The impact of oil and gold price fluctuations on the South African equity market: volatility spillovers and implications for portfolio management

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THE IMPACT OF OIL AND GOLD PRICE FLUCTUATIONS ON THE SOUTH AFRICAN EQUITY MARKET: VOLATILITY SPILLOVERS AND IMPLICATIONS FOR PORTFOLIO MANAGEMENT

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ABSTRACT

This paper aims to study the impact of gold and oil price fluctuations on the volatility of the South African stock market and its component indices or sectors – namely, the financial, industrial and resource sectors – making use of the asymmetric dynamic conditional correlation (ADCC) generalised autoregressive conditional heteroskedasticity (GARCH) model. Moreover, the study assesses the magnitude of the optimal portfolio weight, hedge ratio and hedge effectiveness for portfolios that are constituted of a pair of assets, namely oil-stock and gold-stock pairs. The findings of the study show that there is significant volatility spillover between the gold and the stock markets, and the oil and stock markets. This finding suggests the importance of the link between futures commodity markets and the stock markets, which is essential for portfolio management. With reference to portfolio optimisation and the possibility of hedging when using the pairs of assets under study, the findings suggest the importance of combining oil and stocks as well as gold and stocks for effective hedging against any risks.

Keywords: *Hedge ratio, optimal portfolio weight, ADCC model, crises, hedge effectiveness, Asymmetric, risk, safe haven.*

1. INTRODUCTION

Over the past years, the South African stock market has shown significant growth, with market capitalisation increasing from 545.4 billion dollars in 2005 to 612.3 billion in 2012 and the turnover ratio increasing by 15.6 percentage points during the period 2005 to 2012 (https://data.worldbank.org). This growth has attracted a number of domestic and international investors in search of high yields (Zhang, Li & Yu, 2013).

However, despite their high yields, emerging markets, such as that of South Africa, are known to be vulnerable to shocks from developed markets. A number of studies indicate how emerging markets have been exposed to the different crises, such as: the dot-com bubble crisis from 2000 to 2001; the global financial crisis from 2007 to 2008; and the European debt crisis from 2010 to 2011 (see Heymans & da Camara, 2013). This vulnerability of emerging markets to external shocks has been a concern to policy makers, investors and asset managers, who seek different ways to minimise the risk thereof. For example, asset managers in search of high yields in emerging stock markets often seek effective methods to minimise risk exposure in these markets.

Literature suggests a number of ways to hedge risk exposure in stock markets. For example, Chkili (2016) and Khalfaoui, Boutahar and Boubaker (2015) find that investment in oil and gold markets provides an opportunity to hedge against stock market exposure in developed economies. However, to the best of our knowledge, there is a deficit in the literature that seeks to assess the link among gold, oil and stock markets in the context of emerging market economies, especially for South Africa. Since South Africa is a net oil-importing and net gold-exporting country, there is no doubt that the country may be exposed to shocks in the gold and oil prices. In addition, assessing the extent of shock transmission and the relation between stock markets and commodity (oil and gold) prices should provide insight into how investors' positions can be combined when making hedging decisions (Ewing & Malik, 2013).

There is a significant number of studies which assessed the impact of oil prices on stock market prices in other countries. For example, Huang, Masulis and Stoll (1996) found that higher oil prices result in changes in a country's trade balance and current account, which, in turn, affect important macroeconomic variables that determine stock prices. In later research, Sadorsky

(1999), Anoruo and Mustafa (2007), and Park and Ratti (2008) examined the relationship between oil and the stock market returns in the United States of America (US), finding that oil price fluctuations have a negative effect on stock returns in this country. In contrast, Cong, Wei, Jiao and Fan (2008) concluded that there isn't any significant evidence on the relation between oil price volatility and stock returns in China.

Other studies have assessed whether oil market can be a useful tool for hedging against stock market exposure. For example, Chkili, Aloui and Nguyen (2014) studied the volatility transmission and hedging strategies between US stock markets and crude oil prices. The authors concluded that investors who seek to minimise portfolio risk should include oil and stock assets. Similar studies – by Ewing and Malik (2016), Sadorsky (2012), Sadorsky (2014b), Arouri, Jouini and Nguyen (2012) and Lin, Wesseh Jr. and Appiah (2014) – also find that oil is an effective hedge for stock market exposure.

With regards to the link between gold and stock markets, Coudert and Raymond-Feingold (2011) show that, during periods of crises, stock prices are most likely to drop and investors tend to invest in safer assets, such as gold. Thus, it is expected that the gold market and stock market will co-move, and the combination of instruments within the two markets should provide the best opportunity for hedging. Also relevant are the findings by Baur and Lucey (2010), who examine the constant and dynamic relationship between the stock markets, bonds and gold returns in the US, United Kingdom and Germany, and explore whether gold plays a hedging role against stock market exposure and safe haven during financial crises. The authors conclude that gold can be a useful hedging tool as well as a safe haven against stock market exposure. Similar studies conducted by Hood and Malik (2013) and Ciner, Gurdgiev and Lucey (2013) also suggest that gold has the characteristic of being a good hedge against stock market exposure.

Indeed, there are many studies in developed markets that have studied the role of gold and oil in portfolio diversification and hedging. However, as stated above, there is not enough literature focusing on emerging markets. Among such existing studies is that by Basher and Sadorsky (2016), which assesses the extent of volatility spillovers of oil, gold, volatility index (VIX) and bonds in emerging stock markets (including South Africa), and compares the hedge effectiveness of oil, gold, VIX and bonds against stock market exposure. Their findings show that oil provides a more effective hedge than gold when hedging against stock market risk.

This paper will extend the study by Basher and Sadorsky by assessing the extent of volatility spillover and the possibility of portfolio selection and hedging between the oil, gold and stock markets at a disaggregated or sectoral level rather than at an aggregate level. Indeed, one of the aims of this paper will be to assess the extent of volatility spillover between oil returns and the returns of the resources sector rather than all stock market returns. In so doing, this paper will depart from the past empirical studies that were focused on an aggregate regional, country-specific or global stock market level, such as in Bhar and Nikolova (2009), Hammoudeh, Sari, Uzunkaya and Liu (2013) and Xu and Hamori (2012).

Thus, the purpose of this study is to investigate the correlation and volatility spillovers between oil, gold, and sectoral stock markets by making use of an asymmetric dynamic conditional correlation model (ADCC) of Cappiello, Engle and Shepparad (2006). Moreover, the paper will assess the possibility of optimal portfolio selection and hedging when combining assets from each of the three markets.

The contribution of this paper is threefold. Firstly, instead of focusing only on the impact of gold and oil volatility shocks on the aggregate stock market, as Basher and Sadorsky (2016) did, this study will analyse volatility spillovers between gold, oil and the South African stock market at an aggregated and disaggregated level. Secondly, we will analyse the optimal weights, hedge ratios and effective portfolio weight for pairs of stock-oil and stock-gold portfolios. Lastly, this paper will assess which of the commodities – oil or gold – provides a better hedge against stock market exposure. Our research provides beneficial and extensive information to portfolio managers and investors based on the interaction between the markets under study in the context of South Africa. Furthermore, this study may also serve as a reference for investors, policy makers, portfolio managers and researchers in terms of developing better and more effective trading strategies.

The remainder of this paper is organized as follows; Section 2 provides a review on previous theoretical and empirical literature related to this paper. Section 3 explains the theoretical framework of econometric models which are used in the paper. Section 4 will discuss the process of data collection and empirical results by applying and testing the models discussed in the previous section (section 3). Lastly section 5 will conclude the paper by highlighting and summarizing all the major findings of this paper.

2. LITERATURE REVIEW

This section will focus on examining empirical and theoretical relationships of stock, oil and gold prices.In a pioneering study, Chen, Roll and Ross (1986) explores different economic forces (including oil) which are likely to influence the stock market using ordinary least squares. The paper concludes that oil prices are a risk factor for stock price. Following this study, there has been numerous studies on the relationship between the stock market and oil prices. For example, Jones and Kaul (1996) investigate the effect of oil price shocks to the stock markets in Canada, Japan, United Kingdom and USA using a cash-flow dividend valuation model. The paper concludes that oil shocks have a negative significant effect on stock prices (except for UK).

Sadorsky (1999) examined the dynamic relationship between oil price, stock returns and a number of economic variables in USA. The author makes use of an unrestricted vector auto-regression and concluded that oil price shocks have a negatively significant effect on stock returns. Using a standard market model augmented by oil price factor, Nandha and Faff (2008) investigate the effect of oil price shocks on 35 DataStream global industry indices for the period between 1983 and 2005. The paper show evidence of significant negative impact of oil shocks on all industries' equity returns.

Chiou and Lee (2009) used an Autoregressive Conditional Jump Intensity to study the relationship between oil price shocks and the S&P500 index. The authors find that oil price shocks have a negative impact on S&P500 index. Chiou and Lee also conclude that there are negative asymmetric effects between oil price shocks and S&P500 returns during periods of high oil price volatility. Similar studies by Malik and Ewing (2009), and Sadorsky (2008) also researched on the relationship between the stock exchange market and oil market, and show that there exists a negative correlation between the two markets.

On the contrary, there is a set of studies that argue that there exists a positive relationship between oil prices and the stock market. For example, Basher and Sadorsky (2006) study the linkage between oil price shocks and 21 emerging stock market returns using an international multi-factor model which permits for both conditional and unconditional risk factors. The study show that in emerging markets oil price shocks have a strong positive impact stock market returns. Faff and

Brailsford (1999) research the link between Australian stock market and oil prices using. They found that the stock market has a positive correlation between oil and gas.

Narayan and Narayan (2010) also study the relationship between oil price and stock market in Vietnam by using Gregory and Hansen residual based test. The paper conclude that in the long-run oil price and exchange rate have positive significantly effects on the stock price. In addition, Al-Mudhaf and Goodwin (1993), Sadorsky (2001) and Aloui, Hammoudeh, and Nguyen (2013) also support the argument that oil prices and stock market prices are positively correlated.

However, there are also studies which provide evidence that the oil market has no impact on the stock exchange market. Apergis and Miller (2009) investigate the impact of oil market shocks on eight developed countries' stock markets using a VEC model. The authors find that there is no significant relationship between oil market and the stock market. Furthermore, Hung et al. (1996) also examined the relation between oil future prices and the S&P 500 and found that it is non-existent. The paper used a VAR approach to reach this conclusion. Similar findings are given by Chen et al. (1986), and Lescaroux and Mignon (2008).

Moreover, there is also work which investigates the volatility transmission of oil and the stock market, and the role of oil as a hedging instrument. Kilian and Park (2009) explained that the relationship between oil prices and the stock market can either be positive or negative depending on whether the shock in oil price is driven by demand or supply shocks in the oil market. Therefore, it is important to differentiate between oil-exporting countries and non-oil-exporting countries when investigating this relationship.

On the other hand, there is not much literature on the relationship between gold and the stock market; most studies focus more on the role of gold as a hedge or safe haven. Among studies, Hood and Malik (2013) assess the role of gold, other precious metals and volatility index (VIX) as a hedge and safe haven for the stock market in USA. Using a regression model by Baur and McDermott (2010), the authors conclude that gold serves as a better hedge and safe haven than other precious metals. However VIX serves as a better hedge and safe haven than gold. Similarly, Baur and Lucey (2010) and Ciner, Gurdgiev and Lucey (2013) also suggest that gold has characteristics of a good hedge and a safe haven.

Equally important, there are also studies which investigate the volatility spillovers between gold and the stock market, and the role of gold as a hedge instrument. For example, Arouri, Lahiani, Nguyen (2015) investigate the volatility spillovers between the Chinese stock market prices and gold prices using the VAR-GARCH. The paper suggest that there are volatility spillovers between china's change in stock prices and gold price, and adding gold in a stock portfolio can help minimize stock market risk.

Ewing and Malik (2013) stated that there is strong evidence of volatility spillovers between the gold and stock market. The paper used univariate and bivariate GARCH models to achieve such results. Kumar (2014) study the volatility spillovers between gold and sector stock returns, and the role of gold as a hedge using a generalised VAR-ADCC-BVGARCH model. The study show that the correlation varies over time and during periods of crisis, therefore, including gold in a portfolio provides an effective hedged portfolio. Furthermore, Chkili (2016) used an ADCC-GARCH model, respectively, to study the relation between gold and the stock market. They find correlation to vary over time and suggest that gold is a good hedge and it can also play a role of a safe haven during periods of crises. A similar studies by Gurgun and Unalmis¸ (2014) also suggest that gold is a good hedge and safe haven.

The above studies are among the small body of literature on the relationship between oil, gold and stock prices. The Studies show the relationship of oil, gold and the stock prices, and the role of oil and gold as hedge instruments for the stock market. However, there are few studies which are focused on the relationship between oil, gold and stock prices in African countries. For example, Basher and Sadorsky (2016) investigates the effectiveness of oil, gold, bonds and VIX as hedge instruments for emerging market stocks, using a DCC, ADCC and GO-GARCH to estimate conditional volatilities and correlations. The paper concludes that both oil and gold can be used as hedge instruments, but oil provides a more effective hedge than gold. However, this study fails to provide the role of oil and gold as a hedge for different stock sectors. Contrary to the study by Basher and Sadorsky (2016), this paper will contribute to the literature of the volatility spillovers between oil, gold and stock prices, by evaluating volatility spillovers between oil, gold and seven most volatile stock market sectors in South Africa. Moreover, this paper will advise investors on minimizing portfolio risk using optimal weights and effective hedging strategies.

3. METHODOLOGY

This section explains the methodology used in this study, and it is presented as follows. To begin with, we will explain how to model time varying volatility and correlations among the variables under study. Followed by, an analysis of optimal portfolio weights. Then, we give details on how to compute optimal hedge ratios. To finish, we provide an assessment of hedge effectiveness.

This paper will adopt an asymmetric dynamic conditional correlation model of Cappiello, Engle and Shepparad (2006) to model conditional volatility, correlations, optimal weights and hedge ratios for oil-stock and gold-stock pairs. Recent literature shows that an ADCC model is by far the best model to estimate conditional correlation, variances and covariances among time series because it accounts for both the dynamic correlation and the asymmetric feature of stock market's behavior (Ederington and Guan, 2010, and Chkili, 2016).

3.1 Asymmetric Dynamic Conditional Correlation Model

The ADCC formulated by Cappiello et al. (2006) follows a two-step estimation process. The first step is to estimate the conditional variances. To do so, we first need to obtain random error terms from the conditional mean model. We will use a VAR model as it permits for autocorrelations and cross-autocorrelations in returns.

$$r_{it} = C_i + \sum_{j=1}^{n} \omega_{ij}\, r_{it-1} + \varepsilon_{it}\,, \varepsilon_{it}|F_{t-1} \sim N(0\,, h_{iit}) \tag{9}$$

$$\varepsilon_{it} = e_{it}\sqrt{h_{iit}}\,, e_{it} \sim N(0\,,1) \tag{10}$$

where equation (9) represents the mean equation given as a VAR model with one lag. r_{it} is a 1xn vector of daily returns of oil, gold and major sectors mentioned in the previous section, and it is calculated as $r_{it} = \log\left(\frac{P_{it}}{P_{it-1}}\right) * 100$, where P_{it} is the closing price of i at time t. C_i is the long-term drift coefficient for variable i. The parameter ω_{ij} for $i = j$ indicates the effect of previous i returns on its own current returns. ω_{ij} for $i \neq j$ indicates the effect of lagged j returns on current returns of i. F_{t-1} is the market information available at time $t-1$. Lastly, ε_{it} represents the random error term for variable i at time t.

Equation (10) shows ε_{it} (error terms), and e_{it} represents standardised residuals, which follows a joint normal distribution.

This paper will use the VARMA-GARCH (1, 1) developed by Ling and McAleer (2003) to model conditional variances and covariances. This method is useful when modeling volatility spillovers, because unlike a simple GARCH (1, 1) model, a VARMA-GARCH (1,1) has the ability to show how shocks in one variable can affect the variances of the other variables (Sadorsky, 2012). A VARMA-GARCH (1, 1) is specified as follows:

$$h_{iit} = \varphi_i + \sum_{j=1}^{n} \alpha_{ij}\, \varepsilon^2{}_{it-1} + \sum_{i=1}^{n} \gamma_i \varepsilon^2{}_{it-1} D_{it-1} + \sum_{j=1}^{n} \beta_{ij}\, h_{it-1} \quad (11)$$

where h_{iit} is the conditional variance, φ_i denotes the constant term of the conditional variance equations for i. $\sum_{j=1}^{n} \alpha_{ij}$ for $i = j$ denotes i's own ARCH effect, which measures the short-run volatility persistence. $\sum_{j=1}^{n} \beta_{ij}$ for $i = j$ denotes $i's$ own GARCH terms, which measure the long-run volatility persistence. For $i \neq j$, $\sum_{j=1}^{n} \alpha_{ij}$ and $\sum_{j=1}^{n} \beta_{ij}$ respectively denote the cross ARCH and GARCH terms, which measure the volatility spillovers from j to i. $\gamma_i \varepsilon^2{}_{it-1} D_{it-1}$ captures leverage effects (asymmetry), where D_{it-1} is a dummy variable and equals one when $\varepsilon^2{}_{it-1} < 0$ and 0 otherwise. The term D_{it-1} allows bad news in the market ($\varepsilon^2{}_{it-1} < 0$) to be followed by higher volatilities than good news ($\varepsilon^2{}_{it-1} > 0$) of the same magnitude.

In the second step, we estimate conditional correlations based on the standardised residuals from step one, as follows:

$$H_t = D_t P_t D_t \quad (12)$$

where H_t is an nxn conditional covariance matrix, D_t is a diagonal matrix with conditional standard deviations on the diagonal given, and P_t is the conditional correlation matrix.

$$P_t = \begin{bmatrix} \frac{1}{\sqrt{q_{11t}}} & 0 \cdots & 0 \\ 0 & \ddots & 0 \\ \vdots & & \vdots \\ 0 & 0 \cdots & \frac{1}{\sqrt{q_{nnt}}} \end{bmatrix} * Q_t * \begin{bmatrix} \frac{1}{\sqrt{q_{11t}}} & 0 \cdots & 0 \\ 0 & \ddots & 0 \\ & & \vdots \\ 0 & 0 \cdots & \frac{1}{\sqrt{q_{nnt}}} \end{bmatrix} \tag{15}$$

$$Q_{ijt} = (1 - f_1 - f_2)\bar{Q} + f_1 u_{it-1} u'_{jt-1} + f_2 Q_{ijt-1} \tag{16}$$

where Q_{ijt} is the unconditional variance between i and j, and is a positive definite nxn matrix. $\overline{Q}$ a is an nxn unconditional covariance matrix, u_{t-1} represents standardised residuals and f_1 and f_2 are non-negative parameters, where $f_1 + f_2 < 1$. The time-varying conditional correlation coefficient is expressed as:

$$\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{iit} q_{jjt}}} \tag{17}$$

An asymmetric DCC model will be estimated using a Quasi-Maximum Likelihood Estimation (QMLE) with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm and the T statistics being computed by a robust estimate of the covariance matrix.

4.3.2 Optimal Portfolio Weights

To construct an optimal portfolio that minimizes risk without lowering expected returns, we use a methodology by Kroner and Ng (1998) to construct optimal portfolio weights of a two asset portfolio as follows:

$$w_{SO,t} = \frac{h_{i,t} - h_{ij,t}}{h_{j,t} - 2h_{ij,t} + h_{i,t}} \tag{11}$$

, and

$$w_{SO,t} = \begin{cases} 0, if\ w_{ij,t} < 0 \\ w_{ij,t}, if\ 0 \le w_{ij,t} \le 1 \\ 1, if\ w_{ij,t} > 1 \end{cases} \tag{12}$$

Where $w_{ij,t}$ refers to the weight of j in a portfolio of the two assets defined above at time t and weight of j in the considered portfolio is obtained by $(1 - w_{ij,t})$.

4.3.3 Optimal Hedge Ratios

Alternatively, in order to minimize risk we will follow Kroner and Sultan (1993) regarding risk minimizing hedge ratios of a two-asset portfolio. We typically seek the amount of the short position taken in j in order to minimize the risk of a long position in i. The optimal hedge ratio is as follows:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{i,t}} \tag{13}$$

Where $\beta_{ij,t}$represents the optimal hedge ratio, $h_{i,t}$ and $h_{j,t}$is the conditional variance of asset i, conditional variance of asset j, respectively. $h_{ij,t}$ denotes the conditional covariance of asset i and j.

3.3.4 Measuring the Performance of a Hedged Portfolio

Most studies use the hedge effectiveness index given by Ederington (1979) to analyse the performance of a hedged portfolio (Chkili, 2016 and Basher & Sadorsky, 2016). We will also apply this hedge effectiveness index in our analysis below. The hedge effectiveness index is a comparison of risk between a hedged and an un-hedged portfolio. A hedged portfolio comprises a long position in the underlying stock and a short position in futures' contracts. An unhedged portfolio consists of only a long position in the underlying stock.

A hedge effectiveness index computes the percentage of the variance that is eliminated from an unhedged portfolio by hedging, and is calculated as follows:

$$HE = \frac{Variance_U - Variance_H}{Variance_U} \tag{22}$$

Where $Variance_H$ and $Variance_U$ denote hedged and unhedged variances respectively.
This method compares the variance of the hedged portfolio to that of an un-hedged portfolio. Hence, a higher hedge effectiveness (HE) implies that a higher variance (risk) is eliminated by the hedging strategy.

4. DATA, ESTIMATION AND DISCUSSION OF RESULTS

4.1 Data

The data used in this paper includes daily closing values of: FTSE/JSE All Share Index (JSE), FTSE/JSE Financials (FIN), FTSE/JSE Industrials Index (IND), FTSE/JSE Resources (RES), nearby futures' contract of gold (GOLD) and nearby futures' contract of Brent crude oil (OIL).[1] All prices are expressed in US dollars.[2] The sample period starts from 3 January 2006 and ends on 31 December 2015, taking into account both the global financial crisis and the European debt crisis. We make use of daily data in order to capture the intensity and speed of the dynamic transmission between commodity and stock markets' returns. Data on FTSE/JSE indices is obtained from Inet BFA, while OIL and GOLD data is from Bloomberg. In total, our analysis includes 2581 observations. The sector indices included in this study are weighted by market capitalisation, and they contain a bulk of stocks within their respective economic groups. We thus assume that they can accurately display the aggregate stock price movements of firms within their respective sectors.

Figure 1 below illustrates the returns of JSE, FIN, IND, RES, GOLD and OIL. Looking figure 1, there is clear evidence of volatility clustering for all variables, with a noticeable high spike in 2007 - 2009, which is the result of the global financial crisis of 2008. Moreover, the high volatility clustering from 2010 to 2011 should be attributed to the European debt crisis. OIL also shows high volatility clustering in 2014 to 2015, which could reflect the effects of the oil price crisis. Lastly, there is a spike in GOLD in 2013, which was due to global inflation falling in 2013, reducing the value of gold as a hedge against inflation[3].

Table 2 below represents the descriptive statistics of returns for all variables under study. All time-series here indicate very similar descriptive statistics, especially for the means of the variables. For example, the mean and median values are very close to zero and the unconditional standard deviation is greater than the mean value for all variables. The standard deviation of OIL and RES is greater than the standard deviations of all other variables, which is an indication that OIL and

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[1] Note: we use the futures contract of gold and oil and not their spot prices, because the basic concept of hedging is to build a hedged portfolio that will minimise risk by combining futures' and spots' positions. Therefore, since this paper aims to analyse the hedge effectiveness of oil and gold against stock market exposure, using future prices will be more appropriate to determine optimal hedge ratios.

[2] All the data is denominated in US dollars in order to align our study with other international studies.

[3] Gold is viewed as a hedge instrument against inflation: see Capie, Mills and Wood (2005) for more details.

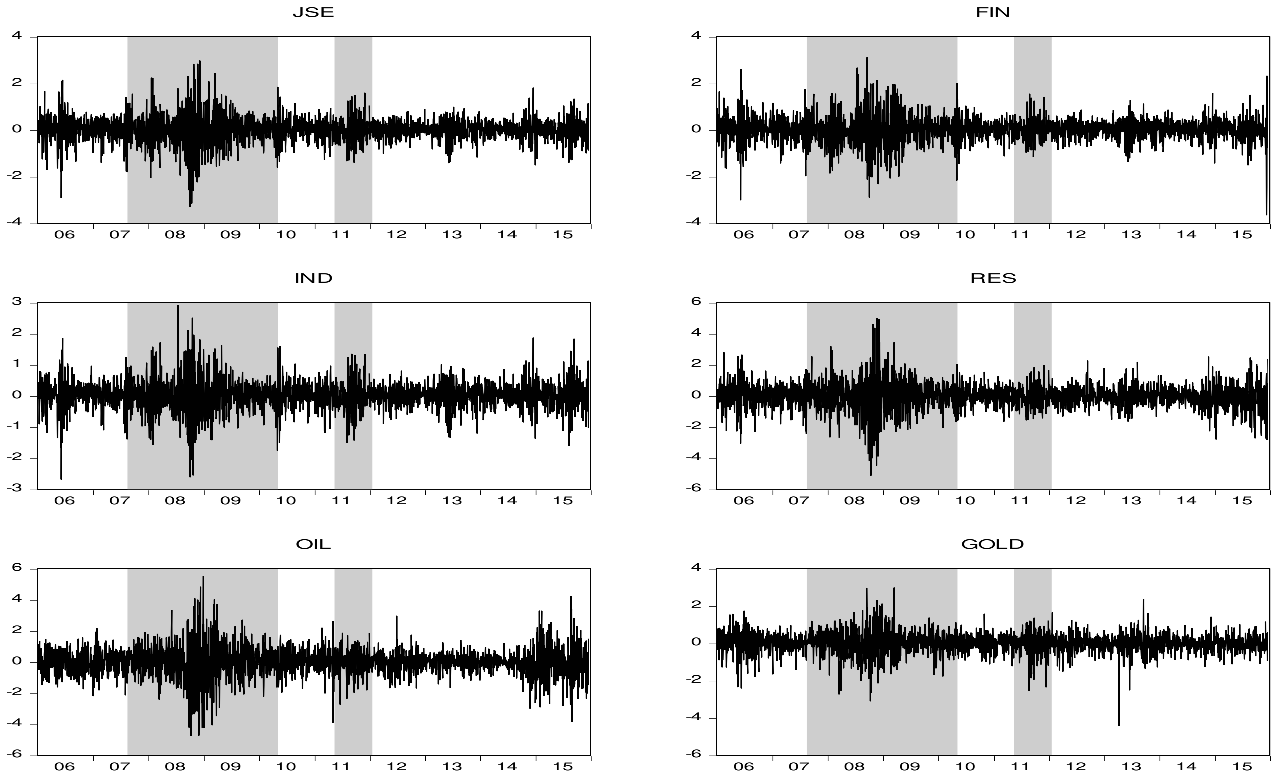
RES are more volatile than the other variables in the study. The least volatile series is IND, with a standard deviation of 1.0838. The skewness and kurtosis for all variables show that the returns are not normally distributed, confirmed by the Jarque-Bera normality test, which is typical for financial time-series behaviour.

Furthermore, we also calculate unconditional correlations of pairs of stock[4]-oil and stock-gold returns. Such correlations between returns are often used to guide portfolio diversification decisions. However, unconditional correlations fail to account for the dynamic behaviour of correlations between returns, which will be addressed below.[5] The correlations for stock-oil pairs are positive for all pairs, suggesting that, over our sample period, increases in oil prices were seen as being indicative of higher earnings in the stock market. However, the correlations for stock-gold pairs are weak and positive for all pairs, except for the RES and GOLD pair. The highest correlation is that of OIL-RES (0.3518) and GOLD-RES (0.3281) pairs. This result is expected, as the resources index includes stocks of companies involved in gold mining and oil exploration. The lowest correlation is observed for the IND-GOLD pair (0.0688). Overall, the correlation of returns between stock-oil and stock-gold pairs under study are relatively low, suggesting that there might be an opportunity for meaningful portfolio diversification.

	JSE	**FIN**	**IND**	**RES**	**OIL**	**GOLD**
Mean	0.0394	0.0327	0.0627	-0.0094	-0.0193	0.0270
Median	0.0450	0.0248	0.0865	0.0000	0.0000	0.0375
Std. dev	1.2705	1.2579	1.0838	1.9309	2.1085	1.2655
Variance	1.6142	1.5824	1.1745	3.7282	4.4457	1.6015
Skewness	-0.1807	-0.1527	-0.1347	-0.0390	-0.0682	-0.5195
Kurtosis	3.8021	3.9456	3.3906	4.1658	3.7725	4.8373
Jarque-Bera (Probability)	1568.6927 (0.0000)	1684.2184 (0.0000)	1244.1261 (0.0000)	1866.8886 (0.0000)	1532.5127 (0.0000)	2632.4927 (0.0000)
Corr. With OIL	0.3240	0.2059	0.2340	0.3518	1.0000	0.2373
Corr. With GOLD	0.2216	0.0395	0.0688	0.3281	0.2373	1.0000

[4] Stock refers to JSE, IND, FIN and RES.

[5] See section 4.2 below.



Note: the shaded area is the global financial crisis and the first and second phases of Eurozone sovereign debt crisis period (see table 1 for more details).

Figure 1: JSE, FIN, IND, RES, GOLD and OIL Returns[6]

4.2 Empirical Results[7]

4.2.1 The ADCC model estimation results from models 1 – 4

Table 4 shows the parameter obtained from the quasi-maximum likelihood estimation of equations (9), (11), (12) and (16), representing the VAR-ADCC-GARCH model. Four models are estimated combining three variables each: gold, oil and each of the three stock market sectors and the aggregate stock market. For example, model 1 contains JSE (aggregate stock), OIL and GOLD; model 2 contains FIN, OIL and GOLD; model 3 contains IND, OIL and GOLD; and model 4 contains RES, OIL and GOLD. To ensure accuracy, we will interpret the returns and volatility spillover results for each model individually. The asymmetry and correlation coefficients results will be interpreted jointly, as the outcomes are similar in all four models.

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[6] Unless specified otherwise, the shaded area in all graphs represents the global financial crisis and the first and second phases of the Eurozone sovereign debt crisis.

[7]To ensure brevity, our interpretation below will we focus on OIL-STOCK and GOLD-STOCK pairs throughout the paper and not OIL-GOLD pairs. We do so because the objective of this study is to examine the impact of oil and gold price fluctuations on the South African equity market, not the relationship between oil and gold.

- **Model 1**[8]

To study the volatility spillovers between the stock markets and commodity markets, it is necessary to first identify the appropriate autoregressive model in order to determine the structure of the volatility model that characterises each of the series. We will employ a VAR model of order 1 (VAR (1)) to model mean returns (equation 9). There are a number of reasons why we use a VAR (1) process to model stock returns. Firstly, numerous recent empirical studies support the use of a VAR (1) process for modelling stock market returns in emerging economies (for example, Chkili, 2016; Kang et al., 2016; Kumar, 2014; Basher & Sadorsky, 2016, etc.). Secondly, this model takes into account the dynamics in market returns and indicates the speedy reaction of markets to new information (Kumar, 2014). Thirdly, it captures the random walk and weak-form efficiency characteristics of stock market prices and commodity prices (Fama, 1965). The same reasons apply to the other three models below.

In table 4, model 1, the mean equation shows that own one period lagged JSE and GOLD returns, denoted by the AR (1) coefficients (represented by ω_{11} and ω_{33} respectively) are not significant. Thus past realisations of JSE and GOLD returns might not be useful in predicting future JSE and GOLD returns respectively. In contrast, the AR (1) coefficient for OIL returns (represented byω_{22}) is significant at a 1% level. This result suggests that past oil price changes can be used to predict its own future returns. Moreover, the mean equation also shows cross returns spillovers (cross-autocorrelations in returns) between the variables under study. We notice that there is a positive significant return spillover from past OIL returns to current JSE returns (ω_{12}). However, there is no significant return spillover from past GOLD returns to the current JSE returns (ω_{13}), implying that current returns of JSE are significantly affected by past returns of OIL, and are unaffected by past returns of GOLD. Furthermore, we do not find any significant return spillover from JSE returns to both OIL (ω_{21}) and GOLD returns (ω_{31}), implying that past JSE returns might not be useful when predicting future OIL or GOLD returns.

The next step when studying the volatility transmission between stock markets and commodity markets involves the estimation of equations (11) and (12). From the variance equation (11) in model 1 (see table 4), we obtain own ARCH (α_{ii}) and GARCH (β_{ii}) coefficients, which

[8] Note: variable order is JSE (1), OIL (2) and GOLD (3).

respectively capture own volatility shock and own volatility persistence in the conditional variance equations. For own ARCH coefficients, α_{11} refers to the ARCH term in the JSE equation, α_{22} refers to the ARCH term in the OIL equation and α_{33} refers to the ARCH term in the GOLD equation. From our results in model 1, the estimated coefficients on own past volatility shocks terms (denoted by α_{ii}) are all significant at a 1% level in each equation, except for the JSE equation, with α_{11} being insignificant. These results indicate that the current conditional volatility of a specific variable (OIL and GOLD) depends on its own past volatility shocks, demonstrating the importance of previous volatility shocks in explaining current conditional volatility.

Similarly, for own GARCH coefficients, β_{11} denotes the GARCH term in the JSE equation, β_{22} denotes the GARCH term in the OIL equation and β_{33} denotes the GARCH term in the GOLD equation. From our results in model 1, it is evident that the estimated coefficients on own past volatility persistence terms (denoted by β_{ii}) are all statistically significant at a 1% level in each equation. These results indicate that the current conditional volatility of a specific variable (JSE, OIL and GOLD) depends on its own past volatility. This finding shows the importance of previous volatility persistence in explaining current conditional volatility.

The results of model 1 also show that all ARCH parameters (α_{ii}) are relatively smaller than GARCH parameters (β_{ii}), implying that the estimated conditional volatility does not swiftly change, owing to a shift in volatility shocks (as shown by the small ARCH coefficients). Instead, conditional volatility tends to gradually evolve over time with respect to large effects of past volatility persistence (this result is similar in all cases under study). This finding will help investors and portfolio managers to develop investment strategies that are focused on current market trends and the long-run volatility persistence. Our results are very close to those of Sadorsky (2012) and Kumar (2014).

In our analysis of the cross volatility transmission between OIL and JSE, and GOLD and JSE[9] under model 1, the coefficients α_{ij} and β_{ij}, where $i \neq j$, denote the short-run and long-run persistence volatility transmission between stock and commodity markets under study respectively. Our coefficients of interest in this case are;

[9] Note: we focus on OIL-STOCK and GOLD-STOCK pairs throughout the paper and not OIL-GOLD pairs because the objective of this study is to study the impact of oil and gold price fluctuations on the South African equity market, not the relationship between oil and gold.

- α_{12}, which captures the short-run volatility shock from OIL to the stock (JSE in model 1, FIN in model 2, IND in model 3 and RES in model 4), and β_{12}, which measures the long-run volatility persistence from OIL to the stock.
- α_{21}, which captures the short-run volatility shock from the stock to OIL, while β_{21} measures the short-run volatility persistence from the stock to OIL.
- α_{13}, which captures the short-run volatility shock from GOLD to the stock, and β_{13}, which measures the long-run volatility persistence from GOLD to the stock.
- α_{31}, which captures the short-run volatility shock from the stock to GOLD, while β_{31} measures the long-run volatility persistence from the stock to GOLD.

We discover that there is a significant short-run and long-run persistence volatility transmission from the oil market (OIL) to the aggregate stock market (JSE), at a 1% level of significance. This result makes economic sense, as higher oil prices may result in higher cost of production, which could reduce a company's profitability and stock prices.

In contrast, there is no evidence of volatility spillovers from the aggregate stock market (JSE) to OIL, implying that there is a unidirectional volatility transmission from OIL to JSE. This result might be owing to the fact that South Africa is a price taker on the global oil market, as it is a relatively minor net oil-importing country (Wakeford, 2006). Arouri et al. (2012) and Mensi, Beljid, Boubaker and Managi (2013) also confirm these results on the volatility transmission between oil and the aggregate stock market.

Regarding the volatility spillovers between the aggregate stock market (JSE) and GOLD, we do not find any significant short-run and long-run persistence volatility spillovers, suggesting that gold is not helpful in forecasting stock trends in South Africa. This finding is supported by Sumner et al. (2010), who concluded that no significant evidence of volatility spillovers between gold and the stock market returns exists. Furthermore, the price of gold is usually linked with negative economic or financial news, signifying that the stock market and gold might be negatively related during periods of economic or financial uncertainty (Kiohos & Sariannidis, 2010).

- **Model 2**[10]

[10] Note: variable order is FIN (1), OIL (2) and GOLD (3).

Turning first to the mean equation results, the mean equation in model 2 shows that own one period lagged FIN and GOLD returns, denoted by the AR (1) coefficients (represented by ω_{11} and ω_{33} respectively), are not significant. This result indicates that past realisations of FIN and GOLD returns are not useful in predicting their own respective future returns. In contrast, the AR (1) coefficient for OIL returns (represented by ω_{22}) is significant at the 1% level. This result suggests that past oil price changes can be used to predict its own future returns. Moreover, the mean equation also shows cross-return spillovers (cross-autocorrelations in returns) between the variables under study. We do not find any significant return spillovers from FIN returns to both OIL (ω_{21}) and GOLD returns (ω_{31}). Similarly, we also do not find any evidence of return spillovers from both OIL and GOLD returns to FIN (represented by ω_{12} and ω_{13} respectively), which implies that past realisations of OIL and GOLD returns do not help predict FIN returns, and that the opposite is also true.

In the variance equation, we obtain own ARCH (α_{ii}) and GARCH (β_{ii}) coefficients, which respectively capture own volatility shock and own volatility persistence in the conditional variance equations. For own ARCH coefficients, α_{11} refers to the ARCH term in the FIN equation, α_{22} refers to the ARCH term in the OIL equation and α_{33} refers to the ARCH term in the GOLD equation. Results in model 2 show that the estimated coefficients on own past volatility shocks (the α_{ii} terms) are all statistically significant at the 1% level in each equation, indicating that the current conditional volatility of a specific variable (FIN, OIL and GOLD) depends on its own past volatility shocks. Thus, this finding shows the importance of previous volatility shocks in explaining current conditional volatility.

Similarly, for own GARCH coefficients, β_{11} represents the GARCH term in the FIN equation, β_{22} signifies the GARCH term in the OIL equation and β_{33} represents the GARCH term in the GOLD equation. Our results in model 2 show that the estimated coefficients on own past volatility persistence terms (β_{ii}) are all significant a 1% level in each equation, indicating that current conditional volatility of a specific variable (FIN, OIL and GOLD) depends on their own past volatility. This finding shows the importance of previous volatility in explaining current conditional volatility, thus volatility persistence in all the three markets. The results in model 2 also show that all ARCH parameters (α_{ii}) are relatively smaller than GARCH parameters (β_{ii}), which is somewhat similar to the results attained in model 1.

We also analyse the cross-volatility transmission between OIL and FIN, and GOLD and FIN in model 2. The results from model 2 results presented in table 4 do not show any significant volatility transmission between the financial sector and either commodity (oil and gold). This finding is consistent with the findings in Kumar's study (2014), which show that there is no volatility transmission between the financial sector and gold in the case of India (which is an emerging economy, as is South Africa).

Regarding the volatility transmission between the financial sector and oil, our results are completely different to those of Arouri et al. (2012). These authors found that there is bidirectional volatility transmission between oil and the financial sector in the US and Europe. A reason as to why our results differ is that with regards to the volatility spillover from the financial sector to the oil market, higher financial shares prices are often a signal of higher production, which may lead to more oil consumption (demand). This is the case for major countries like the US and Europe, which have the market power to influence global oil prices. However, South Africa is a relatively minor net oil-importing country, and its demand for oil does not have much influence on global oil prices. Nevertheless, our findings regarding the volatility spillover from oil to the financial sector are somewhat surprising, because a change in oil prices is anticipated to have an impact on business and consumer confidence, which will ultimately affect the demand for financial products and the financial sector (Arouri et al., 2012).

- **Model 3**[11]

Our results for model 3 (IND-OIL-GOLD) are very similar to those of model 1 (JSE-OIL-GOLD) reported above. Note that the only difference between the two is that we find evidence of the volatility transmission effect between OIL and IND (where α_{12} and β_{12} are significant at a 5% level of significance). Therefore, there is a short-run (negative) and long-run (positive) persistence volatility transmission from OIL to IND, which means that there exists a unidirectional volatility spillover from the oil market to the industrial sector, and oil could be helpful in predicting industrial sector behaviour. These results are not unexpected because the industrial sector is a heavy user of petroleum and oil-related products, hence oil prices may affect profitability and in turn stock prices.

[11] Note: variable order is IND (1), OIL (2) and GOLD (3).

- **Model 4**[12]

In terms of the mean equation results, our results for model 4 are very similar to those of models 1 and 3 above. However, regarding volatility spillovers, there are some differences. We discover evidence of a significant unidirectional volatility transmission from oil to the resource sector (RES). This finding is not surprising, because the resource sector covers the stock of oil and gas companies, which are largely affected by oil price shocks. Therefore, oil may be useful in predicting resources (RES) sector trends. However, we do not detect any significant volatility transmission from RES to OIL. This result is expected, owing to similar reasons provided above, i.e. that South Africa is relatively a minor net oil-importing country and its demand for oil does not have much influence on global oil prices.

Regarding the volatility transmission between GOLD and RES, we notice some slight sign of bidirectional volatility spillovers between gold and resources. The volatility spillover effect from GOLD to RES is positive and significant at a 5% level, which indicates that GOLD price volatility tends to increase the current volatility of RES. This volatility relationship is not unexpected because the resource sector includes mining and precious metal companies, which are directly and positively linked with the gold market. We also find some significant volatility spillover from RES to GOLD. However, the effect of the volatility transmission is weak (significant at the 10% level). At first glance, these results might seem incorrect, given the fact that South Africa is one of the largest gold suppliers in the world, thus, by extension, the gold-mining sector is expected to have an impact on global gold prices. However, gold prices are not particularly responsive to changes in supply, because gold has a very large and diverse set of forces or price drivers.

Overall, our results for stock sectors above offer many interesting insights. It is interesting to note that the resources sector is more affected by the volatility in both oil and gold prices than the other sectors under study. This is probably the case because the sector has a more direct link with the two commodities than other sectors. The sector that is least affected by the volatility in commodities (oil and gold) is the financial sector, as it does not have much of a direct link with oil and gold.

[12] Note: variable order is RES (1), OIL (2) and GOLD (3).

As noted above, this paper does not attempt to study the link between oil and gold price changes. However, it is worth noting that in all four oil-gold-stock trios' volatility models under study, there is a significant return and volatility transmission from OIL to GOLD, at a 1% level of significance. This finding is consistent with the macroeconomics theory that higher oil prices put upward pressure on general price levels of goods and services, particularly in net oil-importing countries (Hooker, 2002). However, since gold is viewed as a good hedge instrument against inflation, owing to its positive correlation with inflation, demand for gold and gold prices are expected to rise (Bampinas & Panagiotidis, 2015). Moreover, higher oil prices generate more revenue for net oil-exporting countries. A proportion of this revenue is then invested in gold to safeguard against economic uncertainties, which also results in higher demand for gold and gold prices (Raza, Shahzad, Tiwari & Shahbaz, 2016).

The estimates for the dynamic conditional correlation parameters $f_1$and f_2 are all significantly positive in all four models and their sums are less than one, indicating the stability of the volatility model and the relevance of the DCC model. Moreover, coefficient γ_1 represents asymmetry coefficient for stocks (which is JSE in model 1, FIN in model 2, IND in model 3 and RES in model 4), γ_2 is the asymmetry coefficient for OIL, while γ_3 represents the asymmetry coefficient for GOLD. From our results in table 5, we note that the asymmetry coefficient of OIL and stocks (JSE, FIN, IND and RES) is significant at a 1% level, indicating the importance of using an asymmetric model (such as the ADCC in this case). The results also indicate that negative shocks in stock or oil returns might result in more volatility than positive shocks of the same magnitude. However, in the case of gold, the coefficient γ_3 is insignificant, contradicting our assumption of leverage effects. This finding is similar to those of the study by Kang et al. (2016), which also showed the presence of asymmetry in stock and oil returns, but found the gold asymmetry coefficient to be insignificant

Table 4: ADCC Parameter Estimates.

	MODEL 1 (JSE- OIL- GOLD)		MODEL 2 (FIN- OIL- GOLD)		MODEL 3 (IND- OIL- GOLD)		MODEL 4 (RES- OIL- GOLD)	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Mean Eq								
C_1	0.0203	0.0148	0.0321**	0.0154	0.0576***	0.0130	-0.0228	0.0289
ω_{11}	-0.0236	0.0183	-0.0025	0.0201	-0.0114	0.0192	-0.0206	0.0188
ω_{12}	0.0537***	0.0099	0.0073	0.0099	0.0278***	0.0087	0.1126***	0.0176
ω_{13}	0.0015	0.0141	-0.0254*	0.0152	-0.0108	0.0143	0.0187	0.0260
C_2	-0.0203	0.0248	-0.0143	0.0254	-0.0137	0.0255	-0.0143	0.0340
ω_{21}	0.0261	0.0267	0.0311	0.0279	0.0251	0.0306	0.0153	0.0191
ω_{22}	-0.0637***	0.0199	-0.0633***	0.0187	-0.0620***	0.0171	-0.0572**	0.0227
ω_{23}	0.0062	0.0226	0.0041	0.0251	0.0035	0.0235	0.0079	0.0274
C_3	0.0110	0.0218	0.0160	0.0201	0.0174	0.0206	0.0127	0.0240
ω_{31}	0.0220	0.0189	0.0144	0.0182	0.0126	0.0221	0.0192	0.0122
ω_{32}	0.0399***	0.0107	0.0418***	0.0115	0.0410***	0.0107	0.0386***	0.0119
ω_{33}	-0.0187	0.0211	-0.0140	0.0252	-0.0168	0.0228	-0.0250	0.0249
Variance Eq								
φ_1	0.0145***	0.0040	0.0231***	0.0049	0.0261***	0.0037	0.0270***	0.0089
φ_2	0.0103	0.0070	0.0104*	0.0061	0.0088	0.0075	0.0126	0.0115
φ_3	0.0164	0.0148	0.0163	0.0139	0.0136	0.0144	0.0175	0.0117
α_{11}	0.0024	0.0106	0.0266***	0.0088	0.0012	0.0050	0.0215	0.0144
α_{12}	-0.189***	0.0060	-0.0098	0.0077	-0.015**	0.0005	0.1905**	0.0101
α_{13}	-0.0079	0.0078	-0.0330	0.0894	-0.0169*	0.0095	0.0118***	0.0011
α_{21}	-0.0134	0.0122	-0.0023	0.0167	-0.0125	0.0211	-0.0154	0.0285
α_{22}	0.0248***	0.0048	0.0243***	0.0048	0.0244***	0.0058	0.0304**	0.0136
α_{23}	-0.0190*	0.0097	-0.0217*	0.0131	-0.0211	0.0137	-0.0208	0.0199
α_{31}	-0.0244	0.0166	-0.0030	0.0126	-0.0350	0.1534	-0.0132	0.0102
α_{32}	-0.0038	0.0089	-0.0053	0.0096	-0.0023	0.0087	-0.0069	0.0086
α_{33}	0.0516***	0.0131	0.0503***	0.0110	0.0472***	0.0129	0.0539***	0.0139
β_{11}	0.9061***	0.0139	0.8999***	0.0120	0.9006***	0.0121	0.9303***	0.0219
β_{12}	0.0360***	0.0115	0.0111	0.0142	0.209**	0.0096	0.9054***	0.0147
β_{13}	0.0198	0.0205	0.0228	0.0282	-0.0401	0.2063	0.0689**	0.0337
β_{21}	0.0141	0.0138	-0.0044	0.0315	0.0105	0.0353	0.0455	0.0816
β_{22}	0.9439***	0.0052	0.9454***	0.0041	0.9453***	0.0080	0.9303***	0.0282
β_{23}	0.0594***	0.0197	0.0637**	0.0301	0.0650**	0.0263	0.0467	0.0585
β_{31}	0.0268	0.0315	0.0333	0.0239	0.0217	0.0337	0.0276*	0.0161
β_{32}	0.0271	0.0248	0.0239	0.0303	0.0205	0.0270	0.0272	0.0268
β_{33}	0.9288***	0.0359	0.9333***	0.0330	0.9391***	0.0333	0.9209***	0.0341
γ_1	0.1359***	0.0153	0.1181***	0.0098	0.1347***	0.0099	0.0799***	0.0124
γ_2	0.0464***	0.0092	0.0459***	0.0097	0.0450***	0.0084	0.0472***	0.0163
γ_3	0.0006	0.0300	-0.0006	0.0261	-0.0008	0.0246	0.0021	0.0264
f_1	0.0172***	0.0035	0.0191***	0.0046	0.0172***	0.0016	0.0220*	0.0125
f_2	0.9747***	0.0063	0.9664***	0.0095	0.9706***	0.0048	0.9627***	0.0391
Log likelihood	-12698.0409		-12840.9968		-12497.9665		-13750.5106	

Note: ***, **, and * indicates the level of statistical significance at 1%, 5% and 10% respectively. Variable order is stock (1) [This includes JSE for model 1, FIN for model 2, IND for model 3, & RES for model 4], OIL (2) and GOLD (3).

Table 5 below represents the diagnostic tests for the estimated models. The Q-statistics test in table 5 confirms that the null hypothesis of no autocorrelation (also known as serial correlation) is not rejected for the estimated VAR-ADCC-GARCH (1, 1) model. Therefore, the estimated model is specified correctly for modelling the dynamic link between stock, oil and gold returns. Thus, we can proceed to the construction of time-varying conditional correlations, portfolio weights and hedge ratios from the estimated model.

Table 5: Diagnostics Tests for Standardised Residuals

	Model 1 (JSE- OIL- GOLD)			Model2 (FIN- OIL- GOLD)			Model3 (IND- OIL- GOLD)			Model4 (RES- OIL- GOLD)		
	JSE	OIL	GOLD	FIN	OIL	GOLD	IND	OIL	GOLD	RES	OIL	GOLD
Q(20)r	23.01	17.21	16.68	29.41	17.48	17.16	28.44	16.92	17.05	21.03	16.80	17.15
p-value	0.29	0.64	0.67	0.08	0.62	0.64	0.10	0.66	0.65	0.40	0.67	0.64
Q(20)r^2	20.49	24.41	21.52	12.35	25.09	22.56	21.47	25.07	19.35	16.12	24.35	22.11
p-value	0.43	0.22	0.37	0.90	0.20	0.31	0.37	0.20	0.50	0.71	0.23	0.33

Note: Q(20)r and Q(20)r^2 represent the Ljunge-Box test statistics of up to 20 lags for standardised and squared standardised residuals.

4.2.2 Time-varying Conditional Correlations

In this section, we analyse the time-varying correlations for specific pairs of stock-oil and stock-gold portfolios[13] obtained from the VAR-ADCC-GARCH model estimated above. Understanding the co-movement between a commodity and the stock markets returns is crucial for portfolio and risk management. Indeed, the traditional asset pricing theory states that portfolio diversification gains are associated with the correlation of assets included in the diversified portfolio. Thus, combining negatively or low positively correlated assets might help reduce the average volatility of a portfolio, as the shifts in one asset can be expected, at the very least, to be reduced by shifts in the other asset.

We will examine how the correlations between stock market returns and commodity futures evolve during normal times as well as during periods of financial turmoil. The reason why we evaluate the correlation between the stock markets and commodities during periods of financial turmoil is because during these periods stock markets tend to be highly volatile (see figure 1 above). Therefore, in order to diversify the high risk associated with these periods of crises, which is when portfolio diversification benefits are needed the most, we need to understand how the two assets co-move. The sample used in this study incorporates two crises periods, namely, the global financial crises and the Eurozone sovereign debt crisis.

[13] Note: this paper mainly focuses on stock-gold and stock-oil portfolios, unless stated otherwise. We do so because the main objective of this paper is to study which commodity (oil or gold) provides the most effective (superior) hedge against stock market exposure.

Before we analyse our results on dynamic correlations, it is important to distinguish between a portfolio diversifier, a hedge and a safe haven. A definition we can consider to be useful in guiding the reader through the rest of this study is that provided by Baur and Lucey (2010), and is as follows;

> A diversifier is defined as an asset that is positively (but not perfectly correlated) with another asset or portfolio on average. A hedge is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio on average. And a safe haven is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil.

Figure 2 below illustrates the time-varying correlations for the specific stock-oil and stock-gold pairs under study. The time-varying correlations seem to be highly volatile over time, indicating that relying solely on static correlations to estimate optimal weights and hedge ratios might be misleading. The correlation for most stock-oil and stock-gold pairs under study seems to be relatively close to their respective unconditional correlations (shown in table 2). In addition, it is interesting to note that the correlation for all pairs under study drastically changes during periods of crisis. This finding is similar to that of most empirical studies (Arouri et al., 2011; Kang et al., 2016), showing that the correlation between stock markets and commodities significantly changes during periods of extreme uncertainty.

Regarding the dynamic correlation between oil and stock markets, the pattern seems similar for the JSE-OIL, FIN-OIL and IND-OIL pairs. For the FIN-OIL and IND-OIL pairs, we notice that the correlation fluctuates between positive and minuscule negative values. During the global financial crisis, which commenced at the end of 2007 or the beginning of 2008, there were negative values of -0.2 for FIN-OIL and -0.1 for IND-OIL. However, during this period, the negative correlation of FIN-OIL and IND-OIL pairs was only temporary (lasting approximately one month, according to our results), as the correlation for both pairs rose dramatically to positive territory (reaching +0.5) when the crisis became more severe. As noted above, the correlation between the aggregate JSE and OIL follows a similar pattern to that of the FIN-OIL and IND-OIL pairs. However, unlike in case of the FIN-OIL and IND-OIL pairs, the correlation between the JSE and OIL does not show negative values during the sample period under study. Yet similar to the FIN-

OIL and IND-OIL pairs, the correlation between JSE-OIL also drops at the end of 2007 and the beginning of the 2008 when the global crisis really emerged, showing a low positive correlation of +0.07, which then rose to +0.7 when the crisis was in full force.

These findings on the co-movement between the stock markets (excluding resources sector) and oil should be expected in the case of South Africa. At the beginning of 2008, the global financial crisis resulted in a negative economic growth in most economies around the world, which led to a decline in demand for oil and a large drop in oil prices. However, at the beginning of 2008, some emerging markets (particularly South Africa) were not yet affected by the global financial crisis (as developed markets were). Therefore, the high volatility in developed stock markets, which signalled a high degree of market risk, may have led to foreign market participants seeking more stable equity markets and higher returns to relocate from developed markets to developing markets. This movement resulted in South African stock prices increasing and moving in the opposite direction to oil, hence the negative correlation between the two assets (oil and stock market prices) at the beginning of 2008. However, as soon as the crisis hit South Africa (which was in the third quarter of 2008), domestic stock markets also dropped significantly, resulting in the two variables (oil and stock market prices) moving in the same direction, hence the increase in correlation when the crisis escalated.

Similarly, the correlation between stock-oil pairs during the Eurozone sovereign debt crisis in 2011 also rose to significantly higher positive values. This high positive correlation between oil and the stock market prices is not surprising, because they are usually linked to economic conditions and variables (Souček, 2013). In contrast, the RES-OIL pair seems to have exhibited a different correlation pattern compared to other stock market sectors with regard to oil. For RES-OIL, we notice that the correlation between RES and OIL fluctuation around positive values for the sample period under study. Moreover, the correlation between RES and OIL increases significantly to high positive values during both periods of crisis. The positive correlation between RES and OIL is understandable, as the resources sector index includes oil companies whose profits depend on the price of crude oil.

Regarding the correlation between gold and the stock markets, our results reveal a similar pattern for all gold-stock pairs (except RES-GOLD). In contrast to the stock-oil pairs' correlation, the correlation between gold and the stock markets dramatically declines, showing negative values during both periods of crisis highlighted in this paper. It is also important to note that the decline in the stock-gold pairs' correlation began to decline before the crisis hit South Africa, and continued during the financial crisis, because gold prices tend to react positively to negative financial or economic news. Therefore, this could be a potential indication that gold may be a safer asset, as a change in gold prices tends to have an inverse relationship with stock market returns during periods of crisis in most cases. Moreover, gold might also a good hedge against stock market exposure because of its low correlation with the stock markets over time. Our results are somewhat similar to those of previous studies by Baur and Lucey (2010) and Ciner et al. (2013), which also suggest that gold has the qualities of a good hedge and a safe haven tool.

However, the RES-GOLD pair correlation seems to exhibit a different trend when compared with other stock market sectors' relationship to gold. For RES-GOLD, we notice that the correlation between the resources sector and gold is exceptionally high over time, because the resources sector includes mining shares, which usually co-move with gold prices. In addition, during both crisis periods under study, the correlation declined to a negative territory for a short period of time, then reverted to high positive territory. The reason for the short-term drop in correlation may be owing to the fact that resources' shares were still classified as 'risky assets' and, during crisis periods, investors avoid investing in risky assets. However, since the resource companies benefit from high gold prices (especially from South Africa as a gold-producing country) during a crisis period, the correlation reverted to positive territory.

Table 6 below presents a summary of statistics for dynamic conditional correlations. In this table, we notice that the correlations for all oil-stock and gold-stock pairs vary between a minimum of −0.35 (IND/GOLD) and a maximum of +0.72 (RES/OIL). Therefore, during periods of negative correlation (as shown in figure 2 for all pairs under study), there is an opportunity for meaningful portfolio diversification.

Our dynamic correlation results provide some information regarding portfolio diversification. Firstly, the correlation between crude oil futures and the South African stock markets (excluding the resources sector) mostly fluctuates below +0.5 during normal times. This fluctuation is a sign that oil could be a useful hedge instrument against the stock markets' exposure during normal times. However, during periods of financial distress, the correlation between crude oil futures and the South African stock markets increases significantly to high positive values. This change could indicate that oil might not be a good hedge or a safe haven against stock markets' exposure, proving that there is limited scope for portfolio diversification for stock-oil portfolios during periods of financial or economic crisis when diversification benefits are needed the most.

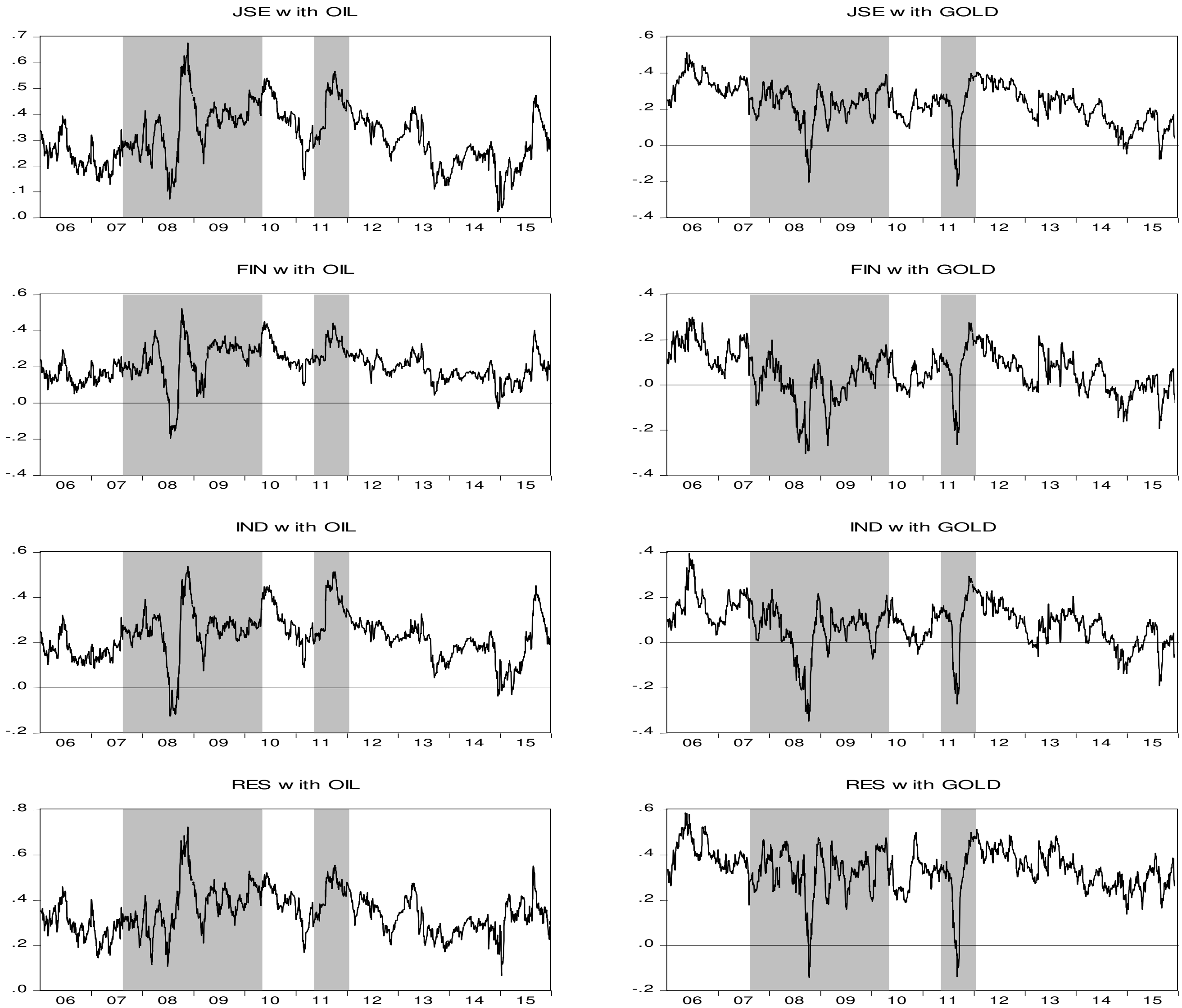
Secondly, the correlation between gold futures and the South African stock markets (excluding the resources sector) mostly fluctuates below +0.4 during normal times. This fluctuation is a sign that gold could be a useful hedge instrument against stock markets' exposure during normal times. Moreover, during periods of financial turmoil, the correlation between gold futures and the South African stock markets increases significantly, reaching negative values. This shift is consistent with the evidence provided by Baur and Lucey (2010) that indicates that gold might be a good hedge and safe haven against stock markets' exposure.

Thirdly, with regards to the correlation between gold or crude oil futures with the resources sector, we notice that the correlation is mostly positive and high. As noted above, this correlation makes economic sense, as the resources sector includes mining, and oil companies co-move with commodity prices (gold and oil in particular). Therefore, our results suggest that commodities (oil and gold) may provide a neither a good hedge nor safe haven for resources stock price risk. Further research on this matter is conducted below.

In conclusion, our results are consistent with findings of Kang et al. (2016), who also indicated that oil could be a hedge against emerging stock market exposure, but there is little scope for portfolio diversification for oil and the stocks portfolio during periods of financial distress. This study by Kang et al. also shows evidence that gold can play the role of a safe haven and hedge against stock markets' exposure during periods of financial distress.

Table 6: Summary Statistics of Time-varying Conditional Correlations

PORTFOLIO	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
JSE/OIL	0.3103	0.1092	0.0212	0.6746
JSE/GOLD	0.2262	0.1123	-0.2291	0.5103
FIN/OIL	0.2047	0.0977	-0.1997	0.5196
FIN/GOLD	0.0501	0.1025	-0.3070	0.2984
IND/OIL	0.2254	0.1050	-0.1275	0.5345
IND/GOLD	0.0745	0.1026	-0.3506	0.3930
RES/OIL	0.3405	0.0929	0.0639	0.7216
RES/GOLD	0.3349	0.0959	-0.1445	0.5843



Note: the shaded area is the global financial crisis and the first and second phases of the Eurozone sovereign debt crisis period (see table 1 for more details).

Figure 2: Time-varying Conditional Correlations Estimated Using the ADCC Model

4.2.3 Optimal portfolio weights results

In this section, optimal portfolio weights or the distribution of weight for a portfolio constituted of pairs of specific stock-oil and stock-gold are calculated from the estimated VAR-ADCC-GARCH models. Figure 3 below illustrates the time-varying optimal portfolio weights for specific pairs of stock-oil and stock-gold portfolios. This figure shows that the optimal portfolio weights fluctuate over time in all cases. However, this does not imply that investors should rebalance their portfolio over time, because rebalancing the portfolio more often would be more expensive considering transaction costs. Investors can simply adjust their portfolio weights according to stock market conditions – that is, whether it is a bear or bull market (Kang et al., 2016).

Regarding optimal weights of stock-oil portfolios, our main interest is the trend of the portfolio weights during periods of turmoil (when portfolio diversification is needed the most). We see that the weights allocated to stocks and oil in a stock-oil portfolio are very volatile during both periods of financial distress under study, owing to portfolio rebalancing as the correlation between the stock markets and oil is also volatile during periods of crisis (see time-varying correlation section above). In addition, it is interesting to note that the optimal weights allocated to OIL in all cases dropped from 2014. This decline is clearly owing to the significant drop in oil prices that started in 2014 amid supply glut, which resulted in high volatility in the oil market.

In contrast to the stock-oil pairs, the stock-gold pairs show that the weights allocated to GOLD rise during both periods of crises under study, while those of stocks decline in all cases. The reason for the drop in weight allocated to stocks during such periods is that stock prices are usually linked to economic conditions and variables, therefore they tend to underperform during periods of economic or financial distress (Souček, 2013). Since gold prices tend to react positively to negative financial or economic news, it is optimal for investors to add more gold futures in their stock-gold portfolio to minimise risk without lowering expected returns during an economic or financial crisis period. This evidence also further supports the 'safe haven' hypothesis of gold in periods of financial distress. In addition, it is interesting to note that the optimal weights allocated to GOLD in most cases dropped in 2014 – clearly the result of the mid-2014 commodity price crash, leading to high volatility in commodity markets.

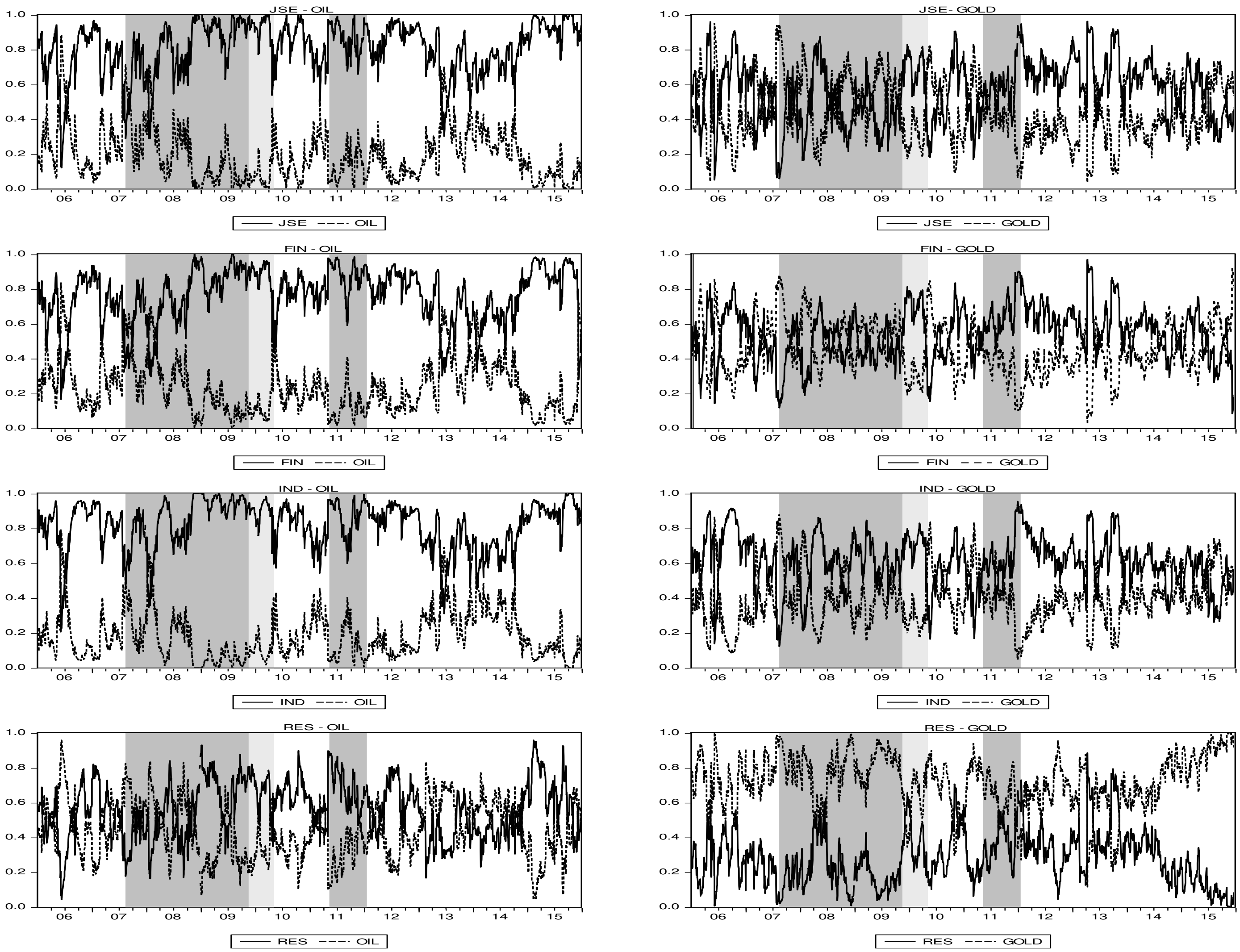
Table 7 below presents a summary of statistics for optimal portfolio weights for the specific pairs of stock-oil and stock-gold portfolios under study. As can be seen from the average values presented in table 6, the average optimal portfolio weights fluctuate from 28% for RES/GOLD to 82% for RES/OIL portfolio. Regarding the stock-oil portfolios, for a one dollar JSE/OIL portfolio, 81% on average should be invested in JSE, while the remaining 19% of wealth is invested in OIL. For the FIN/OIL pair, 76% on average should be invested in FIN, while the remaining 24% of wealth is invested in OIL. For the IND/OIL pair, 82% on average should be invested in IND, while the remaining 18% of wealth is invested in OIL. For the RES/OIL pair, 56% on average should be invested in RES, while the remaining 44% of wealth is invested in OIL.

However, regarding the stock-gold portfolio pairs (in table 7), it can be seen that for a one dollar JSE/GOLD portfolio, 56% on average should be invested in JSE, while the remaining 44% of wealth is invested in GOLD. For the FIN/GOLD pair, 54% on average should be invested in FIN, while the remaining 46% of wealth is invested in GOLD. For the IND/GOLD pair, 60% on average should be invested in IND, while the remaining 40% of wealth is invested in GOLD. For the RES/GOLD pair, 28% on average should be invested in RES, while the remaining 44% of wealth is invested in GOLD.

Overall, our results reveal that in order to minimise risk without lowering the expected returns, portfolio managers or investors should hold more stocks than commodities (oil or gold) in their portfolios in most cases. Our findings are somewhat similar to those of studies by Arouri et al. (2012) and Chkili et al. (2014). In addition, the average optimal weights vary considerably across the stock market sectors under study. Such variation may be due to the differences in the characteristics of the sector stock markets, such as the number of publicly traded companies, sector composition and level of liquidity.

Table 7: Summary Statistics of Optimal Portfolio Weights

PORTFOLIO	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
JSE/OIL	0.81	0.15	0.12	1.00
JSE/GOLD	0.56	0.17	0.05	0.96
FIN/OIL	0.76	0.16	0.16	1.00
FIN/GOLD	0.54	0.15	0.08	0.97
IND/OIL	0.82	0.14	0.20	1.00
IND/GOLD	0.60	0.15	0.12	0.95
RES/OIL	0.56	0.16	0.04	0.96
RES/GOLD	0.28	0.15	0.00	0.89



Note: the shaded area is the global financial crisis and the first and second phases of the Eurozone sovereign debt crisis period (see table 1 for more details).

Figure 3: Time-varying Optimal Portfolio Weights Estimated Using the ADCC Model

4.2.4 Hedge ratios results

This section constructs optimal hedge ratios for specific pairs of stock-oil and stock-gold under study, using the conditional variances and covariances obtained from the ADCC model presented above. Figure 4 shows the time-varying hedge ratios for specific pairs of stock-oil and stock-gold portfolios. It can be noted that the hedge ratios fluctuate significantly over time in all cases. However, this does not mean that investors should rebalance their portfolio over time, as this will increase their transaction costs. Rather, investors can simply adjust their hedging positions with regards to stock market conditions that are bear or bull markets (Kang et al., 2016). Moreover, note that in most cases the hedge ratios are low over time (below one). This finding might suggest the ability of hedging strategies concerning stock-gold and stock-oil portfolios.

As stated above, it is important to understand hedging positions according to economic or market conditions. We are therefore interested in analysing the trend of hedge ratios during periods of crisis. Before we begin our analysis, it is important to note that in our stock-commodity portfolios, the higher hedge ratio makes the commodity futures (OIL or GOLD) less attractive hedging tools against stock market exposure, because investors are required to have higher short positions in order to minimise the risk of investing in stocks. The opposite is true for lower hedge ratios.

Looking at figure 4 below, regarding the optimal hedge ratios of stock-oil portfolios, we see that the hedge ratios were very low during the beginning of the 2008 global financial crisis. However, we notice that when the 2008 financial crisis became more severe and during the 2011 Eurozone sovereign debt crisis, the hedge ratios rose significantly. These results reflect the structural change in the correlation between crude oil futures and the South African stock market returns during the global financial crisis as discussed in the time-varying correlation section above. This correlation is a clear sign that oil could be an ineffective hedge instrument against stock market risk during periods of turmoil.

In contrast to the specific stock-oil pairs' hedge ratio pattern, optimal hedge ratios of stock-gold portfolios under study seem to decline significantly during periods of crisis, as revealed in both the 2008 financial crisis and 2011 Eurozone sovereign debt crisis. The decline in the hedge ratios of stock-gold pairs during periods of turmoil even reached negative values, indicating that holding a long position in gold futures minimises the risk of holding long position in stocks. The reasons for this phenomenon is similar to that stated above – that higher gold prices are usually associated with negative financial news. Thus the negative correlation between gold and the stock market might be strong during periods of uncertainties (Kiohos & Sariannidis, 2010), suggesting that gold might be an effective hedge against stock market exposure during periods of turmoil.

It is also interesting to note that the pattern of hedge ratios of stock-commodity portfolios over time almost exactly follows the trend of their respective time-varying correlations (shown in figure 2), indicating the importance of correlation between assets when determining optimal hedge ratios. Additionally, our results regarding optimal hedge ratios are consistent with those of Kang et al.

(2016), who conclude that while gold can be used to hedge instrument against stock market exposure, oil is an ineffective hedge instrument during periods of turmoil.

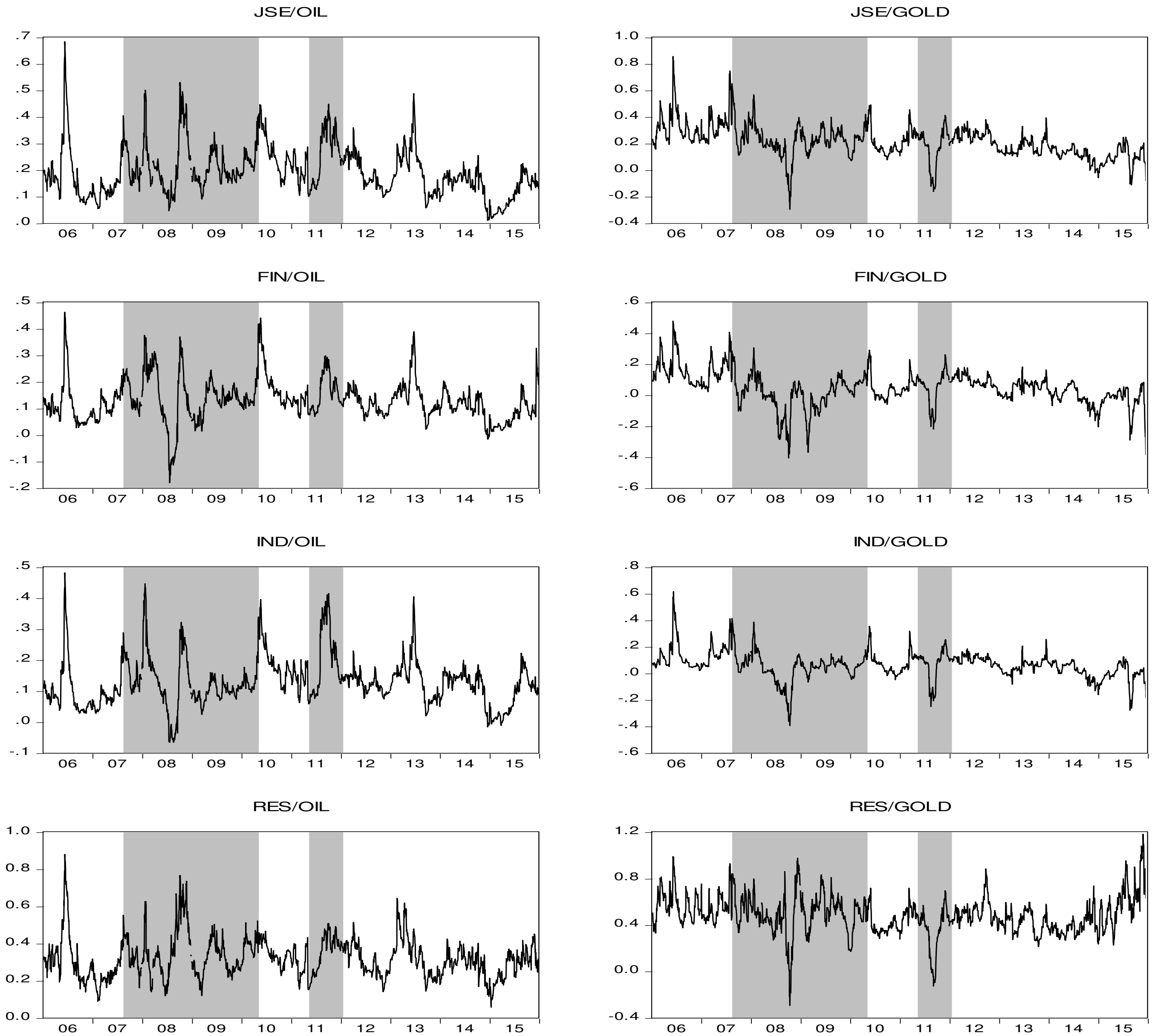
Table 8 presents the summary statistics of hedge ratios for the specific pairs of stock-oil and stock-gold portfolios under study. It can be noted that all average hedge ratios are less than one. Unlike the optimal weights results, the average hedge ratios range from +0.04 for FIN/OIL to +0.48 for RES/GOLD, suggesting that the most effective hedging strategy is to short stocks in the Insurance sector. Regarding the stock-oil portfolio pairs, on average, the hedge ratio for the JSE/OIL pair is +0.19, which implies that a one dollar long position in the stocks market (JSE) can be hedged with 19 cent short position in oil. Concerning sectors, our results suggest that a one dollar long position in FIN, IND and RES stocks can be hedged by a 15 cent, 13 cent and 32 cent short position in oil respectively.

In contrast, regarding the stock-gold portfolio pairs, the average hedge ratio for the JSE/GOLD pair is +0.21, which indicates that a one dollar long position in the stocks market (JSE) can be hedged by taking a 21 cent short position in gold. Concerning sectors, our results suggest that a one dollar long position in FIN, IND and RES stocks can be hedged with a 4 cent, 6 cent and 48 cent short position in gold respectively.

Overall, our findings are somewhat similar to those of recent studies by Arouri et al. (2012), Jouini (2013) and Chkili et al. (2014). Moreover, the average optimal hedge ratios differ considerably across sectors. This variation might be owing to the differences in the characteristics of the sector stock markets, such as the number of publicly traded companies, sector composition and level of liquidity.

Table 8: Summary Statistics of Effective Hedge Ratios

PORTFOLO	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
JSE/OIL	0.19	0.09	0.01	0.68
JSE/GOLD	0.21	0.12	-0.30	0.86
FIN/OIL	0.15	0.08	-0.18	0.46
FIN/GOLD	0.04	0.11	-0.41	0.48
IND/OIL	0.13	0.08	-0.07	0.48
IND/GOLD	0.06	0.10	-0.40	0.62
RES/OIL	0.32	0.11	0.06	0.88
RES/GOLD	0.48	0.16	-0.30	1.18



Note: the shaded area is the global financial crisis and the first and second phases of the Eurozone sovereign debt crisis period (see table 1 for more details).

Figure 4: Time-varying Hedge Ratios Estimated Using the ADCC Model

4.2.5 Hedge effectiveness results

This section analyses the hedge effectiveness of specific hedged portfolios of stock-oil and stock-gold pairs, using equation (22) (see Chapter 3). Hedging effectiveness is an essential tool that allows investors to analyse the quality of a hedge. As discussed in Chapter 3, we will use the hedge effectiveness index proposed by Ederington (1979) to assess the quality of specific hedged portfolios under study. Ederington's hedge effectiveness index measures the variance (risk) reduction of a hedged portfolio relative to an unhedged portfolio (as explained in Chapter 3). Therefore, this measure indicates the percentage of risk (variance) reduced from an unhedged portfolio by hedging. In our study, a hedged portfolio is a portfolio that includes a long position in a stock (for example JSE, FIN, IND and RES) and a short position in commodity future (OIL and GOLD) – for example, taking a long position in JSE and simultaneously taking a short position in OIL. An unhedged portfolio is a portfolio that comprises a long position in stocks (for example a long position on the JSE) only.[14]

Figure 5 below shows the time-varying hedge effectiveness index for specific pairs of stock-oil and stock-gold portfolios. It can be noted that the hedge effectiveness index fluctuates over time in all cases under study. However, our main interest is the trend during periods of crisis. Notice that during periods of crisis, hedge effectiveness seems to be very high in most cases for stock-gold pairs. However, for stock-oil pairs, the hedge effectiveness declines and even reaches negative values (during periods of crisis). These results confirm our statement above that gold is a better hedge than oil against stock exposure during crisis periods. Therefore, as noted above, this result illustrates the need for investors to take into account global financial and economic conditions when assessing the benefits of portfolio diversification.

Furthermore, table 9 shows the average of the hedge effectiveness index. Our results indicate that including oil or gold in a diversified portfolio can help significantly reduce portfolio risk. From table 9, the hedge effectiveness ranges from 30.87% for the RES/GOLD portfolio to 86.33% for IND/GOLD portfolio. In most cases, the hedge effectiveness index is above 40 on average, indicating that at least 40% and above risk is removed from hedging. However, notice that the RES/OIL and RES/GOLD portfolios' hedge effectiveness index is below 40%, which implies that not much risk is eliminated by hedging. The main reason is that the resources sector is directly linked to commodities and, in most cases, the sector's stock prices co-move with commodity prices.

When comparing the hedge effectiveness index for specific stock-oil and stock-gold portfolio hedge effectiveness, our results suggest that gold provides the best hedging effectiveness for each pair (except RES). Our results are consistent with those of Kang et al. (2016), who concluded that

[14]We do so because one of the objectives of this paper is to study which commodity (oil or gold) provides the most effective (superior) hedge against stock market exposure.

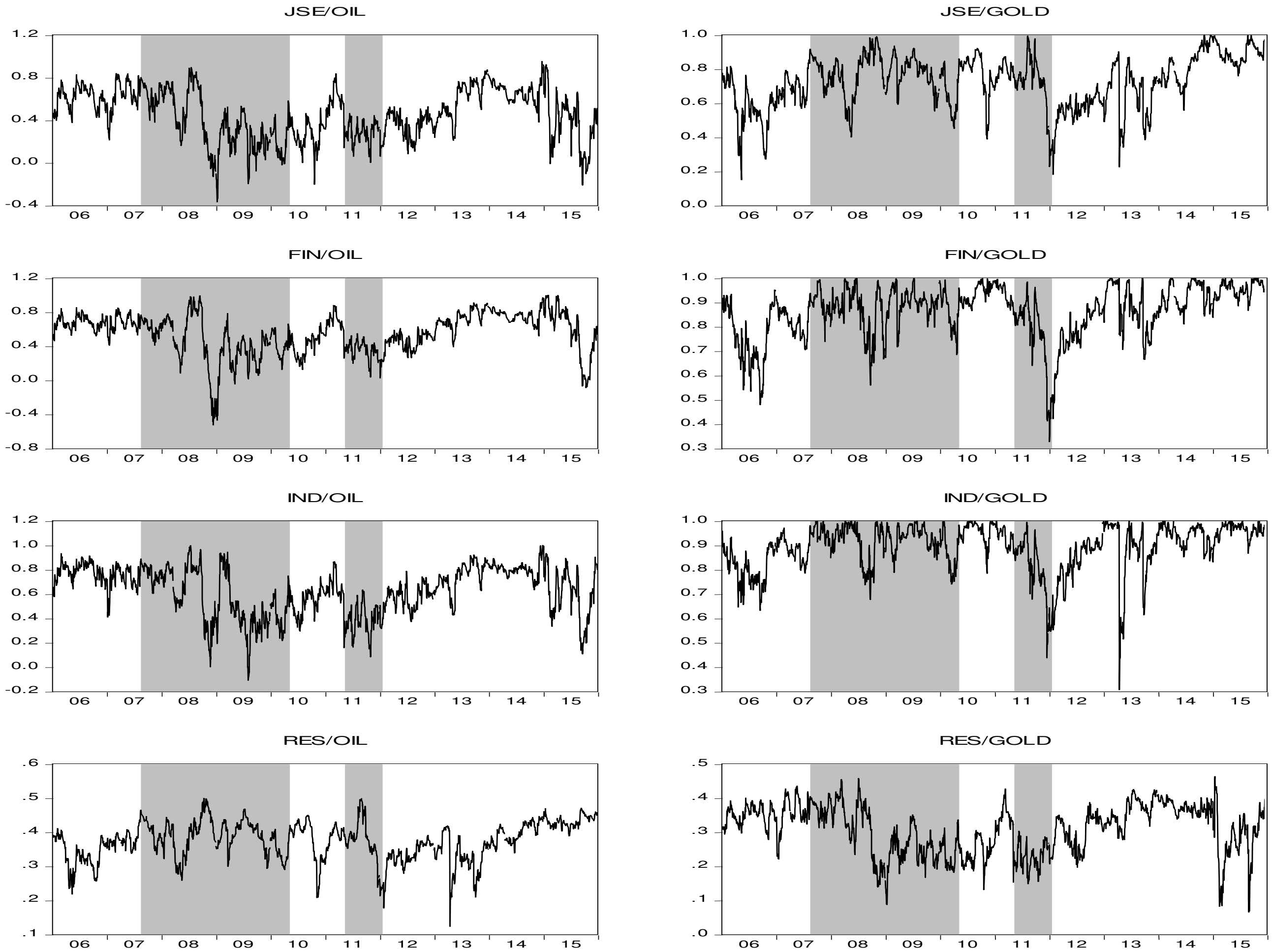
gold is a superior hedge for stock market exposure than oil. However, our findings are contrary to those of Basher and Sadorsky (2016), who assessed the hedging effectiveness of the stock market, oil, gold, VIX and bonds in emerging markets (including South Africa). These authors concluded that oil is a more effective hedge instrument against stock market exposure compared to gold, VIX and bonds. The reason why our results differ may be because Basher and Sadorsky did not account for volatility transmission between the respective markets' studies when modelling conditional volatility, which may have led to an over- or underestimation of stocks, oil and gold volatility (which is then used to compute hedge ratios and hedge effectiveness index) and thus resulted in dissimilar results. Moreover, our results are supported by the fact that gold is usually regarded as a safe haven asset since its prices tend to move in the opposite direction to stock market prices during periods of crisis, as indicated in figure 2. Therefore, we suggest that gold should be deemed as a safe haven tool in South Africa (and a number of countries).

Indeed, our results are consistent with Arouri et al. (2012) and Chkili (2016), who hold the opinion that including oil and gold in a diversified portfolio of stocks will reduce portfolio risk and improve the risk-return characteristics of these portfolios. These results are helpful for investors and portfolio managers, providing them with a better understanding about opportunities for portfolio diversification when including oil or gold in their investment portfolios. The results also highlight the need for investors to take into account global financial and economic conditions when assessing the benefits of portfolio diversification.

Table 9: Hedge Effectiveness Index Measure[15]

PORTFOLIO	HE (%)
JSE/OIL	45.63
JSE/GOLD	72.68
FIN/OIL	55.10
FIN/GOLD	86.25
IND/OIL	63.08
IND/GOLD	86.33
RES/OIL	37.41
RES/GOLD	30.87

[15] For the sake of brevity, the results for time-varying variance of hedged and unhedged portfolios are not provided in this paper. However, the results could be made available upon request.



Note: the shaded area is the global financial crisis and the first and second phases of the Eurozone sovereign debt crisis period (see table 1 for more details).

Figure 5: Time-varying Hedge Effectiveness Index

5. CONCLUSION

This study investigated the impact of oil and gold price fluctuations on the South African stock market. More precisely, the study assessed the extent of volatility spillover between the oil and gold markets and the stock exchange in South Africa. To do so, we analysed the time-varying correlations and volatility transmission between oil, gold and the South African stock market returns, using the VAR-ADCC-GARCH model. Our findings show a significant return spillover from the oil market to stock markets in most cases under study. These results also show that returns in the different sectors of the stock exchange are affected differently by both oil and gold price shocks. For example, the returns in the industrial sector are more affected by oil prices fluctuations than gold, while returns in the resources sector are more affected by changes in gold prices than oil.

We also notice that there is a unidirectional volatility transmission from the commodities market (oil and gold) to South African stock markets, which is due to the fact that South Africa is a small country and does not have much influence on global commodity prices. Furthermore, when assessing the time-varying correlation between commodities (oil and gold) and the stock market, the movement over time fluctuates around the mean. However, it drastically changes during periods of crisis, which is an indication that periods of financial or economic uncertainty might have a significant impact on the link between stock markets and commodities.

Extending our study, we examined optimal portfolio weights, hedge ratios and hedge effectiveness across different portfolios constituted of asset pairs such as oil-stock and gold-stock. Our findings suggest that in order to minimise risk, investors should include oil and/or gold in their investment portfolios, as they provide effective hedge(s) against stock market exposure. In addition, it can be said that oil and gold can be used to hedge against stock market risk and help improve the risk-return characteristics of a diversified portfolio of stocks. We also highlight that optimal weights and hedge effectiveness vary among sectors and periods of economic or financial crises. This result illustrates the need for investors to take into account global financial and economic conditions when assessing the benefits of portfolio diversification.

Our results have a number of policy implications for investors, policy makers, portfolio managers and researchers, such as coming up with better and effective trading strategies, assessing investment and asset allocation and also understanding the relationship between oil, gold and the stock market returns in the context of South Africa.

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