger Cause RIMFINDEX	3.5532	0.0152
RIMFINDEX does not Granger Cause RSAEXR	1.1022	0.3490
RSAEXR does not Granger Cause RJSE	2.4795	0.0619
RJSE does not Granger Cause RSAEXR	0.0685	0.9766

4.6 VAR

Unrestricted VAR models were run with different lag configurations ranging from 1 to 12. Using information criterion, the optimal lag selected was the 1 which had the lowest AIC. The VAR was tested for stability using unit root testing which showed that all roots are within the unit circle. The correlogram of the residuals showed no serial correlation when using the optimal lag. The model was applied to observe the existence/absence of transmission mechanisms between commodities, exchange rates and mining stocks.

Results show that the exchange rate's returns dependency on itself, commodity prices and equity returns are not significant at all lags which is an indication that the hypothesised nexus between the three variables does not exist on the returns. The opposite is notable for the relationship between volatilities. It is also notable that the lag of the JSE mining index has a larger impact on the ER compared to the ER itself, similar to the findings of (Schaling, Ndlovu, & Alagedede, 2014). This affirms the bases of the exchange rate being a commodity currency where a percentage increase in commodity prices transmits to a 0.1% appreciation in the ER. The same effect is observed on security prices. The JSE mining index does not show high significance level expect for the contribution of the lag of security prices on the present day metal price.

These results are different from those of (Arezki, Dumitrescu, Freytag, & Quityn, 2014) whose results indicated that gold volatility explained exchange rate volatility significantly. A large difference between these results is possibly the inclusion of other commodities besides gold in the testing of the relationship between the exchange rate and commodity volatility.

RSAEXR			
Independent variable	**Coefficient**	**T statistic**	**p-value**
RSAEXR(-1)	-0.092913	[-1.40340]	0.1609
RJSE(-1)	0.026160	[0.39311]	0.6944
RIMFINDEX(-1)	0.004486	[0.17952]	0.8576

RJSE			
Independent variable	**Coefficient**	**T statistic**	**p-value**
RSAEXR(-1)	0.038043	[0.21805]	0.8275
RJSE(-1)	-0.307633	[-1.75426]	0.0798
RIMFINDEX(-1)	0.009499	[0.14426]	0.8853

RIMFINDEX			
Independent variable	**Coefficient**	**T statistic**	**p-value**
RSAEXR(-1)	0.297325	[4.77198]	0.0000
RJSE(-1)	-0.193751	[-3.09371]	0.0021
RIMFINDEX(-1)	-0.004520	[-0.19222]	0.8476

GIMFINDEX			
Independent variable	**Coefficient**	**T statistic**	**p-value**
GIMFINDEX(-1)	0.986318	[67.6483]	0.0000
GRSAEXR(-1)	-0.004150	[-0.26452]	0.7915
GJSE(-1)	0.001706	[1.11224]	0.2664

GRSAEXR			
Independent variable	**Coefficient**	**T statistic**	**p-value**
GIMFINDEX(-1)	0.107550	[2.60691]	0.0093
GRSAEXR(-1)	0.780864	[17.5886]	0.0000
GJSE(-1)	0.012607	[2.90467]	0.0038

GJSE			
Independent variable	**Coefficient**	**T statistic**	**p-value**
GIMFINDEX(-1)	-0.044135	[-0.13976]	0.8889
GRSAEXR(-1)	1.185866	[3.48949]	0.0005
GJSE(-1)	0.837185	[25.1985]	0.0000

The variance decomposition of the variables presented in the table below show which shocks are most significant in explaining the changes of different variables. A shock to metal price volatility at period 1 (time t) is solely a result of the behaviour of the market. A shock at period 2 is partially from the volatility of the JSE mining index whose impact is seen to increase at the periods increase. The transmission of the volatility of the JSE mining index to the IMF index is very low which may be an indicator of market efficiency (that information from the South African mining industry is processed slowly in on the LME) or a more likely indicator of the contribution of the South African mining sector towards the prices of the metals in the IMF index.

A shock to the ZAR exchange rate volatility is not only as a result of market specific behaviours or events but is also as a result of changes in the IMF index. Metal price volatility explained 17% of the shock to ZAR volatility at time t. The JSE index increasingly explained the shocks of the ZAR as the periods increased which reiterates the findings of the Granger causality test. The magnitude of these spill overs follows the findings of (Antonakakis & Kizys, 2015) where the volatility of five metals had a 25.7% spill over into the EUR/USD, JPY/USD, GBP/USD currencies.

Shocks the JSE index volatility is impacted by the exchange rate at low levels with increases in impact as the periods increase. It is notable that shocks moving from the JSE index volatility to the ZAR volatility are smaller than those from the ZAR volatility to the JSE index volatility. The overall analysis of the results also shows that the IMF index volatility is the most endogenous of the variables with over 99% percent of its shocks explained by its previous results.. Overall results analysis also shows that the ZAR is the most sensitive of the variables with multiple large sources of volatility when compared to the IMF and JSE indexes. From this one can affirm the hypothesis that the ZAR is indeed a shock absorber.

Variance Decomposition of GIMFINDEX: Period	S.E.	GIMFINDEX	GRSAEXR	GJSE
1	0.000278	100.0000	0.000000	0.000000
2	0.000389	99.92500	0.005481	0.069520
3	0.000473	99.79188	0.009650	0.198468
4	0.000543	99.62634	0.010503	0.363156
5	0.000603	99.44197	0.009226	0.548803

Variance Decomposition of GRSAEXR: Period	S.E.	GIMFINDEX	GRSAEXR	GJSE
1	0.000787	17.34169	82.65831	0.000000
2	0.001009	18.46101	80.97311	0.565884
3	0.001139	19.45267	78.92091	1.626422
4	0.001229	20.33991	76.71221	2.947882
5	0.001297	21.15067	74.49510	4.354231
Variance Decomposition of GJSE: Period	S.E.	GIMFINDEX	GRSAEXR	GJSE
1	0.006021	0.059430	0.006804	99.93377
2	0.007905	0.137118	1.270236	98.59265
3	0.009128	0.448375	3.331285	96.22034
4	0.010043	0.911374	5.648242	93.44038
5	0.010778	1.464509	7.901772	90.63372
Cholesky Ordering: GIMFINDEX GRSAEXR GJSE				

The dynamic impulse response of the VAR shown below shows that the peak responses to return shocks occur in the second period for all configurations indicating a possible lag in the markets and the amount of time it takes for the market to receive new information. This is also an indication of the efficiency of the markets in terms of processing new information. Responses to some shocks last between 2 and 3 days. The response functions indicate that changes to variances move into systems very slowly and persists for longer periods of time which is supportive of volatility clustering.

Table 8 Returns' impulse responses

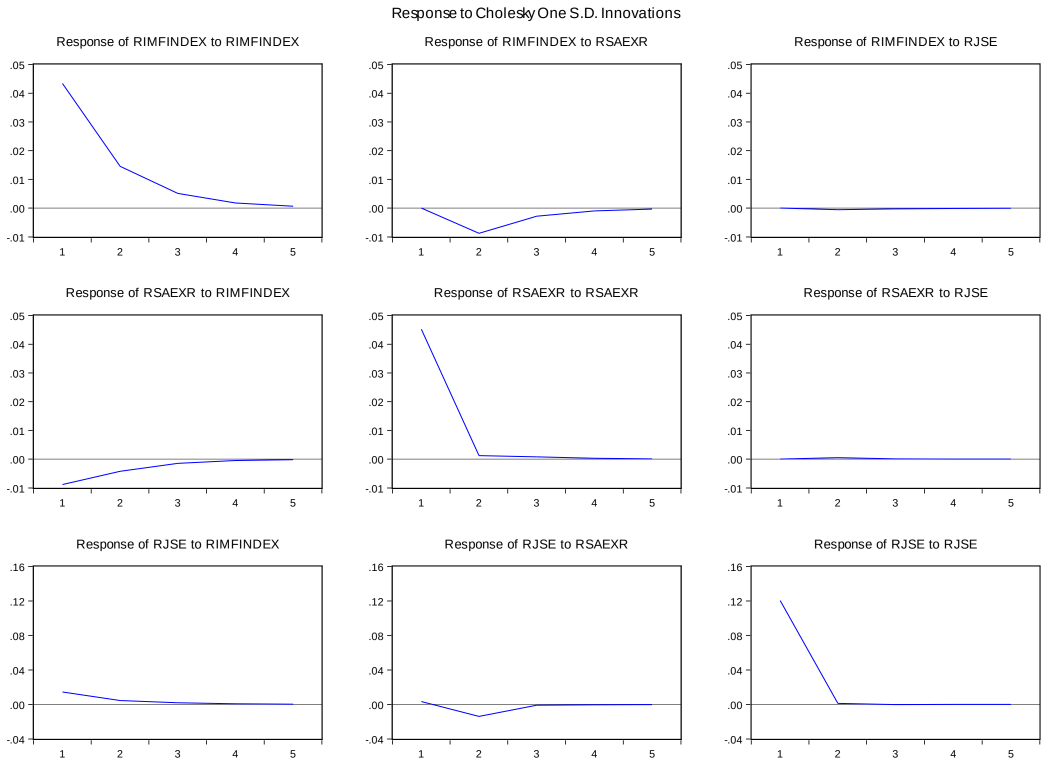
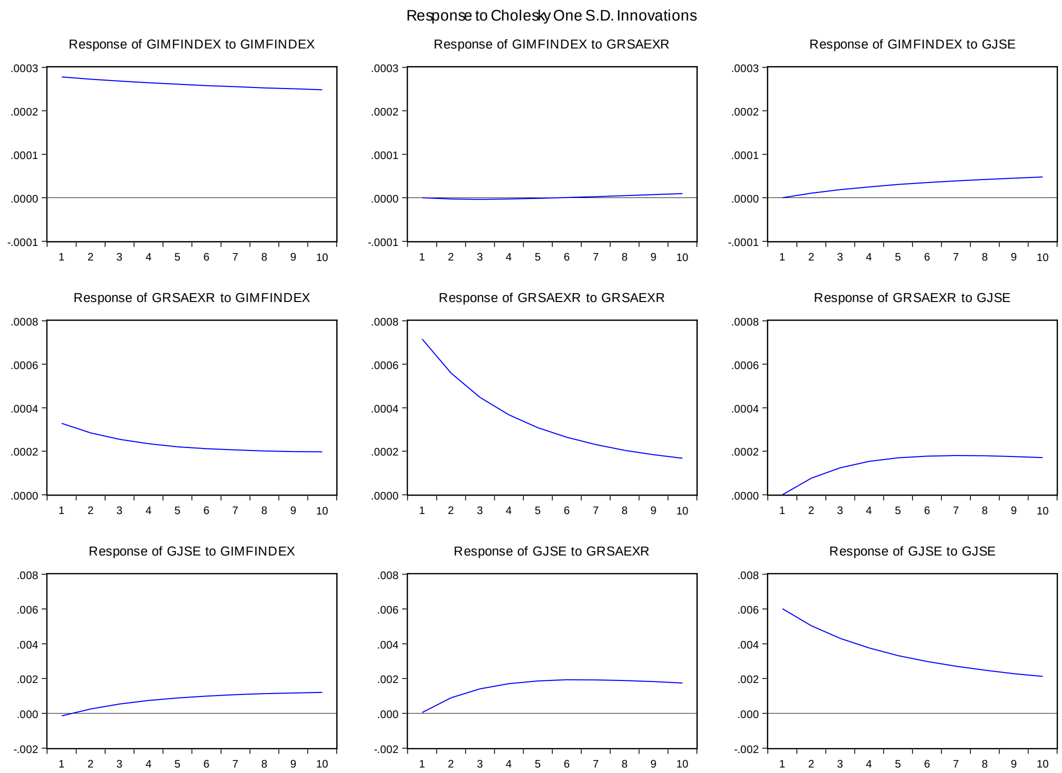


Table 9 Variance impulse responses



4.7 Multivariate GARCH

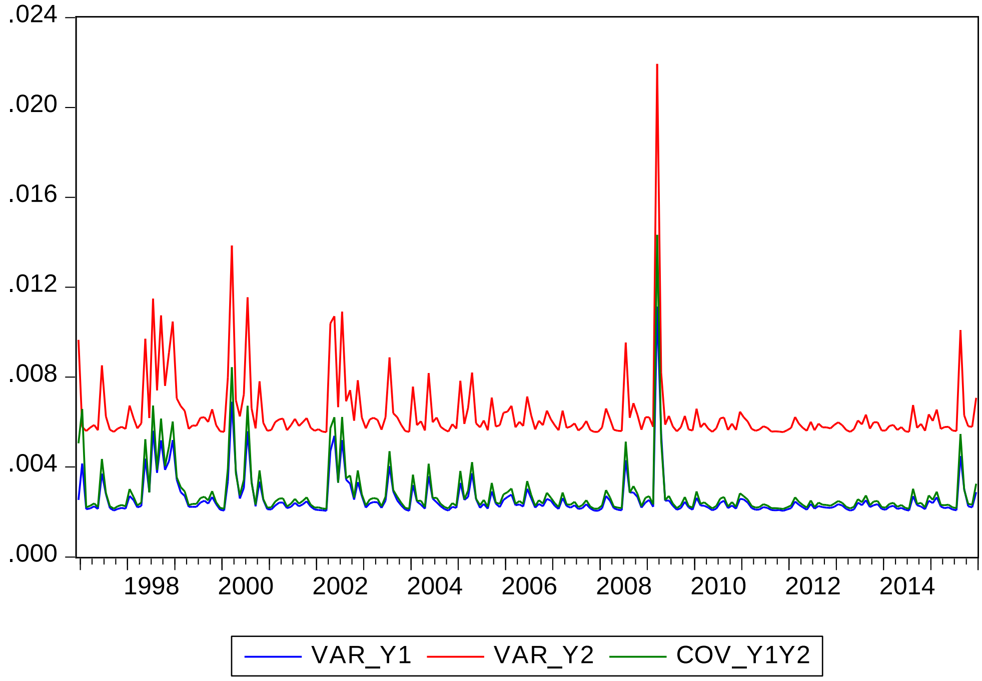
To measure the spill over effects between the variables, a multivariate model, the BEKK-GARCH was used. The multivariate GARCH is an extension of the GARCH(1,1) that involves two stages. The first stage is the estimation of the normal GARCH(1,1) as is presented in section 4.3. Its next stage is the calculation of the co-movement of the variances. The g_{ii} and a_{ii} are GARCH and ARCH terms respectively whereas g_{ij} and a_{ij} terms are covariance between the i and j terms.

Results presented below are a multivariate GARCH with the first variable (*i-terms*) being the IMF index and the second variable (*j-terms*) being the JSE mining index. They show that the constant terms are not significant. All GARCH and ARCH terms are significant. The magnitudes of the coefficients describe the behaviour of the volatility where a large GARCH term accompanied by a low ARCH term is typical of volatility clustering described in previous analysis.

Exchange rate/JSE index GARCH BEKK RESULTS.

BEKK GARCH Results				
	Coefficient	Std. Error	z-Statistic	Prob.
MU(1)	0.005627	0.003346	1.681816	0.0926
MU(2)	0.006656	0.008207	0.811055	0.4173
TETA(1)	-0.011822	0.090918	-0.130030	0.8965
TETA(2)	-0.033821	0.077282	-0.437627	0.6617
OMEGA(1) c_{11}	0.004373	0.114658	0.038138	0.9696
BETA(1) g_{11}	0.661313	0.151108	4.376425	0.0000
BETA(3) g_{21}	0.223708	0.126006	1.775374	0.0758
ALPHA(1) a_{11}	-0.510060	0.096474	-5.287033	0.0000
ALPHA(3) a_{21}	0.001699	0.040108	0.042350	0.9662
OMEGA(3) c_{22}	0.036921	6.613637	0.005583	0.9955
OMEGA(2) c_{21}	-0.102556	2.383477	-0.043028	0.9657
BETA(4) g_{22}	-0.075439	0.422617	-0.178505	0.8583
BETA(2) g_{12}	-0.670757	0.265650	-2.524964	0.0116
ALPHA(4) a_{22}	-0.280007	0.090339	-3.099514	0.0019
ALPHA(2) a_{12}	0.400559	0.307391	1.303093	0.1925
Log likelihood	602.3646	Akaike info criterion		-4.874395
Avg. log likelihood	2.499438	Schwarz criterion		-4.657499
Number of Coefs.	15	Hannan-Quinn criter.		-4.787012

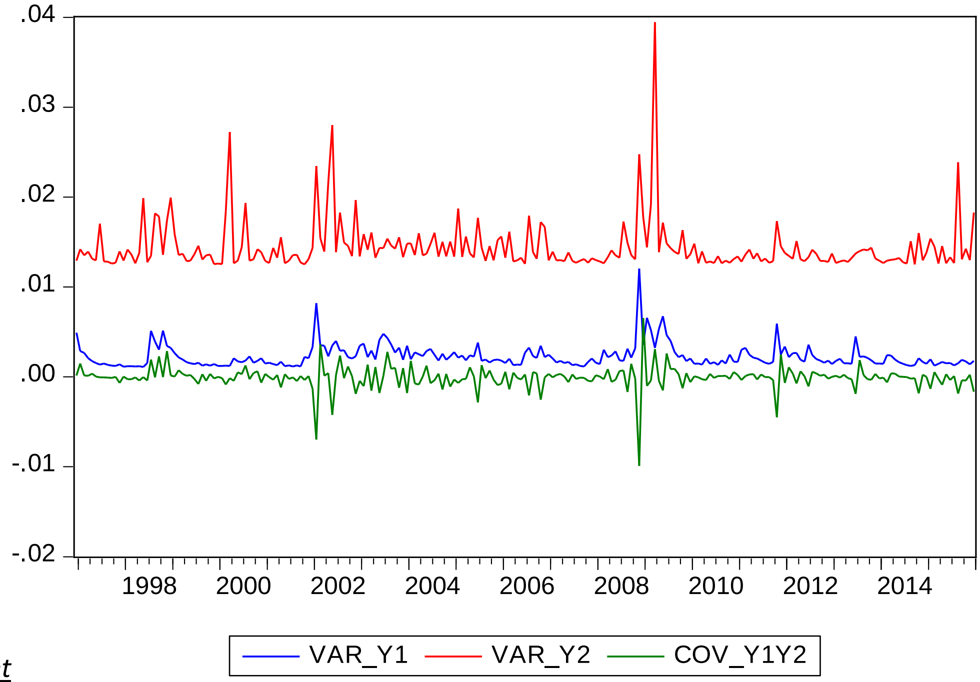
EXR and JSE index covariance movement



IMF index/Exchange rate GARCH BEKK RESULTS.

BEKK GARCH Results				
	Coefficient	Std. Error	z-Statistic	Prob.
MU(1)	0.000693	0.003668	0.189019	0.8501
MU(2)	0.009305	0.003060	3.040866	0.0024
TETA(1)	0.251601	0.064002	3.931113	0.0001
TETA(2)	-0.057555	0.080756	-0.712708	0.4760
OMEGA(1) c_{11}	0.002983	0.007682	0.388270	0.6978
BETA(1) g_{11}	0.931649	0.027753	33.56931	0.0000
BETA(3) g_{21}	-0.109994	0.041729	-2.635904	0.0084
ALPHA(1) a_{11}	0.208938	0.078222	2.671075	0.0076
ALPHA(3) a_{21}	-0.146363	0.036332	-4.028533	0.0001
OMEGA(3) c_{22}	-9.57E-05	0.962121	-9.94E-05	0.9999
OMEGA(2) c_{21}	0.000610	0.013682	0.044552	0.9645
BETA(4) g_{22}	0.895475	0.031059	28.83160	0.0000
BETA(2) g_{12}	-0.232637	0.059905	-3.883422	0.0001
ALPHA(4) a_{22}	-0.324430	0.049990	-6.489871	0.0000
ALPHA(2) a_{12}	-0.121536	0.039717	-3.060085	0.0022
Log likelihood	807.5463	Akaike info criterion		-6.921801
Avg. log likelihood	3.526403	Schwarz criterion		-6.696885
Number of Coefs.	15	Hannan-Quinn criter.		-6.831065

IMF index and EXR covariance movement



5. Conclusion

This paper examined the volatility spill over effects between commodity prices, the South African exchange rate and equity of commodity producing firms. Empirical results showed that there is a high likelihood of volatility clustering in the data as the variance terms for all models were highly significant.

Using GARCH and VAR models, volatility spill overs were detected on the exchange rate from the volatilities of commodity prices and the stocks of commodity producing firms. The spill over from exchange rate to the stocks of South African commodity producing firms also was detected which satisfied the initial hypothesis of the movement of volatility from international commodity prices to the exchange rate and further on to the stocks of mining companies listed on the JSE. This was further supported by the results of the multivariate Garch that showed the quantities of volatility that spills over between variables and well as the consistent but changing relationship over time.

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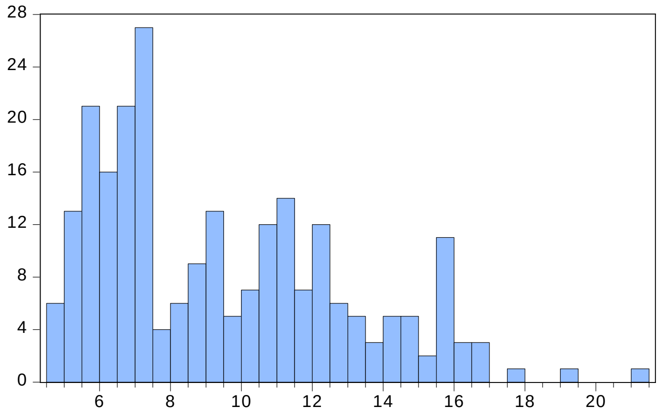
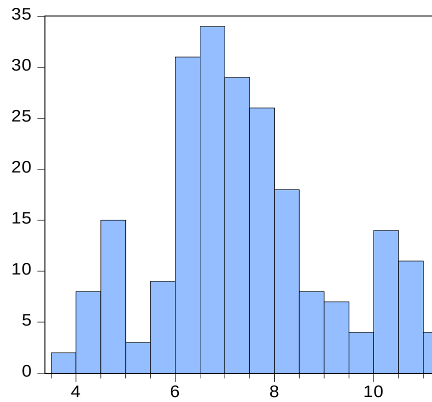
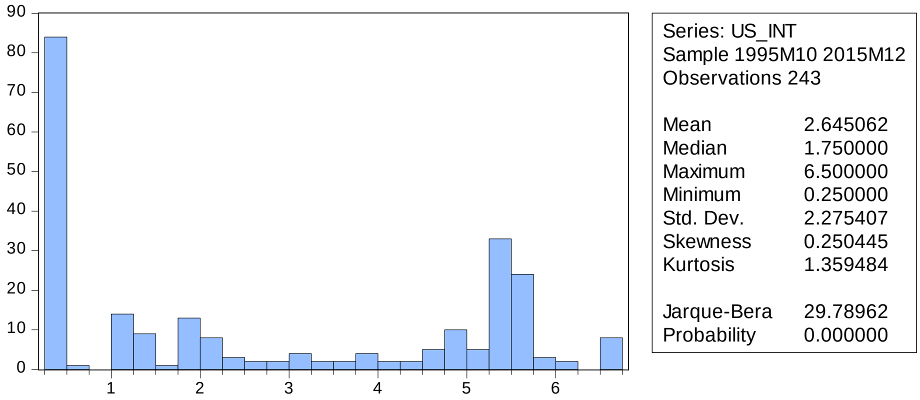
7. *Appendix*

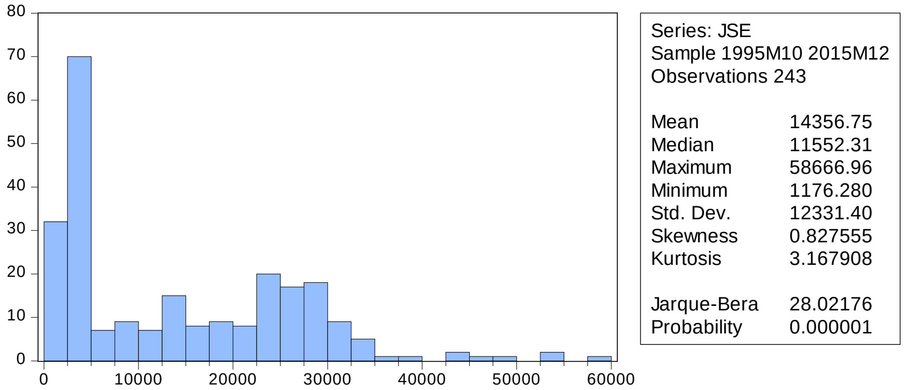


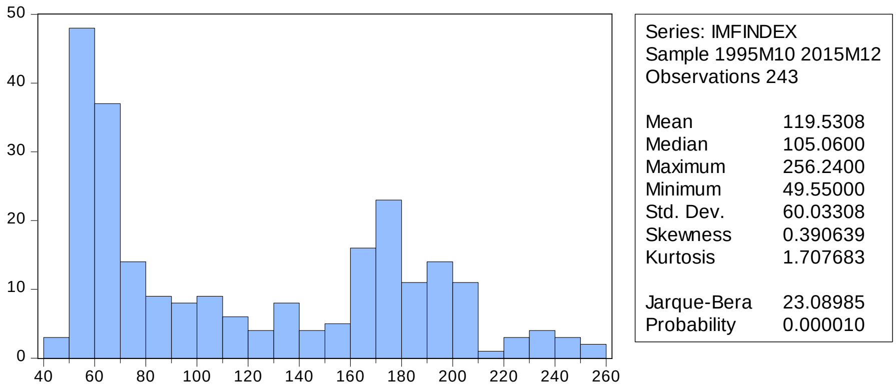
Series: SA_INT
Sample 1996M02 2015M12
Observations 239

Mean	9.448591
Median	8.850000
Maximum	21.47500
Minimum	4.865000
Std. Dev.	3.468209
Skewness	0.715148
Kurtosis	2.738362
Jarque-Bera	21.05395
Probability	0.000027









Heteroscedasticity Test: ARCH RSAEXR			
F-statistic	2.384378	Prob. F(6,226)	0.0297
Obs*R-squared	13.87130	Prob. Chi-Square(6)	0.0311

Heteroscedasticity Test: ARCH IMFINDEX			
F-statistic	2.860242	Prob. F(3,231)	0.0377
Obs*R-squared	8.416664	Prob. Chi-Square(3)	0.0381

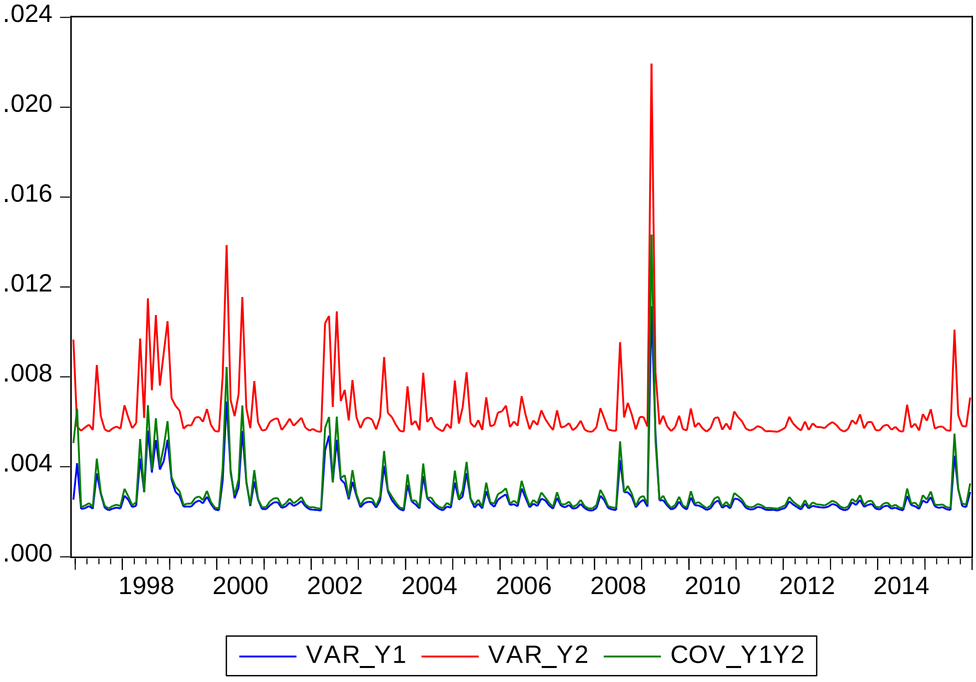
Date: 02/04/17 Time: 14:41 exchange rate old
Sample: 1996M02 2015M12

Included observations: 239

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.032	0.032	0.2467	0.619
.|. |	.|. |	2	0.048	0.047	0.8040	0.669
.|. |	.|. |	3	0.047	0.044	1.3426	0.719
.|. |	.|. |	4	-0.008	-0.013	1.3593	0.851
.|. |	.|. |	5	-0.055	-0.058	2.0908	0.836
.|. |	.|. |	6	-0.061	-0.059	3.0094	0.808
.|. |	.|. |	7	0.036	0.047	3.3389	0.852
.|* |	.|* |	8	0.108	0.119	6.2558	0.619
.|. |	.|. |	9	0.062	0.059	7.2126	0.615
.|. |	.|. |	10	-0.011	-0.035	7.2411	0.703
.|. |	.|. |	11	0.039	0.014	7.6177	0.747
.|. |	.|. |	12	0.001	-0.002	7.6181	0.814
*|. |	.|. |	13	-0.076	-0.059	9.0997	0.765
.|. |	.|. |	14	-0.026	-0.007	9.2728	0.813
.|. |	.|. |	15	0.021	0.028	9.3895	0.856
.|. |	.|. |	16	-0.009	-0.017	9.4100	0.896
.|. |	.|. |	17	0.007	-0.002	9.4233	0.926
.|. |	.|. |	18	-0.022	-0.034	9.5549	0.945
.|. |	.|. |	19	0.032	0.021	9.8252	0.957
.|* |	.|* |	20	0.080	0.087	11.498	0.932
.|. |	.|. |	21	-0.033	-0.017	11.795	0.945
.|. |	.|. |	22	0.019	0.015	11.886	0.960
*|. |	*|. |	23	-0.129	-0.151	16.329	0.841
.|. |	.|. |	24	0.026	0.037	16.510	0.869
.|. |	.|. |	25	-0.002	0.030	16.511	0.899
.|. |	.|. |	26	0.043	0.067	17.019	0.908
*|. |	*|. |	27	-0.077	-0.104	18.632	0.883
.|* |	.|* |	28	0.145	0.120	24.376	0.662
.|. |	.|. |	29	0.032	0.009	24.657	0.696
*|. |	*|. |	30	-0.184	-0.189	33.967	0.282
.|. |	.|. |	31	0.029	0.050	34.194	0.317
.|. |	.|. |	32	0.013	0.053	34.243	0.361
.|. |	.|. |	33	-0.022	-0.006	34.378	0.402
.|. |	.|. |	34	0.054	0.067	35.205	0.411
.|. |	*|. |	35	-0.061	-0.098	36.263	0.410
.|. |	.|. |	36	0.005	-0.061	36.271	0.456

Granger causality in VAR			
Dependent variable: GIMFINDEX			
Excluded	Chi-sq	df	Prob.
GRSAEXR	0.069969	1	0.7914
GJSE	1.237085	1	0.2660
Dependent variable: GRSAEXR			
GIMFINDEX	6.795985	1	0.0091
GJSE	8.437110	1	0.0037
Dependent variable: GJSE			
GIMFINDEX	0.019532	1	0.8889
GRSAEXR	12.17654	1	0.0005

EXR and JSE



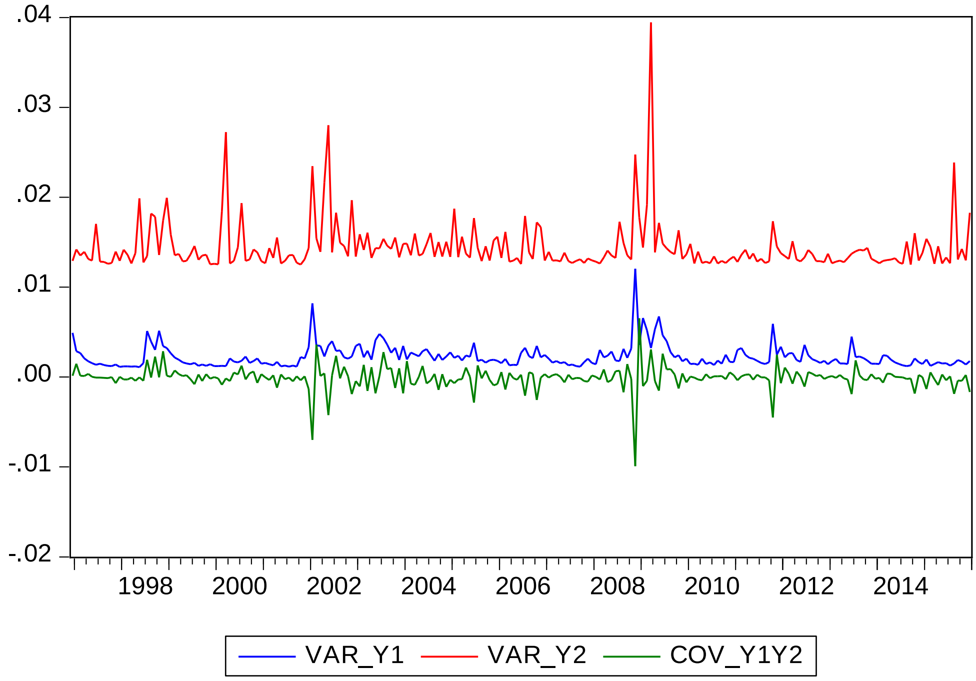
<u>SA JSE (ar(1) ma(1))</u>

LogL: BVGARCH
Method: Maximum Likelihood (Marquardt)
Date: 03/26/17 Time: 16:45
Sample: 1996M12 2015M12
Included observations: 229
Evaluation order: By observation
Estimation settings: tol= 1.0e-05, derivs=accurate numeric
Initial Values: MU(1)=0.09071, MU(2)=0.12808, TETA(1)=0.10000,
TETA(2)=0.10000, OMEGA(1)=0.01838, BETA(1)=0.20000,
BETA(3)=0.20000, ALPHA(1)=0.50000, ALPHA(3)=0.50000,
OMEGA(3)=0.04521, OMEGA(2)=0.00000, BETA(4)=0.20000,
BETA(2)=0.20000, ALPHA(4)=0.50000, ALPHA(2)=0.50000
Convergence not achieved after 100 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
MU(1)	0.005627	0.003346	1.681816	0.0926
MU(2)	0.006656	0.008207	0.811055	0.4173
TETA(1)	-0.011822	0.090918	-0.130030	0.8965
TETA(2)	-0.033821	0.077282	-0.437627	0.6617
OMEGA(1)	0.004373	0.114658	0.038138	0.9696
BETA(1)	0.661313	0.151108	4.376425	0.0000
BETA(3)	0.223708	0.126006	1.775374	0.0758
ALPHA(1)	-0.510060	0.096474	-5.287033	0.0000
ALPHA(3)	0.001699	0.040108	0.042350	0.9662
OMEGA(3)	0.036921	6.613637	0.005583	0.9955
OMEGA(2)	-0.102556	2.383477	-0.043028	0.9657
BETA(4)	-0.075439	0.422617	-0.178505	0.8583
BETA(2)	-0.670757	0.265650	-2.524964	0.0116
ALPHA(4)	-0.280007	0.090339	-3.099514	0.0019

ALPHA(2)	0.400559	0.307391	1.303093	0.1925

Log likelihood	549.2103	Akaike info criterion	-4.665593
Avg. log likelihood	2.398298	Schwarz criterion	-4.440676
Number of Coefs.	15	Hannan-Quinn criter.	-4.574856



IMF and exr (ar(1) and ar(1) ma(1))

LogL: BVGARCH
Method: Maximum Likelihood (Marquardt)
Date: 03/26/17 Time: 16:28
Sample: 1996M12 2015M12
Included observations: 229
Evaluation order: By observation
Estimation settings: tol= 1.0e-05, derivs=accurate numeric
Initial Values: MU(1)=0.02207, MU(2)=0.09071, TETA(1)=0.10000,
TETA(2)=0.10000, OMEGA(1)=0.00674, BETA(1)=0.20000,
BETA(3)=0.20000, ALPHA(1)=0.50000, ALPHA(3)=0.50000,
OMEGA(3)=0.01838, OMEGA(2)=0.00000, BETA(4)=0.20000,
BETA(2)=0.20000, ALPHA(4)=0.50000, ALPHA(2)=0.50000
Convergence not achieved after 100 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
MU(1)	0.000693	0.003668	0.189019	0.8501
MU(2)	0.009305	0.003060	3.040866	0.0024
TETA(1)	0.251601	0.064002	3.931113	0.0001
TETA(2)	-0.057555	0.080756	-0.712708	0.4760
OMEGA(1)	0.002983	0.007682	0.388270	0.6978
BETA(1)	0.931649	0.027753	33.56931	0.0000
BETA(3)	-0.109994	0.041729	-2.635904	0.0084
ALPHA(1)	0.208938	0.078222	2.671075	0.0076
ALPHA(3)	-0.146363	0.036332	-4.028533	0.0001
OMEGA(3)	-9.57E-05	0.962121	-9.94E-05	0.9999
OMEGA(2)	0.000610	0.013682	0.044552	0.9645

BETA(4)	0.895475	0.031059	28.83160	0.0000
BETA(2)	-0.232637	0.059905	-3.883422	0.0001
ALPHA(4)	-0.324430	0.049990	-6.489871	0.0000
ALPHA(2)	-0.121536	0.039717	-3.060085	0.0022

Log likelihood	807.5463	Akaike info criterion	-6.921801
Avg. log likelihood	3.526403	Schwarz criterion	-6.696885
Number of Coefs.	15	Hannan-Quinn criter.	-6.831065