Do US policy uncertainty, leveraging costs and global risk aversion impact emerging market equities? An application of bounds testing approach to the BRICS

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18 June 2015

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Abstract:

'When the United States sneezes, the world catches a cold. And when America recovers, the planet has a spring in its step' – For decades together, this metaphor has seemed an accurate description of the global economy. Through this paper we have tried to examine the short and long term dependence structure between the stock markets of emerging markets and influential global factors (US economic policy uncertainty, the global risk aversion and the cheap borrowing costs in the US) using the BRICS countries (Brazil, Russia, India, China and South Africa) as a case study. The study applies the 'Auto-Regressive Distributed Lag' (ARDL) technique (Pesaran, Shin, &Smith, Journal of Applied Econometrics, 2001) which has taken care of a major limitation of the conventional cointegrating tests, in that they suffer from the pre-test biases. Based on the above rigorous methodology, our evidence tends to suggest that although there have been studies which indicate the impact of the disturbances stemming from the developed world, in the long- run there is a limited impact of these on the BRICS equity markets. These findings are plausible and have strong policy implications for portfolio investing and diversifications by investing in the emerging markets as the BRICS equities could function as a hedge against negative shocks from the developed economies.

Keywords: US Policy Uncertainty, Risk Aversion, Leverage, BRICS

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Introduction:

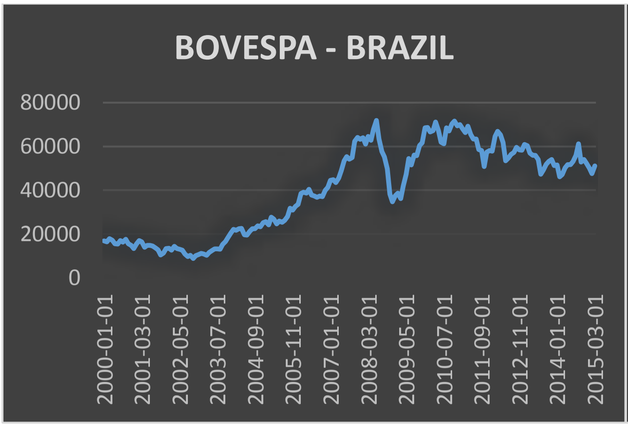
The 'BRIC' acronym was coined by Jim O'Neill in 2001, Goldman Sachs chief global economist, who emphasized on the spectacular economic growth prospects of the Brazilian, Russian, Indian and Chinese economies. South Africa has more recently joined the BRIC economies to now form the BRICS group. Based on recent economic forecasts, Brazil, Russia, India, China and South Africa (BRICS) are anticipated to exhibit exceptionally high economic growth rates over the next 50 years. This will result to BRICS jointly growing larger than the G-6 in US dollar terms (Wilson &Purushothaman, 2003). The BRICS cover 25% of the world's land mass, 40% of the world's population and run increasingly as global market economies (Frank & Frank, 2010). The BRICS share in world GDP and global exports is expected to grow by 2015 from 14% to 21.6% and from 12.4% to 20.1% respectively (at the same time, the US export share is anticipated to decline from 25 to 22%) (Wilson &Purushothaman. 2003). The sustainability of BRICS impressive growth path is subject to further structural and institutional reforms and financial liberalization, foreign investment inflows and international competition (Aye et al., 2014; Chkili& Nguyen, 2014; De Vries et al., 2012; Manamperi, 2014; Pradhan et al., 2013; Sarwar,20I2).

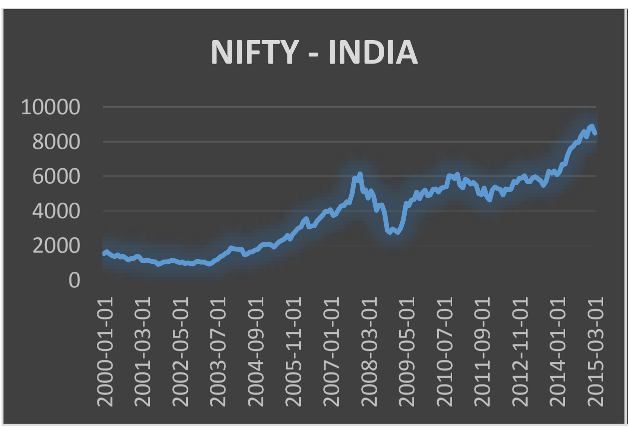
As global investors persistently pursue attractive asset classes to allocate their portfolios on alternative style investing. BRICS capital markets receive increasing international fund inflows(Chenget al., 2007;Chkili&Nguyen, 2014; Ghoshet al., 2009; Sledzik, 2012).

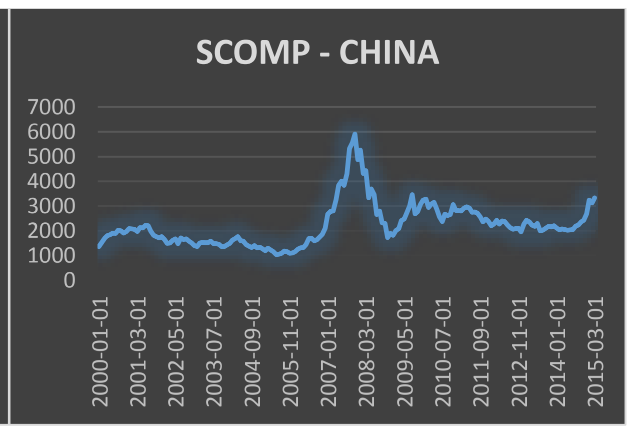
Understanding the functioning ofBRICS equity markets, their dynamic risk-return properties, potential volatility spillover effects, inter- relationships and reactions to shocks, events or news, relative to leading global mature markets, such as the US, remains a crucial issue for international investors, portfolio managers and policy makers.

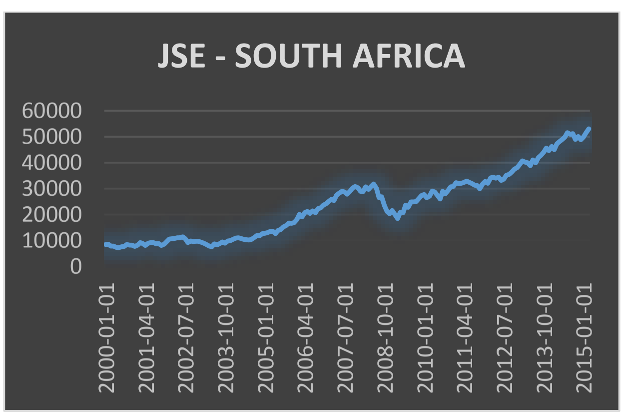
By this paper, we examine how economic factors in the US such as changes the U.S. economic policy uncertainty, the stock market uncertainty as defined by CBOE VIX – a recognized proxy to risk aversion and the cheap borrowing costs influence the performance of BRICS stock markets. Our analysis is motivated by the fact that the BRICS countries are the major recipients of global investment flows and are among the main global consumers of commodities. Therefore, changes in the global economic factors could be a channel through which fluctuations in the world's economic and financial conditions are transmitted to the BRICS stock markets and affect their economic growth. The recent global spillover and contagion effects induced by the 2007-8 US subprime mortgage financial crisis, illustrate this sort of a dynamic interaction between mature and emerging capital markets (Berger & Turtle, 2011). Moreover, international investors are especially interested in the BRICS stock markets' co-movements with theseglobal factors, given that investment, speculation and risk diversification opportunities mayarise.Short and long-run stock market dynamics can have critical implications for asset valuation, portfolio allocation, efficient diversification, hedging, and risk control. If, for instance,return and volatility spillover effects are seen to spread from one market to another at times of market crashes, adverse events or financial crises,portfolio diversification benefits should be expected to remain limited. In this case, global investors would have to adjust their asset allocation decisions in order to mitigate contagion risks (Aloui et al. 2011; Celik, 2012; Kenourgios et al. 2011; Syriopoulos, 2013; Syriopoulos&Roumpis, 2009).

Below is a graphical representation of the movement of the various BRICS stock market indices over the period under consideration.









Despite growing global attention on the BRICS capital markets, the relevant body of empirical research remains surprisingly limited and further insight would be useful. This study attempts to fill some of the gaps in the topic and contributes a range of innovative and fruitful empirical conclusions. The main objectives of this paper are:

- To examine if economic policy uncertainty in the U.S. has any effect on the returns on stock markets in the BRIC (Brazil, Russia, India and China) countries. The current study also investigates how stock market returns in the four countries respond to the U.S. economic policy uncertainty shock
- To acess if the Risk Aversion trades have a significant impact on the BRICS equities
- To understand if favorable leveraging opportunities lead to the movement of capital to the BRICequity markets, driving them up.

This paper tries to investigate if the above factors affect the BRICS equity markets in the long and short-run. We employ monthly data over the period 2000:1 - 2015:3 by using the Autoregressive Distributed Lag (ARDL) cointegration. This paper is organized as follows: Section II reviews on the relevant empirical literature. The theoretical specification, data and the preference for the ARDL cointegration methodology are explained in section III. The empirical results and discussions are presented in section IV. The last section ends with the concluding remarks and policy implications of the paper.

II. Literature Review:

Given the above increased economic integration of the BRICs with the world economy, shocks originated from advanced economies such as the United States can have a significant impact on the BRICs' economies. Trade and financial linkage between countries play an important role in explaining international spillovers (Forbes & Chinn, 2004). Many studies have empirically documented the international spillovers from the US to other countries. (Ehrmann and Fratzscher, 2009) report that the US monetary policy shocks spill over to other equity markets around the world. Kim (2001) shows that long-term yields and output of other countries and output are affected by the US monetary policy shocks; similar findings are reported in other studies (Awad& Goodwin, 1998; Chinn & Frankel, 2004; Ehrmannet al, 2011).

Numerous other studies report the international transmission of financial markets around the world (Ammer et al, 2008; Ehrmann&Fratzscher, 2006; Hausmann&Wongswan, 2011; Wongswan, 2006). In particular, because of the size of the US economy, shocks to the US economy and financial markets can spill over to other countries' financial markets (Bayoumi&Swiston, 2007; Ehrmann&Fratzscher, 2005; Goldberg & Leonard, 2003). King and Wadhwani (1990) argue the correlation between financial markets around the world exists since rational market participants observe and analyze price movements in other stock markets. Moreover, many other studies have examined if macroeconomic variables can predicts the performance of various financial securities (Cooper & Priestley 2005; Menzly et al, 2004; Piazzesiet al, 2005). In addition, studies such as (Bansal et al, 2005; Dzielinski, 2011; Ozoguz, 2009) have documented the impact of uncertainty related to the economy and other policies on the performance of the stock markets. Paster and Veronesi (2011) associate the decreased stock prices to the increase in government policy uncertainty. Furthermore, negative stock returns are associated with increased changes in economic policy uncertainty in the United States (Sum, 2012a) Europe (Sum, 2012b), and five ASEAN countries (Sum, 2012c).

Departing from the aforementioned studies that have a main focus on markets across the world, there have been some notable studies for the BRICS countries. In this empirical literature, the impact of various global factors on these economies stock markets have been considered. These include developed markets equities, oil, credit spreads etc.

Hammoudeh et al. (2013) have examined the interrelationship between the five BRICScountries' equity market indices, and their relationship with the International Country RiskGuide (ICRG)'s three country risk rating factors (economic, financial and political), theS&P500 index and the West Texas Intermediate (WTI) oil price. Ono (2011) on similar lines has examined the systemic impact of oil prices on the stock market returns for the four BRIC countries and finds that increases in oil prices pull up the stock market indicesfor all these countries except Brazil.

Aloui et al. (2011) examined thefinancial interdependences of the BRICemerging markets with the U.S. markets and provide strong evidence of time-varying dependence between them. This dependency is stronger for the commodity-price dependent marketsthan for the finished product export-oriented markets of the BRIC countries. Moreover, they observe high levels of dependence persistence for all market pairs during both bullish and bearish markets.Dimitriou et al. (2013) however find an increasing co-movement between the BRICS and U.S. markets during the post-crisis period(from early 2009 onwards), implying that the dependence is larger in bullish than in bearishmarkets.

Hwang et al. (2013) in a wider study, examined the dynamic conditional correlations between theU.S. and ten emerging stock markets (i.e., the five BRICS markets, South Korea, Thailand,Philippines, Taiwan, and Malaysia). They show that different patterns of the U.S. financial crisis spillovers exist among emerging economies. They also conclude that increasesin the credit TED spread (i.e., the yield difference between the three-month LIBOR rate andthe U.S. three-month Treasury bills) and sovereign CDS spread, both representing higherrisks, decrease the estimated conditional correlations.

Zhang et al. (2013) provide strong evidence that the recent global financial crisis has changed the conditional correlations between the developed (U.S. and Europe) markets and the BRICS stock markets. Also Bekiros (2013) by using linear and nonlinear causal linkages to analyze the volatility spillovers among the U.S., the EU and theBRIC markets - find that the BRICs have become more internationally integrated since the U.S. financial crisis.

While these studies add further evidence to the factors affecting the BRICS stock markets, they bring up a notable dimension on the subject. Namely, the effect of US based factors on the BRICS. Through the paper we try to examine if the metaphor – of the 'US sneezing' used earlier stands true. Although as discussed above there have been studies to understand the effects of several factors on the BRICS equity markets, to our knowledge there seem to be few parallels which can be drawn theoretically or empirically to the study undertaken. This study contributes to the existing literature by making a humble attempt at examining the long and the short run relationship between the BRICS stock market, the policy uncertainty in the US, risk aversion and the interest rates.

III. Underpinnings, Data and Methodology:

Underpinnings based on the above literature:

The emerging markets over the years have been building up the strength of their equity markets (liquidity and depth), however they remain heavily dependent on the foreign money flow. Considering this is majorly in the form of hot/speculative money, investors find avenues to borrow cheapand invest in emerging economy equities which offer considerable higher returns. However during times of the risk-off trades (As seen during the 2007-08 US subprime crisis etc.) this money also quickly finds its way back, whereby this leads to a negative impact on these stock markets. Also the BRICS equity markets also impact each other as the money flows at most times move in tandem and times are substitutive (due to relative strength of the economies).

Through this study we would like to examine if the BRICS equity markets (proxied by the BRICS indices), interest / borrowing cost (proxied by 3MLibor) patterns, risk-off trades (risk aversion - proxied by the VIX index) and the policy uncertainty in the US (proxied by the US policy uncertainty index) have a long term relationship.

Data:

The monthly return data over 2000:1 to 2015:3, pertaining to the study has been collected from four different sources. The data on the stock market indices of Brazil (Bovespa Total Return Index), Russia (Russia MICEX-10 Index), India (NSE – CNX NIFTY Index), China (Shanghai SE Composite Index), South Africa (FTSE/JSE All Share Index) and the 3month Libor are obtained from the Thomson Reuters Datastreamdatabase. Data of economic policy uncertainty index in

United States and CBOE VIX is obtained from the Economic PolicyUncertainty Index websitewww.policyuncertainty.comconstructed by Baker, Bloom, and Davis (2012) and the CBOE website www.cboe.com respectively.

Instead of opting to take one single index such as the S&P BRIC 40 or MSCI BRIC as a proxy for all the BRICS stock indices, we have included each of the BRICS stock index separately as we anticipate that movement of capital into one market would also effect the others.

Methodology:

This study employs a time series technique, in particular, Autoregressive Distributed Lag (ARDL) cointegration method, in order to find empirical evidence of the nature of relations between BRICS equity markets and the factors as alluded to in the introductory paragraphs.

This method has been preferred over traditional regression method for the following reasons:

- Stock markets indices like most other finance variables are non-stationary. This would entail that performing an ordinary regression on the variables will render the results misleading as when statistical tests like t-ratios and F statistics are not statistically valid when applied to non-stationary variables. Performing regressions on the differenced form of these variables will solve the above problem, however this would lead to an even graver mistake. When variables are regressed in their differenced form, the long term trend is effectively removed. Thus, the regression only captures short term, cyclical or seasonal effects. Under this situation, the regression is not really testing long term (theoretical) relationships
- Under traditional regression, the endogeneity and exogeneity of variables is pre-determined by the researcher, usually on the basis of theory. Considering the above study

and as seen in the literature review there is notable absence of established theories apart from probably risk aversion. Cointegration techniques are advantageous in a way that it does not presume variable endogeneity and exogeneity. The data determines which variables are exogenous, and which are exogenous.

- Cointegration techniques for the lack of words, embrace the dynamic interaction between variables whereas traditional regression methods, exclude or discriminate against interaction between variables.

Even though conventional cointegrating procedure has made an important advance on regression analysis, the cointegrating estimates also are subject to a number of limitations(Masih et al, 2008).

- The estimates derived from the cointegrating tests (such as the Johansen test) and the unit root tests (such as, the Augmented Dicky-Fuller, Phillips-Peron, Kwiatkowski-Phillips-Schmidt-Shin etc. which precede the cointegrating tests), are found to be biased. The tests lack power and are biased in favor of accepting the null hypothesis.
- The cointegration tests require the variables to be I(1) but the order of integration of a variable, whether I(1) or I(0), may depend on the number of lags included or whether the intercept and/or the trend are included or excluded in the unit root tests.
- Moreover, the Johansen cointegrating tests have small sample bias and simultaneity bias among the regressors.

To get around the above limitations of the unit root and cointegration tests, this study uses the Auto Regressive Distributive Lag (ARDL) method (bounds testing approach), proposed by Pesaran-Shin-Smith (2001). This approach also does not require the restriction imposed by cointegration technique that the variables are I(1) or I(0), which is the case with the data in the study. (This is seen when the variables have been tested to ensure that they are not I(2) - Appendix)

The existence of long-run relationship among variables is done by constructing an unrestricted error correction model (UECM) with each variable in turn as a dependent variable and then testing whether or not the 'lagged levels of the variables' in each of the error correction equations are statistically significant (i.e., whether the null of 'no long run relationship' is accepted or rejected).The test consists of computing an F-statistic testing the joint significance of the 'lagged levels of the variables' in each of the above error-correction form of the equation. The computed F-statistic is then compared to two asymptotic critical values.

- If the test statistic is above an upper critical value, the null hypothesis of 'no long-run relationship' can be rejected regardless of whether the variables are I(0) or I(1).
- When the test statistic falls below a lower critical value, the null hypothesis of 'no long-run relationship' is accepted regardless of whether the variables are I(0) or (1).
- If the test statistic falls between these two bounds, the result is inconclusive.

If all the F-statistics in all equations happen to be insignificant, then that implies the acceptance of the null of 'no long run relationship' among the variables. However, if at least one of the F-statistics in the error-correction equations is significant, then the null of 'no long-run relationship' among the variables is rejected. In that case there is a long run relationship among the variables. When the F-statistic is significant, the corresponding dependent variable is endogenous and when the F-statistic is insignificant, the corresponding dependent variable is exogenous or called ‘long-run forcing variable’. (For the data under consideration the resultsare part of the Appendix)

After demonstrated of the long run relationship, we can move on to the next stage of the analysis involving the long rung coefficients estimation(after selecting the optimum order of the variables through AIC or SBC criteria) and then estimate the associated error correction model in order to estimate the adjustment coefficients of the error-correction term. As the data used by us is monthly, and considering the variables are equity indices we expect relatively faster adjustment and hence have chosen four for the maximum order of the lags in ARDL model. The error correction version of the ARDL (4, 4,4, 4, 4, 4, 4, 4) that we have estimated is:

$$
\begin{aligned}
DBOV = {} & a_0 + \sum_{i=1}^{4} b_i DBOV_{t-i} + \sum_{i=1}^{4} d_i DMIC_{t-i} + \sum_{i=1}^{4} e_i DNIF_{t-i} + \sum_{i=1}^{4} f_i DSHC_{t-i} + \sum_{i=1}^{4} c_i DJSE_{t-i} \\
& + \sum_{i=1}^{4} g_i DPUI_{t-i} + \sum_{i=1}^{4} h_i DLBR_{t-i} + \sum_{i=1}^{4} i_i DVIX_{t-i} \\
& + \delta_{1_t} LBOV_{t-1} + \delta_2 LMIC_{t-1} + \delta_3 LNIF_{t-1} + \delta_4 LSHC_{t-1} + \delta_5 LJSE_{t-1} + \delta_6 LPUI_{t-1} + \delta_7 LLBR_{t-1} \\
& + \delta_8 LVIX_{t-1} + u_t
\end{aligned}
$$

(e_{t-1}) - lagged error correction term which would be derived from the ECM model would tell us how long it will take to get back to long term equilibrium given a deviation. The coefficient represents proportion of imbalance corrected in each period. The lag structure appropriate to the ECM is determined by Schwarz Bayesian Criteria (SBC), Akaike Information Criteria (AIC), and Adjusted LR Test.

IV. Empirical Results and Discussions:

1. Unit Root Tests:

We begin our empirical testing by determining that the variables used in the study aren't I(2) – Stationary only in the second differenced form and not in the level or first differenced form. In order to proceed with the ARDL technique our variables can be either I(0) or I(1) – stationery in their level form or stationary in their first differenced form. The differenced form for each variable used is created by taking the difference of their log forms. For example, DBOV = LBOV – $LBOV_{t-1}$.We then conducted the Augmented Dickey-Fuller (ADF) the Philips Perron (PP) and the Kwiatkowski–Phillips–Schmidt–Shin(KPSS) test on each variable (in both level and differenced form). The table below summarizes the results. Below is a summary of the ADF test – for the results of the PP & KPSS kindly refer to the Appendix.

Table 1: Summary of the ADF test:

Variable	Test Statistic	Critical Value	Implication
Variables in Level Form			
LBOV	-1.3138	-3.4436	Variable is non-stationary
LJSE	-1.9213	-3.4436	Variable is non-stationary
LLBR	-1.6834 SBC	-3.4436	Variable is non-stationary
	-1.7851 AIC	-3.4389	Variable is non-stationary
LMIC	-1.7245 SBC	-3.4436	Variable is non-stationary
	-1.9376 AIC	-3.4354	Variable is non-stationary
LNIF	-2.3582	-3.4436	Variable is non-stationary
LPUI	-3.2686 SBC	-3.4436	Variable is non-stationary
	-2.7745 AIC	-3.4354	Variable is non-stationary
LSHC	-2.9182 SBC	-3.4389	Variable is non-stationary
	-3.1738 AIC	-3.4608	Variable is non-stationary
LVIX	-3.1503	-3.4436	Variable is non-stationary
Variables in Differenced Form			
DBOV	-8.8570	-2.8970	Variable is stationary
DJSE	-8.9638	-2.8970	Variable is stationary
DLBR	-6.3098	-2.8970	Variable is stationary
	-4.9895	-2.9139	Variable is stationary
DMIC	-7.9184	-2.8970	Variable is stationary
DNIF	-9.1798	-2.8970	Variable is stationary
DPUI	-12.0592 SBC	-2.8970	Variable is stationary
	-10.2453 AIC	-2.9351	Variable is stationary

Variable	Test Statistic	Critical Value	Implication
DSHC	-7.6858 SBC	-2.8970	Variable is stationary
	-4.4567 AIC	-2.9713	Variable is stationary
DVIX	-10.4475	-2.8970	Variable is stationary

Relying primarily on the AIC and SBC criteria, the conclusion that can be made from the above results is that all variablesbeing used for this analysis are I(1) (apart from PUI which is I(0) as per the PP). Also KPSS has conflicting results to the stationarity of many variables in the level form – this is yet another reason for opting for the ARDL approach rather than the standard time series approach. Note that in determining which test statistic to compare with the 95% critical value for the ADF statistic, we have selected the ADF regression order based on the highest computed value for AIC and SBC. In some instances, AIC and SBC give different orders and in that case, we have taken different orders and compared both (for example, this applies to the variable LPUI, LLBR and LMIC, see the table above). This is not an issue as in all cases, the implications are consistent.

2. Selecting the lag length:

In order to estimate the ARDL regression, selection of the lag length is important. The test runs over 4 lags length of 1,2,3 and 4 for the optimum lags. Based on the AIC, SBC and the Adjusted LR test as per Table 1, lag length of 1 has been determined. Thus 1 lag has been further used.

Table 2: Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Order	LL	AIC	SBC	LR test	Adjusted LR test
6	1831	1439	817.541	------	------
5	1789.1	1461.1	941.136	CHSQ(64)= 83.7209[.050]	60.4122[.604]

4	1736	1472	1053.5	CHSQ(128)= 189.8432[.000]	136.9891[.277]
3	1692.5	1492.5	1175.4	CHSQ(192)= 276.9522[.000]	199.8462[.334]
2	1653.5	1517.5	1301.9	CHSQ(256)= 354.9276[.000]	256.1125[.486]
1	1619.6	1547.6 *	1433.5*	CHSQ(320)= 422.7052[.000]	305.0203[.717]*
0	1487	1479	1466.3	CHSQ(384)= 687.9674[.000]	496.4311[.000]

3. Testing long run relationship between the variables:

F-statistics for each equation:

- F (LBOV | LMIC, LNIF, LSHC, LJSE, LPUI, LLBR, LVIX) = 3.8520
- F (LMIC | LBOV, LNIF, LSHC, LJSE, LPUI, LLBR, LVIX) = 0.7537
- F (LNIF | LBOV, LMIC, LSHC, LJSE, LPUI, LLBR, LVIX) = 1.7138
- F (LSHC | LBOV, LMIC, LNIF, LJSE, LPUI, LLBR, LVIX) = 1.6137
- F (LJSE | LBOV, LMIC, LNIF, LSHC, LPUI, LLBR, LVIX) = 3.2964
- F (LPUI | LBOV, LMIC, LNIF, LSHC, LJSE, LLBR, LVIX) = 2.0083
- F (LLBR | LBOV, LMIC, LNIF, LSHC, LJSE, LPUI, LVIX) = 3.2714
- F (LVIX | LBOV, LMIC, LNIF, LSHC, LJSE, LPUI, LLBR) = 3.5770

TABLE 3: F-Statistics for Testing the Existence of Long-Run Relationship

Computed F-Statistic – LBOV	3.8520*
Critical Values at 5 percent level	Lower; upper 2.604; 3.746

The critical values are taken from Pesaran et al. (2001), unrestricted intercept and trend with eight regressors. * denotes rejecting the null at 5 percent level. The range of the critical value at 1 percent and 10 percent are 3.220-4.411 and 2.290-3.383 respectively.

As per the Table 3the calculated F-statistics is higher than the upper bound critical value of 3.746 at the 5% significance level, atleast for one equation (LBOV). This implies that the null hypothesis of no cointegrating long-run relationship can be rejected. These results reveal that a long-run relationship exists between Policy Uncertainty in the US, the Risk Aversion, the Interest Rates and the BRICS equity indices. The evidence of long run relationship rules out the possibility of any spurious relationship existing between the variables. In other words, there is a theoretical relationship existing between the variables.

4. Estimating long run coefficients:

The Error Correction Model's representation of the ARDL model is selected using the Akaike Information Criterion. Following tables provide the estimates of the ARDL long run coefficient for the model. As we are trying to understand the impact of the variables on each of the BRICS markets, Table 4.1-4.5 represent the resultsofEstimatedLong-RunCoefficientsusingthe ARDL Approach – with each market as a dependent variable.

TABLE 4.1: ResultsofEstimatedLong-RunCoefficientsusingthe ARDL Approach – LBOV (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
LJSE	-0.78035	0.20813	0.000*
LLBR	0.036595	0.036755	0.321
LMIC	0.41045	0.097442	0.000*
LNIF	1.1228	0.18464	0.000*
LPUI	0.1611	0.13854	0.247
LSHC	0.11167	0.10938	0.309
LVIX	0.047383	0.1274	0.71
INPT	4.6255	1.0606	0.000*

Note: * denotes significant at 5 percent level

The estimated long run coefficients of the long run relationship above show that the Johannesburg Stock Exchange - JSE, Micex and Nifty have significant effects on the performance of the Bovespa. The coefficient of the Nifty implies that a 1% increase in returns on the Nifty on an average leads to a 1.12% increase in the Bovespa, all things being equal. This effect is also similar to the Micex, whereby a 1% increase in the Micex would lead to a 0.41% increase in the Bovespa. This suggests that these markets complement each other, whereas it is the opposite for the Johannesberg stock exchange whereby a 1% increase in the JSE leads to the Bovespa to drop by 0.78%.

What is however seen is that the US Policy uncertainty, the VIX and the Libor are not statistically significant and thus do not impact the Bovespa.

TABLE 4.2: ResultsofEstimatedLong-RunCoefficientsusingthe ARDL Approach – LMIC (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
LNIF	-0.38757	0.78774	0.623
LBOV	0.78618	0.55795	0.161
LJSE	0.46767	0.59458	0.433
LSHC	0.10499	0.36293	0.773
LLBR	-0.10335	0.13552	0.447
LPUI	-0.26919	0.48583	0.58
LVIX	-0.48975	0.41434	0.239
INPT	-1.0075	3.5502	0.777

Table 4.2 suggests that none of the variables in the model are significant and thus have no impact on the MICEX. This points out to other factors which drive the MICEX such as its growth rather than included variables. As this index and the Russian economy is a commodity driven economy, it could be the case that factors such as oil and other commodity markets drive it.

TABLE 4.3: ResultsofEstimatedLong-RunCoefficientsusingthe ARDL Approach – LNIF (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
LBOV	0.44598	0.21563	0.040*
LJSE	0.4783	0.20427	0.020*
LMIC	0.16598	0.18375	0.368
LSHC	-0.068393	0.16758	0.684
LLBR	-0.098916	0.061834	0.112
LPUI	-0.47125	0.27158	.085**
LVIX	0.086841	0.19732	0.66
INPT	0.077678	1.8503	0.967

Note: * denotes significant at 5 percent level **denotes significant at 10 percent level

The Nifty as per Table 4.3 in the long term is impacted by the Bovespa and the Johannesburg Stock Exchange. It could be the case that foreign portfolio investments into and out of these three countries happens in tandem, which is depicted by the coefficients of LBOV and LJSE. A 1% increase in the Bovespa and the JSE leads to an app 0.45% and 0.47% increase respectively in the Nifty.

Besides the US Policy uncertainty index is significant and negative, this implies that the Indian stock markets do observe economic policy conditions in the US and a 1% increase in the uncertainty leads to the market to go down by 0.47%. This could also indicate that the Nifty is integrated with the US and considering the Foreign Institutional flows originating from the US funds into India, it is not a surprise – If there is uncertainty in the home country, funds and people would want to get out from emerging markets like India.

TABLE 4.4: ResultsofEstimatedLong-RunCoefficientsusingthe ARDL Approach – SHC (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
LNIF	3.0653	1.6239	0.061**
LBOV	-1.4433	1.1162	0.198

LJSE	-0.92015	0.91978	0.319
LMIC	-0.15405	0.41646	0.712
LLBR	0.22187	0.17075	0.196
LPUI	-0.4128	0.64516	0.523
LVIX	0.62097	0.46145	0.18
INPT	8.3408	5.5582	0.135

Note: * denotes significant at 5 percent level **denotes significant at 10 percent level

The above table shows that none of the variables apart from the Nifty are significant. Considering China and India have been two economies which have outclassed the others in the BRICS, they have been major beneficiaries of Foreign Institutional monies. This could be the reason whereby a 1% increase in the Nifty would lead to a 3% increase in the Shanghai Composite and veceversaa fall as well. The Chinese markets have also been suffering from the lack of transparency, which has led to money movement to other markets like India.

TABLE 4.5: ResultsofEstimatedLong-RunCoefficientsusingthe ARDL Approach – JSE (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
LMIC	-0.23586	0.37786	0.533
LNIF	0.81562	0.50579	0.109
LBOV	0.22734	0.61906	0.714
LSHC	0.041694	0.31207	0.894
LLBR	-0.049945	0.10826	0.645
LPUI	0.19747	0.43428	0.65
LVIX	-0.96771	0.68209	0.158
INPT	4.3415	2.2637	0.057

South Africa has been a recent addition to the BRICS and probably that is one reason none of the variables are significant. Being a part of this group would mean that a number of Exchange Traded Funds (ETF's) and Emerging Market funds would make South African equities part of their portfolio, however as discussed being a recent entry this may not reflect in the long run equation. Thus the major determinant of this index would be the country's internal factors, GDP, macro-economic performance etc.

5. Error Correction Models:

A long run relationship between the variables is indicated by cointegration, however there could be a short-run deviation from the long-run equilibrium. Cointegration does not unfold the process of short-run adjustment to bring about the long-run equilibrium. The error correction model in Tables 4.1-4.5 help us to understand this. The 'p' value of the error-correction coefficient indicates if the deviation from equilibrium (represented by the error-correction term) has a significant feedback effect on the dependent variable (i.e. each of the BRICS equity indices). i.e. If the dependent variable is endogenous or exogenous. The error-correction coefficient being significant confirms the significant long-run cointegrating relationship between the variables. Also the speed of short-run adjustment of the dependent variable to bring about the long-run equilibrium is indicated by the size of the coefficient of the error-correction term. The size of the coefficient of the error-correction term is also indicative of the intensity of the arbitrage activity to bring about the long-run equilibrium.

Table 5.1 ResultsofErrorCorrectionModels – ΔLBOV (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
ΔLJSE	0.58197	0.093918	0.000*
ΔLLBR	0.0055568	0.0058009	0.339
ΔLMIC	0.2023	0.047741	0.000*
ΔLNIF	0.0069682	0.061665	0.91
ΔLPUI	0.024463	0.022035	0.268
ΔLSHC	0.016956	0.016429	0.303
ΔLVIX	-0.067815	0.03122	0.031*

Ecm(-1)	-0.15185	0.030294	0.000*

Note: * denotes significant at 5 percent level

Table 5.2 ResultsofErrorCorrectionModels – ΔLMIC (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
ΔLNIF	-0.02707	0.055483	0.626
ΔLBOV	0.47388	0.10829	0.000*
ΔLJSE	0.4713	0.15382	0.003*
ΔLSHC	0.0073332	0.024956	0.769
ΔLLBR	-0.0072188	0.008814	0.414
ΔLPUI	-0.018801	0.033398	0.574
ΔLVIX	-0.034207	0.028815	0.237
ecm(-1)	-0.069845	0.023927	0.004*

Note: * denotes significant at 5 percent level

Table 5.3 ResultsofErrorCorrectionModels – ΔLNIF (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
ΔLBOV	0.055602	0.039358	0.16
ΔLJSE	0.059632	0.038256	0.121
ΔLMIC	0.020694	0.019719	0.295
ΔLSHC	-0.0085269	0.020119	0.672
ΔLLBR	-0.012332	0.0073803	0.097
ΔLPUI	0.015564	0.033368	0.641
ΔLVIX	-0.23362	0.034631	0.000*
ecm(-1)	-0.12467	0.050648	0.015*

Note: * denotes significant at 5 percent level

Table 5.4 ResultsofErrorCorrectionModels – ΔLSHC (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
ΔLNIF	0.020043	0.084604	0.813
ΔLBOV	0.21107	0.10006	0.036*
ΔLJSE	-0.054374	0.048279	0.262
ΔLMIC	0.098756	0.075279	0.191
ΔLLBR	0.013111	0.0093318	0.162
ΔLPUI	0.037025	0.040757	0.365
ΔLVIX	0.036695	0.028919	0.206
ecm(-1)	-0.059093	0.025112	0.020*

Note: * denotes significant at 5 percent level

Table 5.5 ResultsofErrorCorrectionModels – ΔLJSE (DEP)

Independent Variable	Coefficient	Standard Error	P-Value
ΔLMIC	0.10478	0.035784	0.004*
ΔLNIF	0.031303	0.027185	0.251
ΔLBOV	0.3137	0.04974	0.000*
ΔLSHC	0.0016002	0.011984	0.894
ΔLLBR	-0.060705	0.029626	0.042*
ΔLPUI	0.0075786	0.016121	0.639
ΔLVIX	-0.0025568	0.021949	0.907
ecm(-1)	-0.038379	0.021595	0.077

Note: * denotes significant at 5 percent level

The error correction terms of ΔLBOV -> -0.15185(0.000), ΔLMIC -> -0.069845 (.004), ΔLNIF -> -0.12467 (0.015), and ΔLSHC -> -0.059093 (0.020)are significant and also have the correct sign, this implies a moderate speed of adjustment after a shock. In the above cases 15.2%, 7%, 12.5% and 6% of the previous period's (months) shocks adjusts to the long run equilibrium in the current quarter.

Also the 'p'values of the coefficients of the differenced variables indicate if the effects of these variables on the individual BRICS markets are significant. We broadly find similar significant effects of the other BRICS markets as seen in the long run, however in the ΔLJSE ->ΔLLBR and ΔLBOV / ΔLNIF -> ΔVIX significant in the short run. These indicate that in the short run the risk off trade does affect the Brazilian and the Indian stock markets and the leveraging in the case of the South African equity market.

6. Variance Decomposition:

Variance decomposition (VDC) helps us ascertain relative endogeneity and exogeneity. VDC decomposes the variance of forecast error of each variable into proportions attributable to shocks from each variable in the system, including its own. The least endogenous variable is thus the variable whose variation is explained mostly by its own past variations.

I first apply orthogonalized VDCs and obtained the following results. Considering the data is on stock market indices, we forecast for a time horizon of 12 (months) i.e. a year.

	DBOV	DJSE	DLBR	DMIC	DNIF	DPUI	DSHC	DVIX
DBOV	0.56997	0.00145	0.01247	0.00051	0.35369	0.01749	0.01501	0.02942
DJSE	0.12327	0.53533	0.00601	0.00316	0.25635	0.03531	0.02180	0.01877
DLBR	0.00281	0.02497	0.90346	0.02307	0.02174	0.00195	0.01496	0.00706
DMIC	0.10815	0.03329	0.00669	0.57885	0.19897	0.01033	0.03768	0.02604
DNIF	0.01943	0.00244	0.02080	0.00555	0.91137	0.00374	0.02116	0.01552
DPUI	0.01493	0.00290	0.01024	0.00127	0.01752	0.94513	0.00119	0.00683
DSHC	0.02048	0.00044	0.02641	0.00930	0.08018	0.01338	0.84869	0.00112
DVIX	0.07395	0.00257	0.05861	0.00218	0.20191	0.12642	0.00782	0.52655

For the above table, rows read as the percentage of the variance of forecast error of each variable into proportions attributable to shocks from all variables (in columns), including its own. The columns read as the percentage in which that variable contributes to other variables in explaining observed changes. The diagonal line of the matrix (highlighted) represents the relative exogeneity. According to these results, the ranking of indices by degree of exogeneity (extent to which variation is explained by its own past variations) is as per the table below:

No.	Variable
1	DPUI
2	DNIF
3	DLBR
4	DSHC
5	DMIC
6	DBOV
7	DJSE
8	DVIX

However the results above give contradictory results to the VECM. Thus we need to recognize two important limitations of orthogonalized VDCs.

- It assumes that when a particular variable is shocked, all other variables are "switched off"

- More importantly, in orthogonalized VDCs the generated numbers are dependent upon the ordering of variables in the VAR. Thus, the first variable would report the highest percentage andis likely to be specified as the most exogenous variable.

Considering this limitation, we decided to rely instead on Generalized VDCs, which are invariant to the ordering of variables. In interpreting the numbers generated by the Generalized VDCs, we needed to perform additional computations. This is because the numbers do not add up to 100% or 1 as in the case of orthogonalized VDCs. For a given variable, at a specified horizon, we totaled up the numbers of the given row and we then divide the number for that variable (representing magnitude of variance explained by its own past) by the computed total. In this way, the numbers in a row will now add up to 1.0 or 100%. The tables below show the result, we forecast for a time horizon of 12 (months) i.e. a year.

	DBOV	DJSE	DLBR	DMIC	DNIF	DPUI	DSHC	DVIX
DBOV	0.38948	0.06722	0.01293	0.04135	0.26250	0.03992	0.01380	0.17281
DJSE	0.08372	0.45681	0.01415	0.05118	0.20380	0.05246	0.00951	0.12838
DLBR	0.00248	0.01582	0.87169	0.02022	0.02179	0.01174	0.01206	0.04420
DMIC	0.07739	0.06057	0.01123	0.51242	0.16289	0.02544	0.02970	0.12036
DNIF	0.01474	0.00685	0.01916	0.00058	0.74151	0.02180	0.01493	0.18043
DPUI	0.01167	0.00785	0.00962	0.00282	0.02005	0.77542	0.00862	0.16395
DSHC	0.01839	0.00449	0.02309	0.01491	0.07751	0.01723	0.81166	0.03272
DVIX	0.04581	0.00747	0.04492	0.01180	0.15727	0.13111	0.00454	0.59707

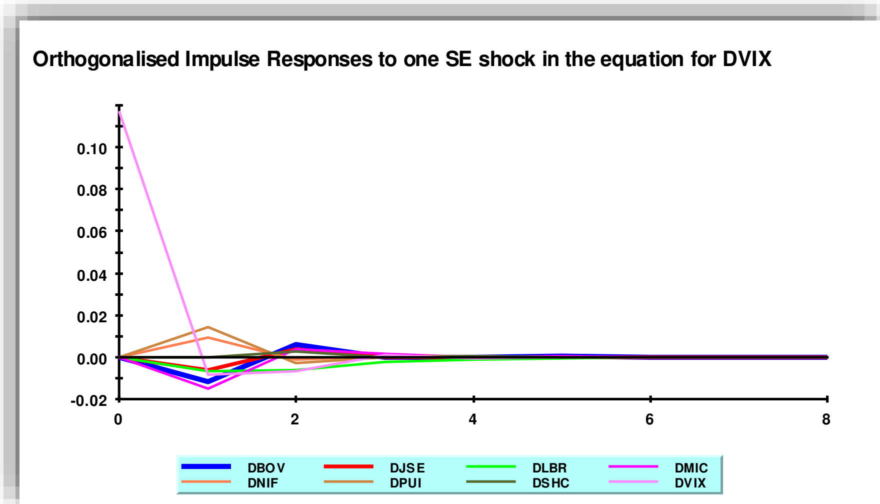
According to these results, the ranking of indices by degree of exogeneity (extent to which the variation is explained by its own past variations) is as per the table below:

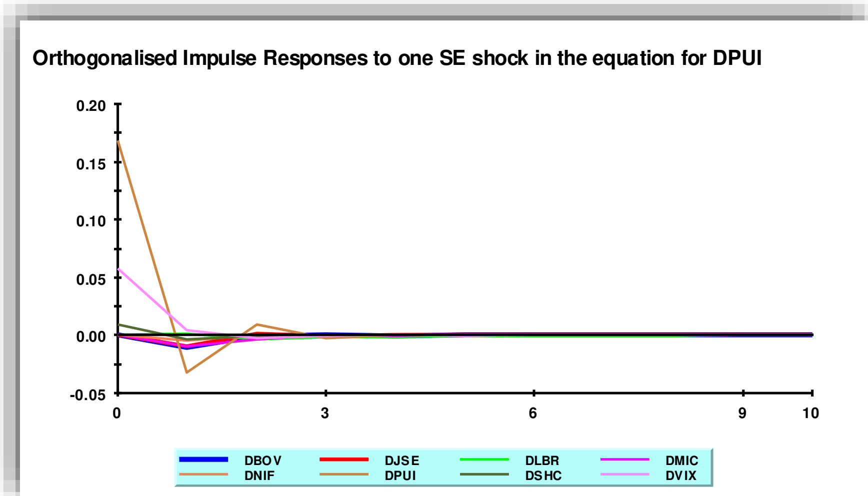
No.	Variable
1	DLBR
2	DSHC
3	DPUI
4	DNIF
5	DVIX
6	DMIC
7	DJSE
8	DBOV

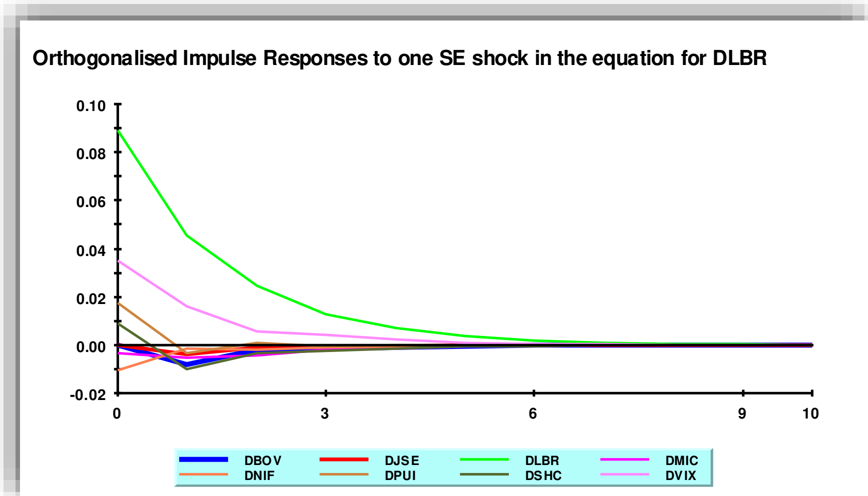
The above results are slightly off with the results as per the VECM, whereby as per the VDC the Shanghai Composite is the second most exogenous variable and the VIX index is the second most endogenous variable. However these results by themselves may not be reliable as all the variable are forced with the same number of lags which is not the case with ARDL, where the optimum number of lags are assigned to each variable. Thus using the first approach to find relative endogeneity/exogeneity may not be appropriate.

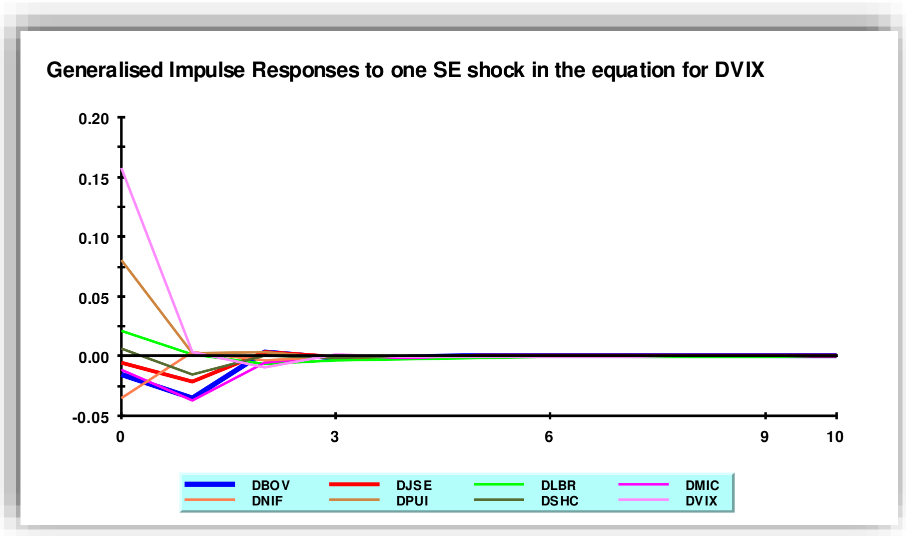
7. Impulse Response:

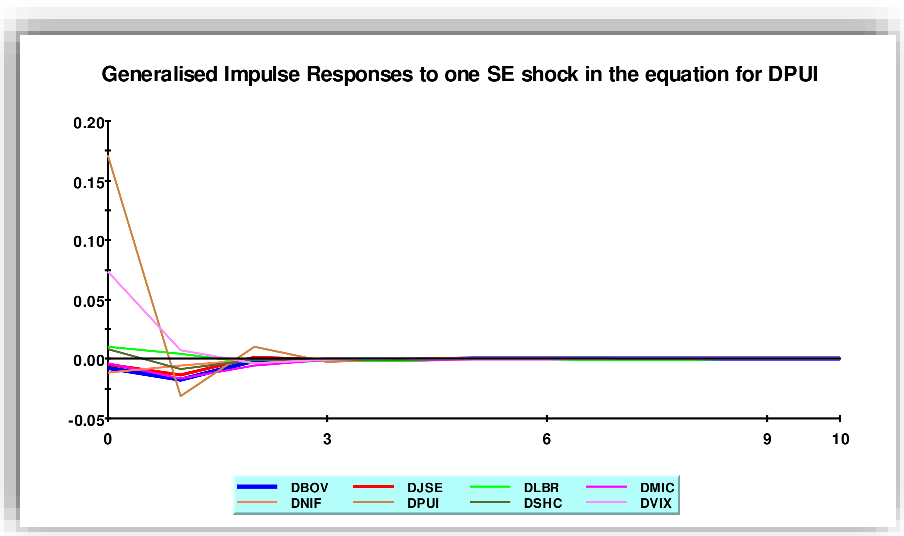
The impulse response functions (IRFs) essentially produces the same information as the VDCs, except that they can be presented in graphical form. Rather than shocking all the variables, in order to make the exercise meaningful below we shock only the exogenous variables of Policy Uncertainty, Libor and the VIX (As per the VECM) and observe the effects on the other variables. What can be seen from the graphs below is that all the variables revert back the equilibrium within a period ranging from two to seven months.

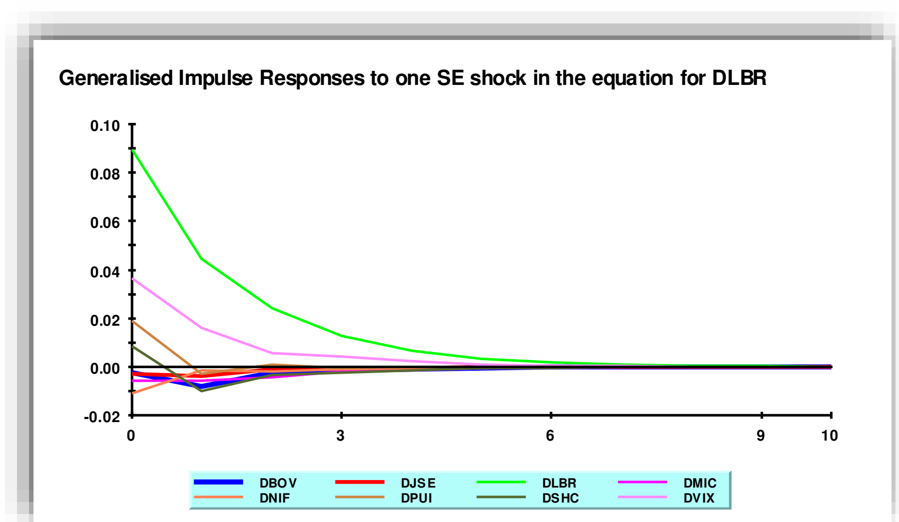

Orthogonalised Impulse Responses to one SE shock in the equation for DVIX
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
0
2
4
6
8
DBOV
DJSE
DLBR
DMIC
DNIF
DPUI
DSHC
DVIX


Orthogonalised Impulse Responses to one SE shock in the equation for DPUI
0.20
0.15
0.10
0.05
0.00
-0.05
0
3
6
9
10
DBOV
DJSE
DLBR
DMIC
DNIF
DPUI
DSHC
DVIX


Orthogonalised Impulse Responses to one SE shock in the equation for DLBR
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
0
3
6
9
10
DBOV
DJSE
DLBR
DMIC
DNIF
DPUI
DSHC
DVIX


Generalised Impulse Responses to one SE shock in the equation for DVIX
0.20
0.15
0.10
0.05
0.00
-0.05
0
3
6
9
10
DBOV
DJSE
DLBR
DMIC
DNIF
DPUI
DSHC
DVIX


Generalised Impulse Responses to one SE shock in the equation for DPUI
0.20
0.15
0.10
0.05
0.00
-0.05
0
3
6
9
10
DBOV
DJSE
DLBR
DMIC
DNIF
DPUI
DSHC
DVIX


Generalised Impulse Responses to one SE shock in the equation for DLBR
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
0
3
6
9
10
DBOV
DJSE
DLBR
DMIC
DNIF
DPUI
DSHC
DVIX

8. Concluding Remarks and Policy Implications:

Brazil, Russia, India, China and India, known as the BRIC countries form a significant part and play an important role in the world economy. Due to the increased economic and financial integration within the world economy shocks originating from the advanced world such as the US can have a significant impact on the BRIC's economies. Based on the data and the result analysis, it seems that although there is co-integration amongst these equity markets and the variables depicting policy uncertainty and risk aversion, they only significantly impact few of the indices in the short run. Most of these markets, over the years have been trying to develop institutions and domestic retail investors to form a back-up to the hot money moving in and out of these markets. It could be the case that they are succeeding in doing so, also could be the case that considering the nuances of the lack of development, transparency, liquidity etc. has been keeping away large institutional sources of money away from the BRICS markets.

This study contributes to further the understanding of global transmission of economic and financial shocks. The finding suggests that the stock market performance in Brazil, Russia, China and South Africa are not linked to the policy uncertainty and risk aversion trades in the U.S. However the findings imply that market participants in the Indian stock markets do observe economic policy conditions in the US.

Another view could be the case that in the long run the factors external to the economies do not affect the BRICS markets much, which could have implication to the investors in the developing world. Thus the BRICS equity markets can be looked at as a great diversification strategy to the developed world.

References:

Ahmad, A. H., Nurazira, M. D. S., &Ainulashikin, M. (2008). Sovereign Credit Ratings and Macroeconomic Variables: An Empirical Analysis on Dynamic Linkages in Malaysia Using Bound Test Approach. The IUP Journal of Applied Economics, 7(6), 29-39.

Al Awad, M., & Goodwin, B. K. (1998). Dynamic linkages among real interest rates in international capital markets. Journal of International Money and Finance, 17(6), 881-907.

Aloui, R., Aïssa, M. S. B., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure?.Journal of Banking & Finance, 35(1), 130-141.

Aye, G. C., Balcilar, M., Gupta, R., Kilimani, N., Nakumuryango, A., & Redford, S. (2014). Predicting BRICS stock returns using ARFIMA models. Applied Financial Economics, 24(17), 1159-1166.

Bansal, R., Khatchatrian, V., &Yaron, A. (2005). Interpretable asset markets?.European Economic Review, 49(3), 531-560.

Bekiros, S. D. (2013). Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. International Review of Financial Analysis, 33, 58-69.

Berger, D., & Turtle, H. J. (2011). Emerging market crises and US equity market returns. Global Finance Journal, 22(1), 32-41.

Celık, S. (2012). The more contagion effect on emerging markets: The evidence of DCC-GARCH model. Economic Modelling, 29(5), 1946-1959.

Cheng, H. F., Gutierrez, M., Mahajan, A., Shachmurove, Y., & Shahrokhi, M. (2007). A future global economy to be built by BRICs. Global Finance Journal, 18(2), 143-156.

Chinn, M., & Frankel, J. A. (2007). Will the euro eventually surpass the dollar as leading international reserve currency?. In G7 Current account imbalances: sustainability and adjustment (pp. 283-338). University of Chicago Press.

Chkili, W., & Nguyen, D. K. (2014). Exchange rate movements and stock market returns in a regime-switching environment: Evidence for BRICS countries. Research in International Business and Finance, 31, 46-56.

Cooper, I., & Priestley, R. (2009). Time-varying risk premiums and the output gap. Review of Financial Studies, 22(7), 2801-2833.

De Vries, G. J., Erumban, A. A., Timmer, M. P., Voskoboynikov, I., & Wu, H. X. (2012). Deconstructing the BRICs: Structural transformation and aggregate productivity growth. Journal of Comparative Economics, 40(2), 211-227.

Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach.International Review of Financial Analysis, 30, 46-56.

Dzielinski, M. (2011). Measuring economic uncertainty and its impact on the stock market. Finance Research Letters, 9(3), 167-175.

Ehrmann, M., Fratzscher, M., &Rigobon, R. (2011). Stocks, bonds, money markets and exchange rates: measuring international financial transmission. Journal of Applied Econometrics, 26(6), 948-974.

Ehrmann, M., &Fratzscher, M. (2006). Global financial transmission of monetary policy shocks*. Oxford Bulletin of Economics and Statistics, 71(6), 739-759.

Ehrmann, M., &Fratzscher, M. (2005). Equal Size, Equal Role? Interest Rate Interdependence Between the Euro Area and the United States*. The Economic Journal, 115(506), 928-948.

Forbes, K. J., & Chinn, M. D. (2004). A decomposition of global linkages in financial markets over time. Review of Economics and Statistics, 86(3), 705-722.

Frank, W. P., & Frank, E. C. (2010). International business challenge: can the BRIC countries take world economic leadership away from the traditional leadership in the near future. International Journal of Arts and Sciences, 3(13), 46-54.

Hammoudeh, S., Sari, R., Uzunkaya, M., & Liu, T. (2013). The dynamics of BRICS's country risk ratings and domestic stock markets, US stock market and oil price. Mathematics and Computers in Simulation, 94, 277-294.

Hausman, J., &Wongswan, J. (2011). Global asset prices and FOMC announcements. Journal of International Money and Finance, 30(3), 547-571.

Hwang, E., Min, H. G., Kim, B. H., & Kim, H. (2013). Determinants of stock market comovements among US and emerging economies during the US financial crisis. Economic Modelling, 35, 338-348.

Kenourgios, D., Samitas, A., &Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. Journal of International Financial Markets, Institutions and Money, 21(1), 92-106.

King, M. A., &Wadhwani, S. (1990). Transmission of volatility between stock markets. Review of Financial studies, 3(1), 5-33.

Manamperi, N. (2014). The short and long-run dynamics between inflation and economic growth in BRICS. Applied Economics Letters, 21(2), 140-145.

Masih, M., &Algahtani, I. (2008). Estimation of long-run demand for money: An application of long-run structural modelling to Saudi Arabia. EconomiaInternazionale/International Economics, 61(1), 81-99.

Menzly, L., Santos, T., & Veronesi, P. (2004). Understanding predictability. Journal of Political Economy, 112(1), 1-47.

Ono, S. (2011). Oil price shocks and stock markets in BRICs. The European Journal of Comparative Economics, 8(1), 29-45.Aloui et al. (2011)

Ozoguz, A. (2009). Good times or bad times? Investors' uncertainty and stock returns. Review of Financial Studies, 22(11), 4377-4422.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289-326.

Pradhan, R. P., Dasgupta, P. R. A. T. E. E. K., &Samadhan, B. (2013). Finance development and economic growth in BRICS: A panel data analysis. Journal of Quantitative Economics, 11(1&2), 308-322.

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets?.Journal of Multinational Financial Management, 22(3), 55-65.

Śledzik, K. (2012). BRICS, MIST (MIKT) or G5-Which'Club'of Economies Has the Biggest Growth Potential?.Available at SSRN 2192004.

Stollinger, R., Pindyuk, O., Hunya, G., Dachs, B., Lennon, C., Poplawski Ribeiro, M., ...& Christie, E. (2009). EU and BRICs: Challenges and opportunities for European competitiveness and cooperation. EUR-OP.

Sum, V. (2012). Economic policy uncertainty and stock market performance: evidence from the European Union, Croatia, Norway, Russia, Switzerland, Turkey and Ukraine. Journal of Money, Investment and Banking, 25, 99-104.

Syriopoulos, T., &Roumpis, E. (2009). Asset allocation and value at risk in shipping equity portfolios. Maritime Policy & Management, 36(1), 57-78.

Syriopoulos, T., Makram, B., &Boubaker, A. (2013). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. International Review of Financial Analysis, 39, 7-18.

Wongswan, J. (2006). Transmission of information across international equity markets. Review of Financial Studies, 19(4), 1157-1189.

Wilson, D., &Purushothaman, R. (2003). Dreaming with brics: The path to 2050 (goldman&sachs, global economics paper no. 99). Goldman Sachs.

Zhang, B., Li, X., & Yu, H. (2013). Has recent financial crisis changed permanently the correlations between BRICS and developed stock markets?.The North American Journal of Economics and Finance, 26, 725-738.