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Are the emerging bric stock markets efficient?

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Abstract

The study examines the weak form efficiency in stock returns for the economies of Brazil, Russia, India and China (BRIC), from January 2000 to December 2010. The study uses LM unit root test with one and two structural breaks as given by Lee and Strazicich (2003, 2004), along with the recently developed ADF type unit root test having two structural breaks as proposed by Narayan and Popp (2010). Subsequently, the BDS and K2k tests were used for checking the i.i.d properties of stock returns. We find the existence of unit root among the stock returns of the BRIC economies. However, these stock returns are not weak form market efficient as they do not follow the i.i.d property indicated by the K2k test that is also required for fulfillment of weak form efficiency (Rahman and Saadi, 2008).

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1. Introduction

The phenomenal growth in emerging markets has attracted the attention of researchers from all over the world. The existence of informational inefficiency in these markets could enable investors to get higher returns.

As pointed out by Singh (1995) developing countries face constraints that are not binding for developed countries, such as low domestic saving ratios and limited access to international capital markets. Studies point to the existence of market inefficiencies in stock markets that discourages foreign and domestic investors. In the absence of an efficient capital market, there can be misallocation of resources that harms economic development of the country.

Existing work in the area of stock market efficiency uses the ADF type unit root test, which examines the weak form efficiency of stock indices. Lee and Strazicich (2003, 2004) show that the ADF type tests of given by Zivot and Andrews (1992) and Lumsdaine and Papell (1997) examine the existence of a break-point for a period prior to the true break-point (i.e., TB_{t-1} rather than TB_t). Hence, both the tests have a bias in estimating the true parameter, which causes a spurious result. This limitation was later overcome by Lee and Strazicich (2003) who proposed the LM based unit root test having two structural breaks. In their subsequent paper in 2004, they proposed a minimum Lagrange Multiplier (LM) unit root test with one break. However, Popp (2008) remarked that spurious regression arose from different interpretations of test parameter under the null and alternative hypothesis, since the parameters impact the selection of the break date. Narayan and Popp (2010) (hereafter NP) solved this problem (following Schmidt and Phillips, 1992) by developing an ADF type test for the case of innovational outlier (IO), where the Data Generating Process is formulated as an unobserved component model. NP (2010) claims that in the new test "critical values (CVs) of the test, assuming unknown break dates, converge with increasing sample size to the CVs when break points are known".
The present study is based on the work of Lee and Strazicich (2003, 2004) LM unit roots tests with incorporation of one break and two breaks. We also use the Narayan and Popp two break unit root test for examining the efficiency of emerging stock markets in BRIC countries.

2. Methodology

Let us consider the following data generating process (DGP) in the application of Lagrange Multiplier (LM) unit root tests; Lee and Strazicich (2004) LM tests with one break and Lee and Strazicich (2004) LM test with two structural breaks.
$y = \delta Z_t + e_{t,}\ \ e_t = \beta e_{t-1} + \varepsilon_t$ ………………. (1), where Z_t a vector of exogenous variables is, δ is a vector of parameters and ε_t is a white noise process, such that $\varepsilon_t \sim NIID(0, \sigma^2)$. first, we will consider the case when there is evidence of one structural break. The Crash model that allows shift in level only is described by $Z_t = [1, t, D_t]'$, and the break model that allows for changes in both level and trend is described as $Z_t = [1, t, D_t, DT_t]'$, where D_t and DT_t are two dummies defined as: $D_t = 1, if\ \ t \geq T_B + 1$, =0, otherwise, and
$DT_t = t - T_B, if\ \ t \geq T_B + 1$, =0, otherwise, where T_B is the time period of the break date.

Next, let us consider the framework that allows for two structural breaks. The crash model that considers two shifts in the level is described by $Z_t = [1, t, D_{1t}, D_{2t}]]'$, and the break model that allows for two changes in both level and trend is described as $Z_t = [1, t, D_{1t}, DT_{1t}, D_{2t}, DT_{2t}]'$, where D_{jt} and DT_{jt} for j = 1, 2 are appropriate dummies defined as above, such as,

$D_{jt} = 1, if\ \ t \geq T_{Bj} + 1$, =0, otherwise, and

$DT_{tj} = t - T_{Bj}, if\ \ t \geq T_{Bj} + 1$, =0, otherwise, where T_{Bj} is the j[th] break date.

The main advantage of (Lee and Strazicich, 2003, 2004) approach to unit root test is that it allows for breaks under the null (β = 1) and alternative (β < 1) in the DGP given in equation (1). This method uses the following regression to obtain the LM unit root test statistics

$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta \tilde{S}_{t-j} + u_t$ ……………………… (2), where $\tilde{S}_t = y_t - \tilde{\Psi}_t - Z_t \tilde{\delta}, t = 2, \ldots, T; \tilde{\delta}$ denotes the regression coefficient of Δy_t on ΔZ_t and $\tilde{\Psi}_t = y_t - Z_1 \tilde{\delta}, y_1$ and Z_1 being first observations of y_t and Z_t respectively. The lagged term $\Delta \tilde{S}_{t-j}$ are included to correct for likely serial correlation in errors. Using the above equation, the null hypothesis of unit root test $(\phi = 0)$ is tested by the LM t-statistics. The location of the structural break or structural breaks is determined by selecting all possible breaks for the minimum t-statistic as follows:

$\ln f\tilde{\tau}(\bar{\lambda}_i) = \ln_{\lambda} f\tilde{\tau}(\lambda)$, where $\lambda = T_B / T$.

The search is carried out over the trimming region (0.10*T*, 0.80*T*), where *T* is sample size and T_B denotes date of structural break. We determined the breaks where the endogenous two-break LM t-test statistic is at a minimum. The critical values are tabulated in Lee and Strazicich (2003, 2004) for the two-break and one-break cases respectively. To select the lag length (k) we use the't-sig' approach[1] proposed by Hall (1994). This involves starting with a predetermined upper bound *k*. If the last included lag is significant, *k* is chosen. However, if k is insignificant, it is reduced by one lag until the last lag becomes significant. If no lags are significant k is set equal to zero.

In a recent study, Narayan and Popp (2010) developed a more advanced unit root test is than vis-à-vis the LS (2003, 2004) unit root tests. It is an ADF type IO (Innovational Outlier) unit root test, specifies the Data Generating Process (DGP) as an unobserved components model. Secondly, it allows break under null and alternative hypothesis and Narayan and Popp claim that the "critical values (CVs) of the test, assuming unknown break dates, converge with increasing sample size to the CVs when break points are known". Therefore, it identifies the break point more accurately than the earlier tests. Further, Narayan and Popp (2010) claimed that the rejection frequency is relatively less in their test. Therefore, we used NP test also in our analysis.

Narayan and Popp (2010) defined the test as follows[2]. Suppose, we consider an unobserved components model to represent the DGP and the DGP of the time series y_t has two components, a deterministic component (d_t) and a stochastic component (u_t), as follows:

$y_t = d_t + u_t$,....................(3) ,

$u_t = \rho u_{t-1} + \varepsilon_t$,....................(4) , $\varepsilon_t = \Psi^*(L) e_t = A^*(L)^{-1} B(L) e_t$,....................(5)

e_t is a white noise process, such that $e_t \sim NIID(0, \sigma^2)$. By assuming that the roots of the lag polynomials *A*(L)* and *B(L)*, which are of order *p* and *q*, respectively, lie outside the unit circle NP (2010) considered two different specifications for trending data- one allows for two breaks in level (denoted as model 1 i.e., M1) and the other allows for two breaks in level as well as slope

[1] The't-sig' approach has been shown to produce test statistics which have better properties in terms of size and power than information-based methods such as the Akaike Information Criterion or Schwartz Bayesian Criterion (see for example, Hall 1994, Ng and Perron, 1995).

[2] This section is havely drawn from the study Narayan and Popp (2010).

(denoted as model 2 i.e., M2). The specification of both models differs in terms of the definition of the deterministic component, $d_{t,}$:

$$d_t^{M1} = \alpha + \beta t + \Psi^*(L)(\theta_1 DU'_{1,t} + \theta_2 DU'_{2,t}), \ldots\ldots\ldots\ldots\ldots (6)$$

$$d_t^{M2} = \alpha + \beta t + \Psi^*(L)(\theta_1 DU'_{1,t} + \theta_2 DU'_{2,t} + \gamma_1 DT'_{1,t} + \gamma_2 DT'_{2,t}), \ldots\ldots\ldots\ldots\ldots (7)$$

With $DU'_{i,t} = 1(t > T'_{B,i}), DT'_{i,t} = 1(t > T'_{B,i})(t - DT'_{B,i}), i = 1,2.$ ....(8)

where, $T'_{B,i}$, i = 1, 2, denote the true break dates, θi and γi, indicate the magnitude of the level and slope breaks, respectively. The inclusion of $\Psi^*(L)$ in Equations (3) enables the breaks to occur slowly over time i.e., it assumes that the series responds to shocks to the trend function the way it reacts to shocks to the innovation process e_t (Vogelsang and Perron, 1998). This process is known as the IO model and the IO-type test regressions to test for the unit root hypothesis for M1 and M2 can be derived by merging the structural model (3)-(7). The test regressions can be derived from the corresponding structural model in reduced form as follows:

$$y_t^{M1} = \rho y_{t-1} + \alpha_1 + \beta^* t + \theta_1 D(T'_B)_{1,t} + \theta_2 D(T'_B)_{2,t} + \delta_1 DU'_{1,t-1} + \delta_2 DU'_{2,t-1} + \sum_{j=1}^{k} \beta_j \Delta y_{t-j} + e_t, ..(9)$$

With $\alpha_1 = \Psi^*(1)^{-1}[(1-\rho)\alpha + \rho\beta] + \Psi^{*\prime}(1)^{-1}(1-\rho)\beta, \Psi^{*\prime}(1)^{-1}$ being the mean lag,

$$\beta^* = \Psi^*(1)^{-1}(1-\rho)\beta, \phi = \rho - 1, \delta_i = -\phi\theta_i \, and D(T'_B)_{i,t} = 1(t = T'_{B,i} + 1), i = 1,2.$$

$$y_t^{M2} = \rho y_{t-1} + \alpha^* + \beta^* t + \kappa_1 D(T'_B)_{1,t} + \kappa_2 D(T'_B)_{2,t} + \delta_1^* DU'_{1,t-1} + \delta_2^* DU'_{2,t-1} + \gamma_1^* DT'_{1,t-1} + \gamma_2^* DT'_{2,t-1}$$
$$+ \sum_{j=1}^{k} \beta_j \Delta y_{t-j} + e_t, \ldots(10)$$

where equation (13) and (14) are IO-type test regression for M1 and M2 respectively, $\kappa_i = (\theta_i + \gamma_i), \delta_i^* = (\gamma_i - \phi\theta_i), and \ \gamma_i^* = -\phi\gamma_i, i = 1,2.$

In order to test the unit root null hypothesis of ρ = 1 against the alternative hypothesis of ρ < 1, we use the t –statistics of $\hat{\rho}$, denoted $t_{\hat{\rho}}$, in Equations (9) and (10). Since it is assumed that true break dates are unknown, $T'_{B,i}$ in equations (9) and (10) has to be substituted by their estimates $T'_{B,i}$, I = 1, 2, in order to conduct the unit root test. The break dates can be selected simultaneously following a grid search procedure or a sequential procedure comparable to Kapetanios (2005). Narayan and Poop (2010) have preferred sequential procedure as because it is far less computationally demanding therefore; we have also followed sequential procedure.

The first step in this case is the search for a single break according to the maximum absolute t-value of the break dummy coefficient θ_1 for M1 and κ_1 for M2. Thereafter, we impose the restriction $\theta_2 = \delta_2 = 0$ for M1 and $\kappa_2 = \delta = \gamma = 0$ for M2 and hence, we have:

$$T'_{B,1} = \begin{cases} \arg\max_{T_{B,1}} \left| t_{\hat{\theta}_1}(T_{B,1}) \right|, \ for \ M1, \\ \arg\max_{T_{B,1}} \left| t_{\hat{\kappa}_1}(T_{B,1}) \right|, \ for \ M2 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Therefore, in the first step, the test procedure reduces to the case described in (Popp, 2008). Imposing the first break $\hat{T}_{B,1}$ in the test regression, we estimate the second break date $\hat{T}_{B,2}$. Again we maximize the absolute t-value; this time θ_2 for M1 and κ_2 for M2. Hence, we have:

$$T'_{B,2} = \begin{cases} \arg\max_{T_{B,2}} \left| t_{\hat{\theta}_2}(\hat{T}_{B,1}, T_{B,2}) \right|, \ for \ M1, \\ \arg\max_{T_{B,2}} \left| t_{\hat{\kappa}_2}(\hat{T}_{B,1}, T_{B,2} \right|, \ for \ M2 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots (12)$$

3. Data and Results

We used the monthly average stock indexes of the stock markets of Brazil (Bovespa Index of São Paulo Stock, Mercantile & Futures Exchange), Russia (MICEX index of MICEX Stock exchange), India (SENSEX index of Bombay Stock exchange) and China (SSE composite Index of Shanghai Stock Exchange) for the period January 2000 to December 2010. The data were collected from *Financial Indicators database* of *OECD Stat*, provided by OECD.

The result of LM one break unit root is given in Table I. While allowing for one break, we are unable to reject the null hypothesis of unit root in any of the four study variables. While allowing for two structural breaks in LM tests, the result (as given in Table II) was different from the one break LM test results. In model II, by allowing two breaks in the intercept / constant and trend, we were able to reject the null hypothesis of unit root for the Brazilian, Indian and Chinese markets. Only in the case of Russia we were unable to reject the null hypothesis. For Brazil, Russia and Indian indices, we identified break points in 2008. For China, the breaks occurred in 2007, 2005 or in 2009.

Narayan and Popp (2010) observed that the LM unit root tests as suggested by Lee and Strazicich reject the null hypothesis more frequently, since it is oversized when a break is allowed in the null. The results of Narayan and Popp (2010) unit root test with two break points are given in Table III. As claimed by Narayan and Popp, the NP test rejected the null hypothesis in one out of four cases, against the LM two break tests. Only in the context of Brazilian index (in model II), we rejected the null of the unit root in NP test at 10% level of significance. For Brazil, the break points came in 2002 and 2008, while for Russia the breaks occurred in 2004 and 2008.The Indian index experienced breaks during 2003, 2006 and 2008. For China, both Model I and II had the break points in 2006 and 2007.

The unit root test results indicated that the BRIC stock indices were nonstationary. However, this is not a sufficient condition for random walk hypothesis (Rahman and Saadi, 2008). Rahman and Saadi (2008) suggest that the random walk hypothesis requires nonstationarity in stock prices and serially uncorrelated increments. This necessitated testing of independent and identically distributed (*i.i.d.*) stock returns. Hence, we tested the *i.i.d.* characteristics of the stock returns of BRIC stock markets using the powerful test proposed by Brock, Dechert, and Scheinkman (1987) (henceforth BDS) and designed by Brock, Dechert, Scheinkman, and LeBaron (1996).

The BDS test is a nonparametric test with the null hypothesis that the series in question are *i.i.d.* against an unspecified alternative. The test is based on the concept of correlation integral, a measure of spatial correlation in *n*-dimensional space originally developed by Grassberger and Procaccia (1983). We consider a vector of *m* histories of the stock indices of BRIC economies,

$$r_t^m(r_1, r_{1+1}, ..., r_{t+m-1})$$

The correlation integral measures the number of *m* vectors within a distance of ε of one another. We define the correlation integral as;

$$C_m(\varepsilon, T) = \frac{2}{T_m(T_m - 1)} \sum_{t<s} I_\varepsilon(r_t^m, r_s^m)$$

where the parameter m is the embedding dimension; T is the sample size; $T_m = T - m + 1$ is the maximum number of overlapping vectors that we can form with a sample size T; and I_ε is an indicator function that is equal to one if $\|r_t^m - r_s^m\|$ and equal to zero otherwise. A pair of vectors r_t^m and r_s^m is said to be ε apart, if the maximum-norm $\|.\|$ is greater or equal to ε. Under the null hypothesis of independently and identically distributed random variable, $C_m(\varepsilon) = C_1(\varepsilon)^m$. Using this relation, we define the BDS test statistic as

$$BDS(m,\varepsilon) = \frac{C_m(\varepsilon,T) - [C_1(\varepsilon)]^m}{\sigma_m(\varepsilon,T)/\sqrt{T}}$$

where $\sigma_m(\varepsilon,T)/\sqrt{T}$ is the standard deviation of the difference between the two correlation measures $C_m(\varepsilon,T)$ and $[C_{1(}(\varepsilon)]^{m}$. For large samples, the BDS statistic has a standard normal limiting distribution under the null of *i.i.d.* If index price changes are not *i.i.d.* random variables, then $C_m(\varepsilon) > C_1(\varepsilon)^m$.

However, the BDS test statistic is sensitive to the choice of the embedding dimension *m* and the distance *ε*. As mentioned by Scheinkman and LeBaron, (1989) if we attribute a value that is too small for *ε*, then the null hypothesis of a random *i.i.d.* process gets accepted too often, regardless of whether it is true or false. It is also not safe to choose too large a value for *ε*. To deal with this problem, Brock, Hsieh, and LeBaron (1991) suggest that *ε* should equal 0.5, one, 1.5 and two times the standard deviations of the data. For the choice of the relevant embedding dimension *m*, Hsieh (1989) suggested a consideration of a broad range of values from two to ten. Following Barenett et al. (1995, we implement the Brock FIX test for a range of *m*-values from two to ten.

However, note that the selection of m and *ε* has not guided by any statistical theory and it is arbitrary. Kočenda (2002) has proposed a modified version of the BDS test, where he solved the problem of arbitrary selection of *ε*, by considering an OLS-estimate of the correlation dimension over a range of *ε*-values. Kočenda (2002) developed his test statistic by calculating the slope of the log of the correlation integral versus the log of the proximity parameter over a broad range of values of the proximity parameter for different embedding dimensions. The slope coefficient

β_m is estimated as $\beta_m = \dfrac{\sum_{\varepsilon}\left(\ln(\varepsilon) - \overline{\ln(\varepsilon)}\right)\cdot\left(\ln(C_m(\varepsilon)) - \overline{\ln(C_m(\varepsilon))}\right)}{\sum_{\varepsilon}\left(\ln(\varepsilon) - \overline{\ln(\varepsilon)}\right)^2}$

where $\ln(\varepsilon)$ is the log of proximity parameter or (tolerance distance), $\ln(C_m(\varepsilon))$ is the correlation integral value is the embodying dimension and the variables with a bar denotes the mean of their counterparts without a bar. Since a range of different tolerance distances *ε* is used β_m is not arbitrarily depend on the arbitrary choice of *ε*. The same is true for the choice of dimension m. Again a range of dimensions m is used which gives enough variety to capture more complex dimensional structure without eliminating unexplored opportunities.

One theoretical feature of the slope coefficient β_m is that under the null hypothesis the data are i.i.d, these slopes should equal the respective embodying dimension m at which the statistic is calculated (i.e. $\beta_m = m$). However the slope coefficient estimates β_m is smaller than the respective embodying dimension m, i.e. $\beta_m \le m$. If the data is identically and independently and distributed (i.i.d), then the slope coefficient β_m must stay within certain confidence intervals. In this paper we used both the BDS test and the alternative test proposed by Kočenda (2002) to examine the i.i.d properties of BRIC stock returns.

For the BDS test, we have done the estimation till m=10 and taken the values of *ε* as 0.5, 1, 1.5 and 2. The results of the BDS test and the K2k test are given in table IV. The table shows that

BDS tests are sensitive to the value of ε. In case of Brazil and China, we took ε as 1.5 and 2 and got a significant result, which implies that the stock return of Brazil does not follow *i.i.d*. However, when we took ε as 0.5 and 1, we got different results. For India and Russia, the BDS test rejected the null hypothesis of *i.i.d*. The last column of the table IV presents the results of the K2k test for all the four stock indices. (Note that the K2k test is based on a range of ε values, instead of merely taking an arbitrarily value of ε as in BDS). The K2k results for the ε values from 1.6 to 1.9 provided evidence against the *i.i.d* null of stock returns at1% level of significance for all the four BRIC stock indices.

4. Conclusion

We have examined the random walk characteristics of BRIC stock indices by using the unit root test with one break as developed by Lee and Strazicich (2004) and the two breaks as developed by Lee and Strazicich (2003) and Narayan and Popp (2010). We found mean reversion to be responsive to the methodology employed. The LM unit root test with a single break revealed the existence of unit root for all the four indices. For the case of two breaks, we rejected the null hypothesis of the unit root for Brazil, India, and China.

Finally, we applied the unit root test proposed by Narayan and Popp (2010) for the stock indices of BRIC. We found that stock markets of Russia, India and China had a unit root; for Brazil, the null hypothesis was rejected at the 10% level of significance.

Further, to test the *i.i.d* property, we applied BDS and K2k test and found that the BRIC stock returns did not follow *i.i.d* and therefore, we cannot say that the BRIC stock indices are weak form efficient, in spite of possessing a unit root.

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Table I: Results of Lee and Strazicich Unit root test with one structural break.

	Model 1			Model2		
Country	T_{B1}	Test statistics	k	T_{B1}	Test statistics	k
Brazil	2005:01	-1.3822	0	2003:09	-2.5653	0
Russia	2008:09	-2.6316	10	2006:06	-2.9414	1
India	2008:03	-1.7890	3	2004:03	-2.7560	3
China	2009:07	-2.8811	4	2006:10	-3.4444	4

Note: (1) Mode 1 presents Results for LM unit root test with one structural break in intercept/constant only and Model 2 presents Results for LM unit root test with one structural break in intercept/constant and trend both. (2) T_{B1} is the dates of the structural breaks. (3) k is the lag length. (4) *, **,@ denote statistical significance at the 10%, 5% and 1% levels respectively.

Table II: Results of Lee and Strazicich Unit root test with two structural breaks

Country	T_{B1}	T_{B2}	Test statistics	k	T_{B1}	T_{B2}	Test statistics	k
Brazil	2002:08	2005:01	-2.09	10	2003:02	2008:07	-5.66*	11
Russia	2007:03	2008:09	-2.92	10	2006:05	2008:09	-4.25	10
India	2006:08	2008:03	-1.93	3	2003:04	2008:05	-5.00**	3
China	2007:03	2009:07	-3.17	7	2005:01	2007:05	-5.53*	10

Note: (1) Mode 1 presents Results for univariate LM unit root test with two structural break in intercept/constant only and Model 2 presents Results for univariate LM unit root test with two structural breaks in intercept/constant and trend both. (2) T_{B1} and T_{B2} are the dates of the structural breaks. (3) k is the lag length. (4) *, **, @ denote statistical significance at the 10%, 5% and 1% levels respectively.

Table III: Results of Narayan and Popp (2010) unit root test with two structural breaks

Variable	Model I				Model II			
	Test statistic	TB1	TB2	k	Test statistic	TB1	TB2	k
Brazil	-2.45	2002:02	2002:08	0	-4.71@	2002:09	2008:08	4
Russia	-3.40	2008:08	2008:10	1	-4.49	2004:08	2008:11	1
India	-3.52	2006:05	2008:05	5	-4.40	2003:05	2006:05	5
China	-2.79	2006:11	2007:10	4	-3.27	2006:11	2007:10	4

Note: (1)*, **, @ indicates significant at 1%, 5% and 10% respectively. (2) Model 1 assumes two breaks in level and Model 2 assumes two breaks in level as well as slope. (3) T_{B1} and T_{B2} are the dates of the structural breaks. (4) *k* is the lag length.

Table II: Results of BDS test and alternative BDS test (K2k test) suggested by Kocenda (2002)

	ε=0.5	1.5	1.0	2.0	0.6-1.9
Dimension	BDS Statistic	BDS Statistic	BDS static	BDS static	K2k test
Brazil					
2	-0.014094**	-0.015267*	0.010881***	0.010852**	0.821*
3	-0.013471**	-0.015385***	0.016256**	0.021072**	0.882*
4	-0.011598***	-0.015504	0.017120**	0.033703**	0.938*
5	-0.009880	-0.015625	0.015042**	0.040211**	0.994*
6	-0.009452	-0.015748	0.012152**	0.046816**	1.052*
7	-0.007195	-0.015873	0.008424**	0.048955**	1.111*
8	-0.007331	-0.016000	0.005640**	0.057642**	1.173*
9	-0.005243	-0.016129	0.003621**	0.060405**	1.234*
10	-0.002914	-0.016260	0.002616**	0.065569**	1.296*
China					
2	-0.015270*	-0.015267**	0.004765	0.000611	0.865*
3	-0.011912***	-0.015385	0.012723	0.012848	0.973*
4	-0.005979	-0.015504	0.014247	0.022937	1.083*
5	0.002048	-0.015625	0.015889**	0.042973**	1.185*
6	0.012027	-0.015748	0.014078**	0.061909**	1.279*
7	0.020874	-0.015873	0.011644**	0.073831**	1.365*
8	0.028257	-0.016000	0.008459**	0.086628*	1.448*
9	0.038753	-0.016129	0.005592***	0.094110*	1.521*
10	0.046240	-0.016260	0.003320***	0.101451*	1.588*
India					
2	0.013479*	0.020823**	0.018955**	0.014183**	0.865*
3	0.010725*	0.033513**	0.026899**	0.022924***	0.973*
4	0.007073*	0.040286**	0.027157**	0.028809***	1.083*
5	0.003342**	0.038689**	0.020867**	0.035855***	1.185*
6	0.001549**	0.043834**	0.016427**	0.052361**	1.279*
7	0.000649***	0.045533**	0.010732***	0.068533**	1.365*
8	0.000319	0.043100**	0.007148***	0.082104*	1.448*
9	0.000109	0.037909**	0.004957	0.090419*	1.521*
10	-6.93E-06	0.033516**	0.004096***	0.097042*	1.588*
Russia					
2	0.015867*	0.027349*	0.023221*	0.018635*	0.748*
3	0.011918*	0.051022*	0.032668*	0.039452*	0.794*
4	0.005894*	0.060904*	0.027964*	0.054411*	0.839*
5	0.002314**	0.063205*	0.021267**	0.066803*	0.885*
6	0.000775	0.062779*	0.015490**	0.079105*	0.93*
7	-4.70E-05	0.062798*	0.010701**	0.089549*	0.977*
8	-4.92E-05	0.061080*	0.006403***	0.099581*	1.026*
9	-1.56E-05	0.053524*	0.004049	0.094544*	1.075*
10	-4.26E-06	0.050596*	0.003469	0.101325*	1.124*

*,**,*** indicates significance at 1%,5% and 10% respectively