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Crude Oil Price shocks to Emerging Markets: Evaluating the BRICs Case

Salman Khan[1]

Abstract

In this paper we investigate the relationship between the crude oil and the stock market in terms of returns and volatility-spillover for the BRIC countries by using cointegration and the VECM-MGARCH technique. The results reveal that the oil and the market returns are cointegrated in all the markets. The results from VECM indicate stable, bidirectional, long-run relationship between oil prices and market returns while short-run linkages were found to be absent in all the cases except Russia where it significantly affects the BRENT prices. In terms of shock transmission and volatility spillover, the relationship is significant and bidirectional in all the cases. The analyses conclude that BRIC countries stock markets are highly integrated with the oil market.

JEL Classification: C32, E32

Key Words: Multivariate GARCH, Cointegration, Oil Price, Stock markets, VECM

1. Introduction

Goldman Sachs coined the term BRIC that stands for Brazil, Russia, India and China in a Global Economics Paper (2001), "Building Better Global Economic BRICs". Since then the term BRIC has caught the attention of financial economists as well as analysts to their role in the growth of global economy. The BRICs contributed approximately 30% to global growth during 2000-08 compared with almost 16% in the previous decade. While the G7's contribution fell from 70% in the 1990s to 40% on average during the current decade. Share of China stands at approx. two thirds of the BRICs share. The BRIC stock market also performed well despite going through recent credit crisis. BRICs equity indices have grown to new levels since 2003: aprox. 6 times in Brazil, 4 times in Russia, 5 times in India and 2 times in China.

In order to sustain the high growth rates, BRICs largely depend on crude oil. The oil consumption statistics reveal that China share of consumption stands at 7.8 million bbl/d of crude oil in 2008 making it the second-largest oil consumer in the world behind the United States. Energy Information Administration (EIA) forecasts that 'China's oil consumption will continue to grow during 2009 and 2010, with oil demand reaching 8.2 million bbl/d in 2010. This anticipated growth of over 390,000 bbl/d between 2008 and 2010 represents 31% of projected world oil demand growth in the non-OECD countries for the 2-year period' according to the July 2009 Short-Term Energy Outlook. Second in the line is India that in 2008 reached to the status of fifth largest oil consumer in the world. In 2008, India consumed almost 2.92 million bbl/d. Brazil stands as the 10th largest energy consumer in the world. Total primary energy consumption in Brazil has increased significantly in recent years, due to continued economic growth. The largest share of Brazil's total energy consumption comes from oil (49%, including ethanol).Next is Russia which is a net exporter of crude oil. Russia gets half of its energy demand from natural gas while around 19% from crude oil.

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In BRICs, the crude oil prices plays vital role in policy making since the change in oil prices can seriously affect the growth of these economies. The affects can increase the cost of production while at the same time creating inflation. These affects can have a direct role on the equity markets in terms of consumer confidence and level of growth. The oil price related affects can be higher for net importers than net exporters. In our case, among BRIC we will study the impact on both types i.e., Brazil, India and China as net importers while Russia as net exporter.

2. Literature Review

The relationship between oil prices and equity returns has been one of the most studied research subject. Some of the earlier studies finding indicates less or no relationship between the oil prices and equity returns see Chen, Roll, and Ross (1986), Hamao (1989). Ferson and Harvey (1995) study concluded that oil price does have significant impact of stock returns by studying 18 equity markets. Kaneko and Lee (1995) developed multi-variable VAR model to assess the pricing influence of economic factors on U.S. and Japanese stock market returns. The variables used in this study are: risk premium, growth rate, term premium, inflation, terms of trade, oil prices, exchange rates and excess stock returns. They find the average values of excess stock returns, rates of inflation, risk premiums and term premiums to be higher for the United States than for Japan. Jones and Kaul (1996) concluded that the United States and Canadian stock market's reaction to oil price shocks can be entirely explained on the basis of changes in the expected value of future real cash flows.

Huang et al. (1996) studied the oil-equity relationship in U.S. context by using vector autoregression technique (VAR) and concluded that there is no impact on the broad market index such as S&P500. On the contrary, Sadorsky (1999) in his paper explored the oil-equity relationship based on VAR. He finds existence of a negative relationship both in terms of return and volatility. Later, Sadorsky (2001) finds positive relationship between oil and gas equity index and the price of crude oil in Canada. Faff and Brailsford (1999) and Sadorsky (2003) performed studies on the relationship between the oil price and the industrial sector returns. Both the studies find strong linkages between oil and equity returns however, the impact of oil on different sectors varied. Maghyereh, Aktham (2004) studied the dynamic linkages between oil price shocks and stock market returns in 22 emerging economies. They used VAR model on daily data for 1998 to 2004 and found weak evidence about a relationship between the oil price shocks and stock market returns in these emerging economies.

Papapetrou (2001) studied the oil-equity relationship with reference to Greece economy in a multivariate VAR setup and concluded high impact of oil prices in explaining the equity returns. Recently, Cong, Wei, Jiao, & Fan (2008) conducted a study on Chinese equity market with respect to oil price shocks and found no significant effect on the real stock returns except oil related sectors. Basher and Sadorsky (2006) used a multi-factor arbitrage pricing model and found strong evidence that oil price risk impacts returns of emerging stock markets. Sadorsky (2008) shows that increases in firm size or oil prices reduce stock market price returns, and increases in oil prices have more impact on stock market returns than decreases in oil prices do. Agren (2006) studied the volatility spillover from oil prices to stock markets. He applied asymmetric Multivariate GARCH-BEKK model on the aggregate stock markets of Japan, Norway, Sweden, the UK and the US and found strong evidence of volatility spillover for all stock market except Sweden.

This study adds to the growing literature on the relationship between oil prices and stock prices. The paper draw its originality from the methodology used i.e., VECM-MGARCH(BEKK). The paper attempts to model the short-run as well as long-run linkages along with volatility spillover over a sample of Brazil, Russia, India and China (BRIC). To our knowledge no study has used this robust methodology on key emerging markets out of which Russia is a net exporter of crude while the rest are net importers. This provides additional insights that can be useful for analysts in portfolio diversification as well as policy makers.

The rest of the study is organized as follows. Section 3 touch upon data analysis. Section 4 develops the econometric model utilized. Section 5 discusses the empirical results based on cointegration and VECM technique. Section 6 explores the volatility linkages based on VECM-MGARCH(BEKK) approach. Section 7 draws conclusions.

3. Data Analysis:

The data consists of BRENT[2] crude oil price basket, Bolsa Oficial de Valores de São Paula (BOVESPA Index), Russian Trading System (RTS Index), Bombay Stock Exchange (BSE Sensex Index) and Shanghai Stock Exchange (SSE Composite Index). The stock indices are in local currency to avoid any distortions caused by the currency devaluations of the respective countries. Each index is highly liquid in a given stock exchange. For example, BOVESPA represents 70% of all capitalization with more than 15.583% contribution from OIL/energy sector. BSE Sensex is composed of 30 most liquid stocks with 23.41% of capitalization linked to oil/energy sector.

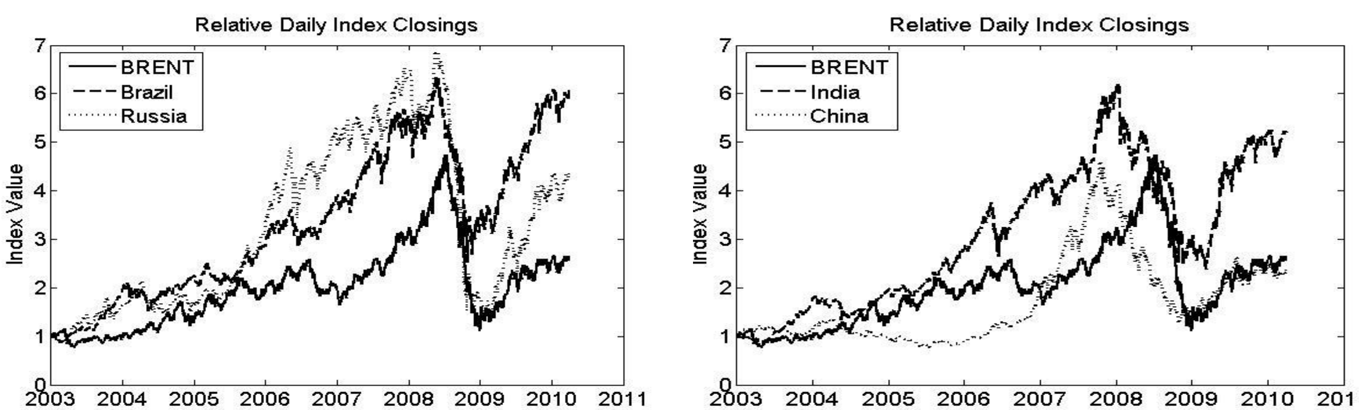

Figure.1.1 All Indices from 2-Jan-2003 to 31 March 2010

[2] Brent Blend is a combination of crude oil from 15 different oil fields in the North Sea. It is less “light” and “sweet” but still excellent for making gasoline. It is primarily refined in Northwest Europe, and is the major benchmark for other crude oils.

RTS Index is a capital-weighted price index of the 50 most liquid stocks. Approximately 40% of the stocks traded on the RTS Stock exchange are represented by three companies: Gazprom, Rosneft and LUKoil, all oil based companies. Chinese SSE composite index is made up of 44 most liquid stocks with a moderate influence of OIL/energy companies. The data is obtained from DataStream for the period 02 February 2003 to 31 March 2010 as daily closing prices. The total number of observation for each index is 1870. Fig.1.1 shows the price comparison of each series over the period approx. 7 years.

Among the BRICs in 2008 crisis, Russia's decline was the most striking; its equity index lost over three-quarters of its value. China's index fell by almost two-thirds and India's Sensex more than halved. Brazil's lost around a third of its value. It can be seen that Russia and Brazil closely mapping the BRENT prices while India and China are mostly lagging the BRENT prices. The descriptive statistics of all the series are given in Table 1.1.

Table 1.1: Descriptive Statistics

Parameters	**BRENT**	**Brazil**	**Russia**	**India**	**China**
			(2-Jan-2003 - 31 March 2010)		
Mean	0.00052	0.00096	0.00079	0.00088	0.00046
Median	0.00086	0.00167	0.00227	0.00165	0.00033
Maximum	0.18130	0.13677	0.20204	0.15990	0.09034
Minimum	-0.16832	-0.12096	-0.21199	-0.11809	-0.09256
Std. Dev.	0.02388	0.01919	0.02328	0.01727	0.01770
Skewness	0.04689	-0.11164	-0.64852	-0.13667	-0.21417
Kurtosis	7.83346	8.46024	14.13825	10.80104	6.26170
Jarque-Bera test	277.230*	114.287*	167.798*	122.579*	486.506*
JB P-value	*(0.00100)*	*(0.00100)*	*(0.00100)*	*(0.00100)*	*(0.00100)*
Ljung-Box Q-test: Q(16)	38.047*	24.546*	79.035*	53.851*	32.185*
LBQ(16) P-value	*(0.00149)*	*(0.07824)*	*(0.00000)*	*(0.00001)*	*(0.00946)*
Ljung-Box Q-test: Q(20)	39.257*	42.220*	82.855*	55.819*	35.066*
LBQ(20) P-value	*(0.00619)*	*(0.00259)*	*(0.00000)*	*(0.00003)*	*(0.01976)*
Arch Test (16)	193.466*	627.972*	525.158*	161.063*	142.375*
Arch(16) P-value	*(0.00000)*	*(0.00000)*	*(0.00000)*	*(0.00000)*	*(0.00000)*
Arch Test (20)	302.106*	636.373*	542.779*	164.709*	153.256*
Arch(20) P-value	*(0.00000)*	*(0.00000)*	*(0.00000)*	*(0.00000)*	*(0.00000)*
Cross Correlation					
BRENT	1				
Brazil	0.18281	1			
Russia	0.06861	-0.00153	1		
India	0.17385	0.30890	0.04858	1	
China	0.07553	0.16457	0.03533	0.21459	1

**Significant at 5% level*

Brazil has the highest mean return among all the indices while Russia has the largest volatility. China closely assimilates the BRENT both in terms of return and volatility. The high return and volatility exhibited by the BRIC countries are general characteristics attributed to emerging economies see Harvey (1995). All the return series suffers from negative skewness and high kurtosis i.e., leptokurtic. The means that the returns are mostly concentrated in tails of the distribution. The distinguishing feature reside among the sample-series is that Russia has the highest negative skewness as well as largest kurtosis among all the series making it the most volatile market among the BRIC sample.

The Jarque-Bera statistics rejected the null hypothesis of normality in all the return series. We used Ljung Box Q test at various lags to test the presence of serial correlation in sample series and reject the null hypothesis of no serial correlation in all the cases. The Fig.1.2 shows volatility clustering i.e., large changes in returns are followed by large changes while small changes are followed by small changes. To test whether there is presence of autoregressive conditional heteroscedasticity (ARCH) effects, we employ the Engels (1982) ARCH test. The test given in Table 1.1 rejects the null hypothesis confirming that the presence of ARCH effects in the residuals of all the return series.

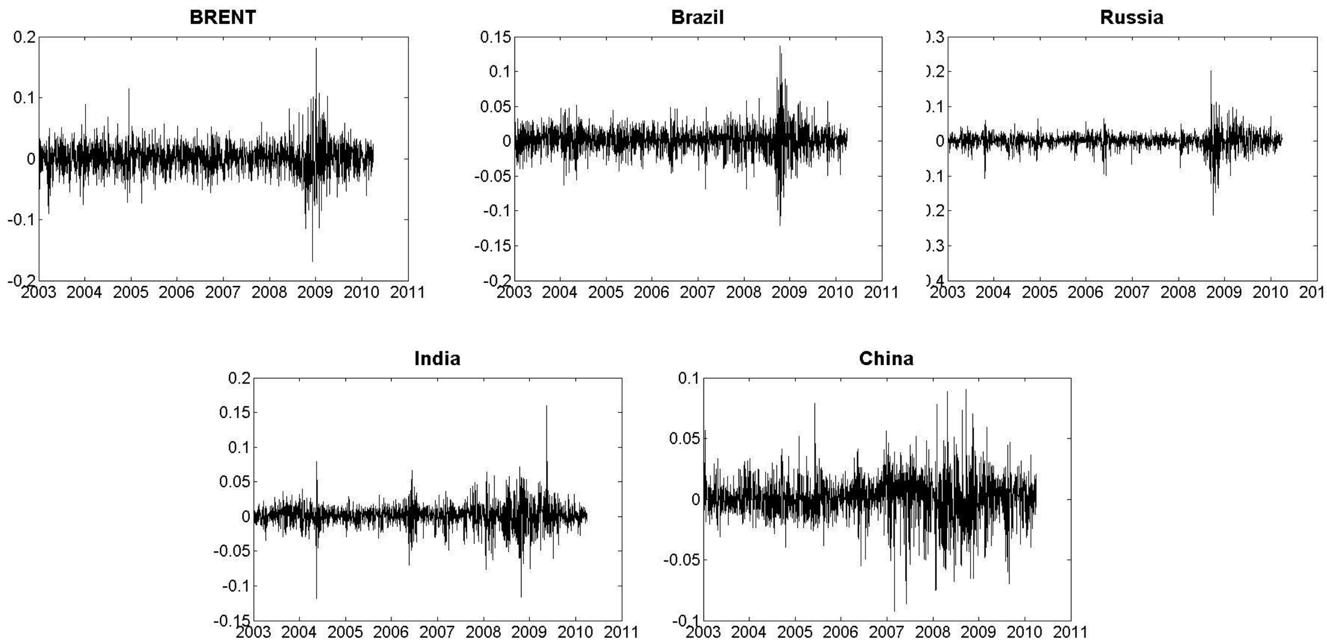

Figure.1.2 Daily volatility for all indices from 2-Jan-2003 till 31 March 2010

4. Methodology:

In this paper we analyse the static and dynamic relationships in the asset returns using only the return vectors. Most financial studies use log return series instead of price series. The main reason is that the log return series has attractive and tractable statistical properties. However, the return series represents lagged difference and therefore are mostly found stationary. This poses a problem such that the error representation seems suitable to study the short term and long term effect for non stationary price series while we intend to employ the return series instead.

Cointegration and VECM(p) techniques require the input data to be integrated i.e., non stationary, cointegrated at I(1). There is limited litrature on whether VECM(p) can be used with the stationary data. Beck and William (1993) argue that the error correction models were developed prior to the theory of cointegration and are flexible enough to model stationary data that are long memoried. While counter arguments comes from Durr (1993 a,b) and Smith (1993) such that cointegration implies error correction and that error correction models in turn imply cointegration. As such, they see error correction models as unsuitable for stationary data.

Error correction model provide theoretical tractability between the two processes i.e., short versus long-run behavior rather than just combination of the two. In our paper context, this allows consideration of oil time series dynamic effects that include both short term shocks and long term equilibrium. In finance, empirical research do not often use unit roots, however, the researchers quite often have stationary data such as in our case the return series that contains long cycles or has some component that responds to both short and long-term forces. So far its rare to find applied work that has taken into account such a possibility. Sreedharan (2004) focus was on error correction process based on stock return series(stationary) for Open, High, Low and Close. They concluded that through the return generation process (RGP) the “cointegrating” returns exhibit significant explanatory power in a VECM setup.

Keele and Boef (2004) provide analytical evidence that it is entirely appropriate to estimate an error correction model with stationary data. They concluded that the error correction model is both a theoretically desirable and empirically feasible approach to stationary data. They proposed autoregressive distributed lag ADL(1,1) estimation with a restriction such that the coefficients for the lag of the endogenous variable and the lag of the exogenous variable must be statistically signifficant and when regressed on the first difference of endogenous variable . If not, error correcting behavior does not occur and the one should consider some other dynamic specification. The return data (stationary) used in this paper well qualified this restriction and therefore was found suitable for a proposed VECM setup.

The cointegration technique was first introduced by Engel and Granger(1987) for testing Granger causality. Two or more variables are said to be cointegrated i.e., they show long run equilibrium relationship, if they share common trend. If these variables continue to have a common trend then Granger causality must exists in at least one direction. This process helps to rule out the possibility of spurious relationship among the variables as well. Nevertheless, the direction of Granger causality remains unknown. To solve this problem, vector error correction model (VECM) is used. Engle and Granger demonstrated that “once a number of variables are found to be cointegrated, there always exists a corresponding error-correction representation that implies that changes in the dependent variable are a function of the level of disequilibrium in the cointegrating relationship (captured by the error-correction term) as well as changes in other explanatory variable(s)”. We use the VECM representation proposed by Engel and Granger(1987). Following set of equations will constitute our VECM model,

$$R_{1,t} = \mu_1 + \sum_{i=1}^{p} \alpha_{1,i} R_{1,t-i} + \sum_{i=1}^{q} \beta_{1,i} R_{2,t-i} + \sum_{i=1}^{r} \gamma_{1,i} EC_{t-r} + \varepsilon_{1,t} \quad (1)$$

$$R_{2,t} = \mu_2 + \sum_{i=1}^{p} \alpha_{2,i} R_{1,t-i} + \sum_{i=1}^{q} \beta_{2,i} R_{2,t-i} + \sum_{i=1}^{r} \gamma_{2,i} EC_{t-r} + \varepsilon_{2,t} \quad (2)$$

where $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t})^T | \Omega_{t-1} \sim N(0, H_t)$.The parameter $R_{1,t}$ represents the returns of BRENT at time *t* while $R_{2,t}$ represents the returns of *Brazil*, *Russia*, *India*, *China* in pairs with BRENT.

The parameters μ_1 and μ_2 are constants, the $\alpha_{1,i}$ and $\beta_{2,i}$ coefficient of the lagged return of the respective indices, the $\beta_{1,i}$ and $\alpha_{2,i}$ are the coefficents of the cross market lagged returns, the $\gamma_{1,i}$ and $\gamma_{2,i}$ represents the coefficents of the respective error correction term EC_{t-r} and EC_{t-r}. This representation not only tells us the direction of Granger causilty between the variables but also to differentiate between short-run and long-run Granger causality.

If variables are cointegrated, then in the short-term, the deviations from long term equilibrium will feedback on the changes in the dependent variable in order to force the movement towards the long-run equilibrium. If the dependent variable is directly maneuvered by the long term equilibrium error then the dependent variable is responding to this feedback. If not, it is responding only to short-term shocks to the stochastic environment. The F-Tests points towards the short term causal link and significance of t-tests of the lagged error correction terms indicate the long term equilibrium causal link. We will employ impulse response functions (IRF) in order to check the stability of the system employed. IRF essentially map out the dynamic response of a variable due to a one-period standard deviation shock to another variable, Masih and Masih (1997). If the system of the Eq.(1) and Eq.(2) are stable than any shock should decline to zero while if the system is unstable then the shock would not converge to zero.

The approach in Eq.(1) and (2) are widely used in literature to capture the short and long term effects of information flow across the market see Booth, So, and TSE (1999). The short term effects are captured by the cross market lagged returns while long term effects are captured by the error correction terms. A number of papers indicate that the volatility and information flow are highly correlated see Ross (1989) and Chan, Chan and Karolyi, (1991). We use Engle (1995) Multivariate GARCH with BEKK parameterization in order to analyze the cross market shocks and conditional volatility which is given as,

$$H_{t+1} = C^{'}C + B^{'}H_tB + A^{'}\epsilon_t\epsilon_t^{'}A \tag{3}$$

The matrices of the coefficients A, B and C in our case are given as follows,

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & a_{22} \end{bmatrix} \text{and } C = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} \tag{4}$$

Where H_{t+1} is the conditional covariance matrix. In bivariate case, the parameter B explains the relation between the current conditional variance to past conditional variances. The parameter A measures the extent to which conditional variances are correlated with past squared errors i.e., it captures the effects of shock or volatility. The total number of estimated parameters is eleven. In our case, the Eq.(3) will be of form,

$$h_{11,t+1} = c_{11}^2 + b_{11}^2 h_{11,t} + 2b_{11}b_{12}h_{12,t} + b_{21}^2 h_{22,t} + a_{11}^2\varepsilon_{1,t}^2 + 2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2\varepsilon_{2,t}^2 \tag{5}$$
$$h_{22,t+1} = c_{12}^2 + c_{22}^2 + b_{12}^2 h_{11,t} + 2b_{12}b_{22}h_{12,t} + b_{22}^2 h_{22,t} + a_{12}^2\varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{22}^2\varepsilon_{2,t}^2 \tag{6}$$

Eqs. (5) and (6) explains how shocks and volatility are transmitted over time and across the indices. We will estimate these equations for two pair of series at a time. The terms $\varepsilon_{1,t}, \varepsilon_{2,t}$ in Equations (5) to (6) are the residuals obtained from Equations (1) and (2). We will estimate four bivariate GARCH(1,1) equations. These are formed by using the BRENT with Brazil, Russia, India and China i.e., (1 X 4). The symbol $h_{11,t}$ explains the conditional variance for the first index at time t and $h_{12,t}$ represents the conditional covariance between the first and the second index. The residual or error term in each equation represent the effect of unexpected shocks on different indices. For instance the terms $\varepsilon_{1,t}^2$ and $\varepsilon_{2,t}^2$ reflects the deviations from the mean due to unanticipated shock in a particular market. The cross products like $\varepsilon_{1,t}, \varepsilon_{2,t}$ explains the shock in the first and the second market at time t.

We maximized the likelihood function following the Berndt, Hall, Hall and Hausman (BHHH) algorithm given in Eq.(7) assuming the errors are normally distributed.

$$(\theta) = -T ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} ln(|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad (7)$$

Where θ is the estimated parameter vector and T is the number of observations. Engle and Kroner (1995) suggested algorithm was used to obtain the initial conditions.

5. Empirical Analysis:

We use augmented Dickey Fuller (ADF) along with Phillips-Perron (PP) univariate test (without drift) to analyze the presence of unit roots in all the sample time series. The results are given in Table1.2. In case of price series, both the tests could not reject the null hypothesis at 5% confidence level claiming that all the series are generated by non stationary process. However, in case of return series, both the test leads to opposite results i.e., the series are generated by stationary process.

Table 1.2: ADF and PP Unit Root Tests

Augmented DF unit root test for AR(1) model without drift						
		Price Series			***Return Series***	
Variables	**H°**	**ADF t-statistic**	**P-Value**	**H°**	**ADF t-statistic**	**P-Value**
BRENT	0	0.1665	0.7130	1	-16.9834	0.001
Brazil	0	1.4562	0.9642	1	-17.9496	0.001
Russia	0	0.2097	0.7288	1	-15.6281	0.001
India	0	1.1385	0.9345	1	-17.2900	0.001
China	0	0.1424	0.7041	1	-16.1127	0.001
Phillips-Perron unit root test for AR(1) model without drift						
		Price Series			***Return Series***	
Variables	**H°**	**PP t-statistic**	**P-Value**	**H°**	**PP t-statistic**	**P-Value**
BRENT	0	0.1554	0.7089	1	-43.5158	0.001
Brazil	0	1.3935	0.9595	1	-43.0929	0.001
Russia	0	0.2654	0.7492	1	-38.5968	0.001
India	0	0.9846	0.9146	1	-39.6987	0.001
China	0	0.1898	0.7215	1	-43.6392	0.001

**H°=1 represents the rejection of the null hypothesis that the series is integrated I(0) i.e., the series does not have a unit root and is therefore stationary.*

The number of lags i.e.,6 have been determined with likelihood ratio test. Nevertheless, the test was performed from a minimum lag of 1 to maximum lag of 20 and in all cases no change in hypothesis results was detected. The exercise also included the ADF and PP test with drift, however, the results obtained remained similar to AR and PP –without drift. Next we move to the VECM(6) based on return series in order to analyses the short term and long term casualty effect of each paired time series i.e., BRENT-Brazil, BRENT-Russia, BRENT-India, BRENT-China.

i) BRENT-Brazil Returns:

Table 1.3 comprise of three major analytical components. The Granger Casualty is given for each series along with Johnson Cointegration Test[3] for the cointegrating terms. The upper most panel explain the relevant estimated parameters that are significant at 5% level only along with error correction terms. We reject the null hypothesis of no integration between BRENT and Brazil indices using Johnson MLE cointegration test with Trace and Eigen statistics. This result implies that there exists two long run equilibrium relationship among these indices i.e., highly integrated. The existence of a cointegrating relationship indicates that the two price series are integrated and are expected to have a common stochastic trend.

The presence of cointegration leads us to estimate VECM(6). The result show that there is a robust long-run relationship between the two indices i.e., significant at 5% level, and is bidirectional in nature. In other words BRENT crude oil price closely influence the Brazil index in the long run and vice versa. We find absence of short-run relationship between BRENT and Brazil index. This is shown by the Granger Casualty test given in table 1.3.

Table 1.3: Vector Error Correction Model(BRENT-Brazil)

Parameters	**BRENT**	**t-stat**	**P-Value**	**Parameters**	**Brazil**	**t-stat**	**P-Value**
	Dependent Terms				**Dependent Terms**		
Constant	0.00037	0.66476	0.50629	*Constant*	0.00113*	2.51538	0.01198
BRENT(-5)	0.07492*	2.22586	0.02614	*Brazil(-1)*	0.20774*	3.23980	0.00122
				Brazil(-2)	0.16248*	2.81285	0.00496
				Brazil(-6)	0.05253*	2.20342	0.02769
EC BRENT	-0.00112*	-2.04398	0.04110	*EC BRENT*	0.00771*	17.39408	0.00000
EC Brazil	0.00919*	16.83685	0.00000	*EC Brazil*	0.00221*	4.99414	0.00000
Diagnostics							
R^2	0.5183				0.504		
$e'e$	0.0006				0.0004		
Granger Causality Test							
Variable	***F-Value***	***Probability***		***Variable***	***F-value***	***Probability***	
BRENT	2.11179*	0.04910		BRENT	0.69313	0.65523	
Brazil	0.91315	0.48427		Brazil	2.67004*	0.01392	
Johnson Cointegration Test							
H_0:r=0;H_1:r=1	***Trace Statistics***	***Crit95%***	***Crit99%***	***Eigen Statistics***	***Crit95%***	***Crit99%***	
r≤0	576.317	15.494	19.935	307.265	14.264	18.52	
r≤1	269.052	3.841	6.635	269.052	3.841	6.635	

**Significant at 5% level*

[3] ...a series *X*, is said to be integrated of order *d*, if it has an invertible ARMA representation after being differenced *d* times. For example, a stationary series is indicated by I(0), whereas a non-stationary series in levels, but stationary in first differences is indicated by I(1) see Masih and Masih (1997).

The results point towards the Brazil emerging economic status and long term crude oil dependence to fuel its economy. The absence of short-term linkages is indicative of the fact that Brazil imports of crude oil is decreasing because of increase in indigenous production of crude oil. The impulse response function shown in Figure1.3 also indicates that a shock to Brazil index will cause a temporary shock to BRENT and will smooth out in less than a month while on the other hand, a shock to BRENT price index will cause a temporary but short lived shock to Brazil equity index. Interpreting differently, the BRENT-Brazil relationship is strong, bidirectional and stable in long term.

ii) BRENT-Russia Returns:

In BRENT versus Russian case, both enjoy short-run as well as long-run relationships. For BRENT-Russia, there exist two cointegrating relationships at 5% significance level. This is indicative of a strong bi-directional relationship between the two indices. In short-run, the Russia depends on BRENT and vice versa i.e., the F-statistics are highly significant in both equations. In lead-lag relationship, Russia plays leading role in influencing the BRENT prices while BRENT lags in both the equations i.e., Russia(-1). The short-term linkages and lead-lag relationship can be expected as Russia is one of the main crude oil exporters in the world. The long-run relationship between the two indices is highly significant at 5% level and points to the same earlier reasoning. From R^2 statistics it is clear that BRENT depends on Russia more than Russia depends on BRENT.

Table 1.4: Vector Error Correction Model(BRENT-Russia)

Parameters	**BRENT**	**t-stat**	**P-Value**	**Parameters**	**Russia**	**t-stat**	**P-Value**
	Dependent Terms				**Dependent Terms**		
Constant	0.00027	0.51408	0.60726	*Constant*	0.00069	1.28309	0.19962
BRENT(-3)	0.10973*	2.37696	0.01756	*BRENT(-6)*	0.05199*	2.30137	0.02148
BRENT(-4)	0.08585*	2.16121	0.03081				
BRENT(-5)	0.09187*	2.89335	0.00386				
Russia(-1)	-0.35880*	-6.49659	0.00000				
EC BRENT	-0.00897*	-16.9307	0.00000	*EC BRENT*	0.00312*	5.84208	0.00000
EC Russia	-0.00311*	-5.86465	0.00000	*EC Russia*	-0.00785*	-14.6801	0.00000
Diagnostics							
R^2	0.5460				0.4513		
$e'e$	0.0005				0.0005		
Granger Causality Test							
Variable	***F-Value***	***Probability***			***Variable***	***F-value***	***Probability***
BRENT	2.47810*	0.02166			*BRENT*	2.29934*	0.03244
Russia	25.33982*	0.00000			*Russia*	1.50467	0.17269
Johnson Cointegration Test							
H_0:r=0;H_1:r=1	***Trace Statistics***	***Crit95%***	***Crit99%***	***Eigen Statistics***	***Crit95%***	***Crit99%***	
$r \leq 0$	537.531	15.494	19.935	310.055	14.264	18.52	
$r \leq 1$	227.476	3.841	6.635	227.476	3.841	6.635	

**Significant at 5% level*

The impulse response function shown in Figure1.3 implies what happens when a one standard deviation of shock is introduced in the estimated VECM(6) on a given variable. We see that there are considerable fluctuations in the first few days but these smoothes out over a period of approx. 20 days for Russia. While in case of BRENT, a Russian originated shock experience less volatility however smooth out in a similar period to that of Russia. This indicates the short-term as well as stable long-term relationship between the two indices.

iii) BRENT-India Returns:

We find two cointegrating relationships between BRENT and India. Both are found to be significant at 5% level. The short term casual relationship does not exist between the two indices. However, the long run relationship indicated by the error correction terms is significant at 5% confidence level. The results imply that BRENT-India are closely integrated and influences each other in long term which can be largely contributed to the economic dependence of India on crude oil.

Table 1.5: Vector Error Correction Model(BRENT-India)

Parameters	**BRENT**	**t-stat**	**P-Value**	**Parameters**	**India**	**t-stat**	**P-Value**
	Dependent Terms				**Dependent Terms**		
Constant	0.00044	0.78992	0.42968	*Constant*	0.00093*	2.30010	0.02155
BRENT(-5)	0.07903*	2.36465	0.01815	*India(-1)*	0.12303*	2.18940	0.02869
				India(-4)	0.08941*	2.26521	0.02362
EC BRENT	-0.00236*	-4.29532	0.00002	*EC BRENT*	0.00637*	15.9540	0.00000
EC India	0.00903*	16.40604	0.00000	*EC India*	0.00276*	6.92514	0.00000
Diagnostics							
R^2	0.5107				0.4645		
$e'e$	0.0006				0.0003		
Granger Causality Test							
Variable	***F-Value***	***Probability***		***Variable***	***F-Value***	***Probability***	
BRENT	2.41085*	0.02524		*BRENT*	0.65035	0.68991	
India	1.01932	0.41072		*India*	1.65002	0.12961	
Johnson Cointegration Test							
H_0:r=0;H_1:r=1	***Trace Statistics***	***Crit95%***	***Crit99%***	***Eigen Statistics***	***Crit95%***	***Crit99%***	
r≤0	553.707	15.494	19.935	285.226	14.264	18.52	
r≤1	268.481	3.841	6.635	268.481	3.841	6.635	

**Significant at 5% level*

Impulse response function in Figure1.3 shows that shock originating in Indian stock markets has low level of impact on BRENT and vice versa. In both the cases the shock subsides after a few days, however, in case of India the shock stays longer than BRENT.

iv) BRENT-China Returns:

In case of BRENT-China, we find two cointegrating relationships at 5% significance level. The F-statistics at 5% significance level points towards absence of short term linkages between the two markets. However, there is a strong long-run relationship detected between BRENT-China. The long-run relationship is negative for both the markets. This result implies that increase in BRENT price index will reduce the Chinese stock index and vice versa. As the crude oil becomes expensive, the cost of business goes up resulting in decrease in index.

Table 1.6: Vector Error Correction Model(BRENT-China)

Parameters	**BRENT**	**t-stat**	**P-Value**	**Parameters**	**China**	**t-stat**	**P-Value**
	Dependent Terms				**Dependent Terms**		
Constant	0.00051	0.92945	0.35278	*Constant*	0.00039	0.95498	0.33971
BRENT(-3)	0.08348*	2.53389	0.01136				
EC BRENT	-0.00849*	-15.4023	0.00000	*EC BRENT*	0.00266*	6.51396	0.00000
EC China	-0.00390*	-7.08076	0.00000	*EC China*	-0.0060*	-14.7428	0.00000
Diagnostics							
R^2	0.5094				0.5112		
$e'e$	0.0006				0.0003		
Granger Causality Test							
Variable	***F-Value***	***Probability***		***Variable***	***F-value***	***Probability***	
BRENT	2.58564*	0.01693		*BRENT*	0.65660	0.68484	
China	1.48757	0.17850		*China*	3.03821*	0.00585	
Johnson Cointegration Test							
H_0:r=0;H_1:r=1	***Trace Statistics***	***Crit95%***	***Crit99%***	***Eigen Statistics***	***Crit95%***	***Crit99%***	
r≤0	516.229	15.494	19.935	276.489	14.264	18.52	
r≤1	239.74	3.841	6.635	239.74	3.841	6.635	

* *Significant at 5% level*

The impulse response function in Figure 1.3 exhibits the shocks arising from Chinese index to BRENT oil price. The shocks from either price index sustain for a while and stabilize in the long run. This indicates the stability of the VECM system employed.

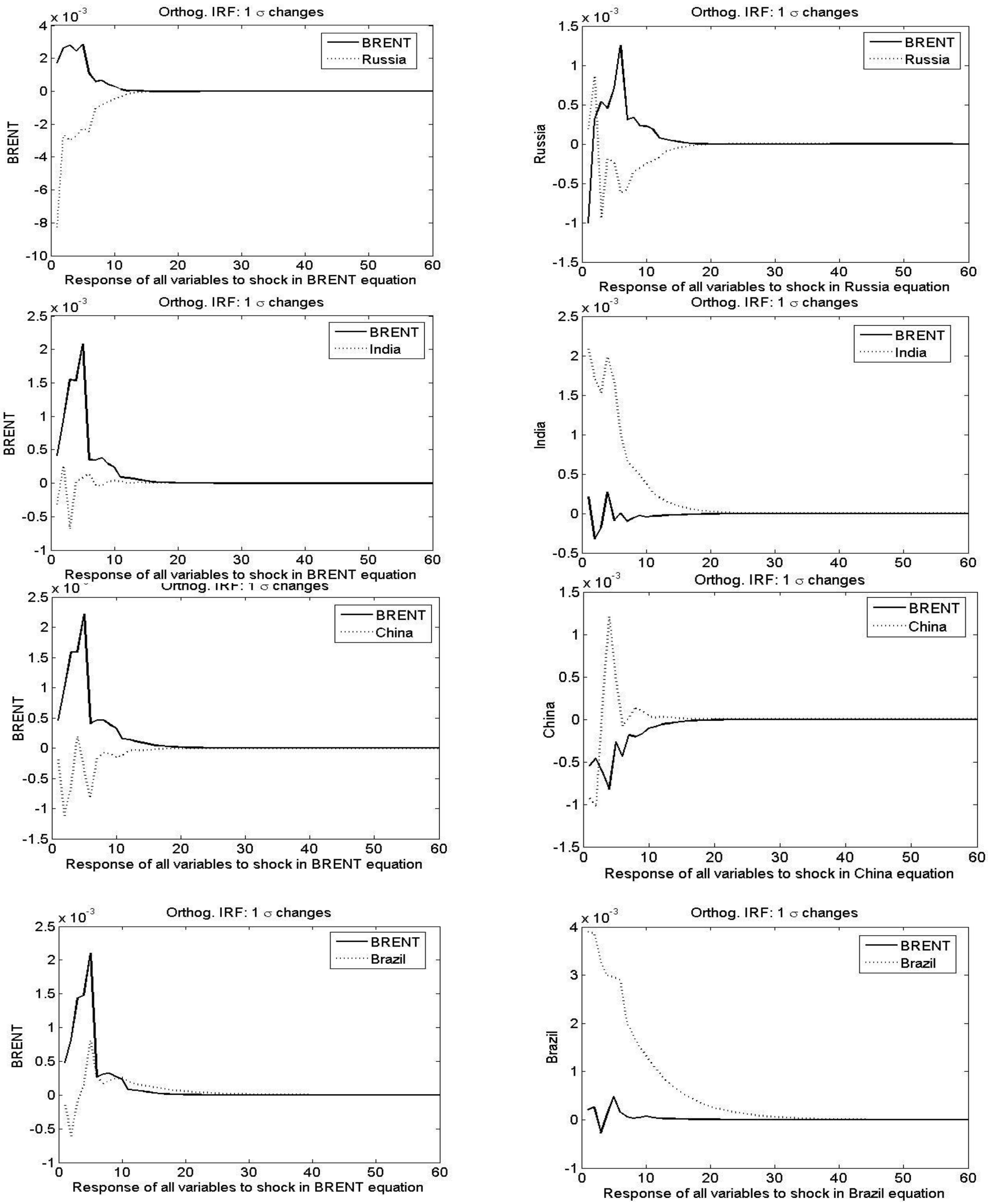

Figure.1.3 Impulse Response Functions based on estimated VECM(6)

6. Volatility Spillover Analysis:

In analyzing the volatility spill over we estimate the VECM(6)-MGARCH(1,1) from Eq.(5) and (6) and the results are given in Table 1.7. The fitted conditional covariances are shown in Figure 1.4. Most of the news shock (ARCH) and conditional volatility (GARCH) is generated by the relevant index itself as indicated by the diagonal parameters a_{11} ,a_{22} and b_{11} ,b_{22} . The off diagonal parameters of ARCH effects or news impact i.e., a_{12} ,a_{21} is determined to be bidirectional at 5% significance level in almost all the indices versus BRENT. In case of BRENT-Brazil, news shock from BRENT reduces the conditional volatility in Brazil market while on the other hand shock from Brazil increases the conditional volatility of BRENT. Similar interpretation can be provided for BRENT-Russia and BRENT-China with the exception of BRENT-India where both indices effect each other in a positive manner i.e., contributes towards each other volatility. The results are consistent with the economic reasoning that the demand of the BRIC essentially drives the BRENT price and any shock to the demand will have positive (increasing) effects on BRENT price.

Table 1.7: Multivariate Garch(1,1)[2-Jan-2003 - 31 March 2010]

Parameters	BRENT/Brazil		BRENT /Russia		BRENT /India		BRENT /China	
	Coeff	S.E	Coeff	S.E	Coeff	S.E	Coeff	S.E
C11	2.89040*	0.52148	2.32539*	0.23593	1.35230	2.92191	2.18457*	0.26079
C12	-0.32648*	0.10920	-0.34534	0.28736	1.16713	2.02370	-0.18431*	0.00777
C22	2.97093*	0.33434	3.53878*	0.26168	2.08028*	0.62802	1.80023*	0.28136
a11	0.17033*	0.00079	0.13260*	0.00070	0.13401*	0.00084	0.15840*	0.00051
a21	0.03741*	0.00067	0.00001	0.00004	0.00391*	0.00008	0.02246*	0.00026
a12	-0.08776*	0.00115	-0.04751*	0.00020	0.09715*	0.00092	-0.05524*	0.00079
a22	0.25131*	0.00095	0.34714*	0.00098	0.37782*	0.00166	0.25605*	0.00146
b11	0.97028*	0.00005	0.98251*	0.00002	0.98899*	0.00006	0.98152*	0.00002
b21	-0.01162*	0.00011	-0.00647*	0.00003	0.00197*	0.00005	-0.00295*	0.00001
b12	0.04244*	0.00031	0.02931*	0.00004	-0.03993*	0.00011	0.01558*	0.00009
b22	0.95209*	0.00015	0.92433*	0.00014	0.91861*	0.00021	0.96120*	0.00016
LogLik	-16289.8		-16455.5		-16012.4		-16222.3	
LBQ(16)$_i$	18.24(0.3102)*		14.43(0.5669)*		12.84(0.6842)*		14.73(0.5445)*	
LBQ(16)$_i$^2	10.90(0.8154)*		13.36(0.6460)*		17.29(0.3669)*		20.62(0.1936)*	
LBQ(16)$_j$	12.07(0.7395)*		22.99(0.1140)*		19.69(0.2347)*		15.84(0.4641)*	
LBQ(16)$_j$^2	10.84(0.8194)*		15.12(0.5158)*		12.79(0.6877)*		8.90(0.9174)*	
Arch Test (16)$_i$	10.88(0.8166)*		12.63(0.6995)*		16.73(0.4035)*		19.82(0.2283)*	
Arch Test (16)$_j$	11.06(0.8059)*		14.60(0.5541)*		12.20(0.7303)*		8.99(0.9140)*	

**The parameter values are significant at 5% confidence level.*
***The LBQ$_i$ and LBQ$_i$^2 represents Ljung-Box Q-test of residuals and squared residuals at 16 lag, while ARCH represents the Engel's ARCH test at 16 lags. The subscript i denotes BRENT while subscript j denotes Brazil, Russia , India and China respectively.*

In case of GARCH effects i.e., the off diagonal parameters b_{12} ,b_{21}, are found to be bidirectional at 5% significance level. The off diagonal parameters of GARCH essentially explain the cross market volatility spillover. In case of BRENT-Brazil, BRENT increases the volatility of the Brazil stock index while Brazil reduces the BRENT volatility. This is the case for BRENT-

Russia and BRENT-China while in case of BRENT-India the relationship reverses. The economic substance behind the results implies that volatility in BRENT crude oil prices affects the BRIC markets.

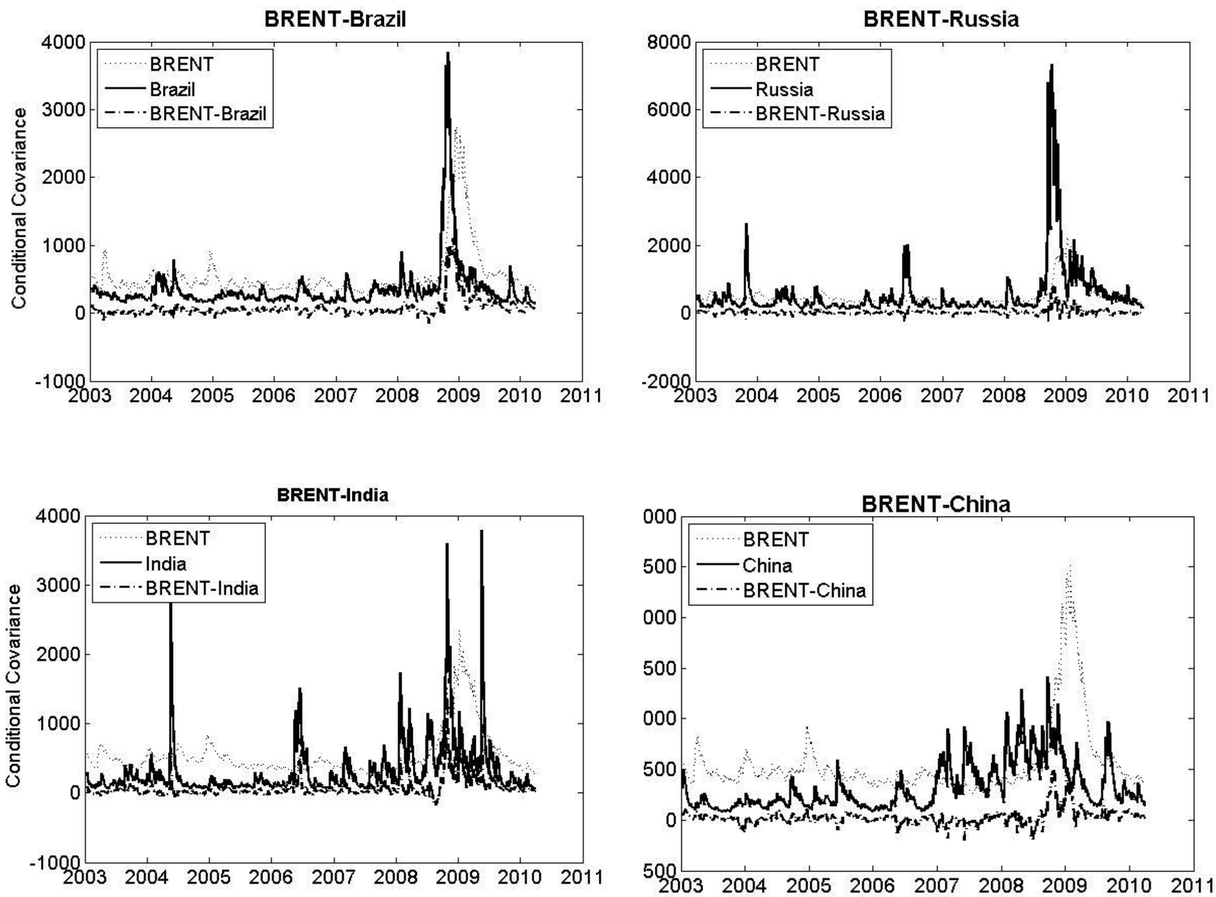

Figure 1.4: Conditional Covariance of all Indices in the Sample

7. Conclusions

Based on cointegration and VECM analysis we find that overall BRICs have strong, stable, bidirectional and long-term relationship with the BRENT price index. However, the results illustrate absence of short-term linkages of crude oil importing countries with BRENT except Russia where it can influence the short term oil prices. We also study the volatility spillover effects and found that BRICs equity markets are highly interconnected with crude oil market where shocks and spillover are found to be significant and bidirectional.

References:

Agren, Martin, 2006. Does Oil Price Uncertainty Transmit to Stock Market ?. Working Paper 23, Uppsala University.

Basher, Syed A.,Sadorsky, Perry, 2006. Oil price risk and emerging stock markets. Global Finance Journal, Elsevier, vol. 17(2), pages 224-251.

Booth, G. G., So, R. W., & Tse, Y. 1999. Price discovery in the German equity index derivatives markets. The Journal of Futures Markets, 19(6), 619-643.

BP Statistical Review of World Energy. 2009. Available at http://www.bp.com/

Chan, K., Chan, K. C. and Karolyi, G. A., 1991. Intraday volatility in the stock index and stock index futures markets. Review of Financial Studies, 4, 657-684.

Chen, N. -F., Roll, R., & Ross, S. A. 1986. Economic forces and the stock market. Journal of Business 59, 383−403.

Cong, R.-G., Wei, Y.-M., Jiao, J.-L., & Fan, Y. 2008. Relationships between oil price shocks and stock market: An empirical analysis from China. Energy Policy, 36(9), 3544-3553.

Dickey, D.A., Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 49, 1057–1072.

Faff, R. W., & Brailsford, T. J. 1999. Oil price risk and the Australian stock market. Journal of Energy Finance and Development 4, 69−87.

Engle, R. F., & Granger, C. W. J. 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica: Journal of the Econometric Society, 55(2), 251-276.

Engle, R., Kroner, K., 1995. Multivariate simultaneous generalised ARCH. Economet. Theory 11, 122–150.

Ferson,W.W., & Harvey, C. R.1994. Sources of risk and expected returns in global equity markets. Journal of Banking and Finance 18, 775−803.

Hamao, Y. (1989). An empirical examination of the arbitrage pricing theory: Using Japanese data. Japan and the World Economy 1, 45−61.

Harvey, C.R., 1995. Predictable risk and return in emerging markets. Rev. Financ. Stud. 8 (3), 773–816.

Huang, R. D., Masulis, R.W., & Stoll, H. R. 1996. Energy shocks and financial markets. Journal of Futures Markets 16, 1−27.

Johansen, S. (1988). Statistical analysis of cointegration vectors. Journal of economic dynamics and control, 12(2/3), 231-254.

Kaneko, T., & Lee, B. S. 1995. Relative importance of economic factors in the U.S. and Japanese stock markets. Journal of the Japanese and International Economies 9, 290−307.

Maghyereh, Aktham.2004 . Oil Price Shocks and Emerging Stock Markets :A Generalized VAR Approach. Int. Journal of Applied Econometrics and Quantitative Studies, vol 1-2.

Masih, Abul M.M., Masih, Rumi. 1997. On the temporal causal relationship between energy consumption, real income, and prices:some new evidence from asian-energy dependent nics based on a multivariate cointegration vector error-correction approach. Journal of Policy Modeling 19(4):417-440

Papapetrou, E. 2001. Oil price shocks, stock markets, economic activity and employment in Greece. Energy Economics 23, 511−532.

Ross, S., 1989. Information and volatility: The no-arbitrary martingale approach to timing and resolution irrelevancy. Journal of Finance 44, 1-17.

Sadorsky, P. 1999. Oil price shocks and stock market activity. Energy Economics 21, 449−469.

Sadorsky, P., 2001. Risk factors in stock returns of Canadian oil and gas companies. Energy Economics 23, 17–28.

Sadorsky, P. 2003. The macroeconomic determinants of technology stock price volatility. Review of Financial Economics 12, 191−205.
Sadorsky, P. (2004). Stock markets and energy prices. Encyclopedia of Energy Vol. 5 (pp. 707−717). New York Elsevier.
Sadorsky, P. 2008. Assessing the impact of oil prices on firms of different sizes: Its tough being in the middle. Energy Policy, 36(10), 3854-3861.