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THE RESPONSES OF BRICS EQUITIES TO CHINA'S SLOWDOWN: A MULTI-SCALE CAUSALITY ANALYSIS

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The responses of BRICS equities to China's slowdown: a multi-scale causality analysis

Abstract: Growth in China has been slowing in 2015 below its long-run average. This worsening outlook has been synchronized among emerging markets with sharp slowdown. The paper looks at the responses of four BRICS (Brazil, Russia, India and South Africa) stock markets to deepening worries over slowing growth in the world's second-largest economy. To properly examine the peculiarities of these spillovers, we carry out relatively new methods that rise in signal theory: the causality testing-based Empirical Mode Decomposition (EMD) and the frequency domain causality test. These techniques allow capturing hidden factors driving uncertainty spillovers within BRICS stock markets. The results support robust evidence that the severity of China's slowdown impact was not uniform across BRICS equities. In particular, South Africa hasn't been rattled as badly as Brazil, Russia and India (in this order). The intensity of bilateral trade and investment relationships, the position of market in terms of regulation and securities exchanges, the financial system efficiency, the gold's role as safest haven and the distribution of companies belonging to cyclical and defensive industries in overall stock market indices have been put forward to explain the heterogeneous BRICS responses.

Keywords: China's slowdown; BRICS equities; multi-scale causality analysis.

JEL codes: F36; G11; G15.

1. Introduction

Most of 2015 saw a considerable drop of Shangai market. It had fallen 30 percent over the last quarter of 2015 as more than half listed companies filed for a trading halt in an essay to avoid big losses. The economic growth of China, the second-biggest economy in the world, slowed considerably to a six-year low of 6.9 percent, adding to concerns that the world economy is entering a period of low growth that will extend into the next coming years. Its strong contribution to the global growth attaining 38 percent in 2014 draw attention to the painful effects of this economic slow-moving on Chinese trade partners. In 2014, China imported US dollars 123 billions' worth of goods from the United States, US dollars 194 billion from Japan, and US dollars 211 billion from the Eurozone[4]. If this stalling growth in China has been exacerbated by cyclical factors (a backlash against massive stimulus plans, monetary tightening, the eurozone crisis), it would have nevertheless a structural character. Indeed, the demographic changes, the environmental constraints with respect hydrocarbon resources, and especially the slowdown of catching up process, reinforce the weakness of China's economic development and support the idea of a growth durably below 10 percent (Roucher and Xu 2014).

The fundamental purpose of this paper is to measure how react the countries making up the so-called BRICS (Brazil, Russia, India, and South Africa[1]) to this new situation. Precisely, we focus on the Chinese downturn effects on BRICS financial markets. This idea is recognized by the fact that most of empirical research supports evidence that stock returns are positively related to economic activity and has a good power in predicting output growth(see, for example, Fama 1990, Galliger 1994, Mauro 2000, Kim 2003, Chen and Chen 2011, Croux and Reusens 2013 and Bououiyour et al. 2015 a). In addition, studying both co-movement and causality among international stock markets has long been a popular research topic in finance (Lin et al. 1994, Karolyi and Stulz 1996, Forbes and Rigobon 2002, Brooks and Del Negro 2004, etc.) as it has relevant implications for asset allocation and investment management. Since the seminal work of Grubel (1968) on the benefits of international portfolio diversification, this issue has received a particular attention. However, these studies provided often conflicting results, mainly due to different sample data and analysis methods. It must be pointed out that the majority of works on financial markets spillovers have used the covariance of excess returns (Phylaktis 1999), bivariate and multivariate cointegration models (Taylor and Tonks 1989, Kasa 1992), OLS, standard Granger causality test or multivariate

[1] We keep the same acronym throughout the rest of our study, even if it concerns only four countries.

GARCH models (Levy and Sarnat 1970, Solnik 1974, Masih and Masih 2001, Sharkasi et al. 2004 and Phuan et al. 2009, etc.). Such complexity in this issue makes its analysis with these econometric techniques difficult. The volatile and speculative behaviors of stock markets strengthened the focus on models that allow capturing dynamic dependencies in data. Since actors across various stock markets operate distinctly, it seems required to carry out more elaborate tools that control for the time varying dynamics in time series. Very little strand of literature on this topic followed this strategy by differentiating between short-, medium- and long-term investments horizons using Fourier transform, wavelet-based approaches (Fernandez 2005, Rua and Nones 2009, Raghavan 2010, Shah et al. 2014, among others) or frequency domain causality test (for example, Candelon et al. 2008, Bouoiyour et al. 2015 a).

This work extends previous literature in the following important aspects. First, given its great contribution to global growth and its power in the world, one can suppose that a faltering pace of China's economic growth may be a source of structural break in the international stock market integration; hence a fundamental purpose of this study is to address whether the deepening Chinese slowdown exacerbate uncertainty spillovers among BRICS equities. Second, while the importance of contemporaneous information spillovers across stock markets was approved, there is generally a lack of in-depth investigation of instantaneous risk spillovers within international financial markets. Since it is obvious that all processes we have to deal are very complex, using decomposition methods to a given sequence may be appropriate. The goal of this research is to have a transform that would not only enable to deal with non-stationarity (Fourier transform) and nonlinearity (wavelet) problems, and which has no a priori assumptions regarding these properties of time-series investigated. The method used herein is a new data analysis tool devoted to difficult situations and vacillating frameworks where conventional tools are malapropos. The empirical mode decomposition (EMD) was introduced by Scientists in NASA team in 1998 to provide proper data for studying atmospheric processes (Huang 1998). For finance and economics topics, EMD is a substantial addition to time-series methods with practical applications, allowing disentangling linkages into distinct modes, prompting instantaneous frequencies as functions of time that give more complete information about imbedded structures. More accurately, EMD makes local and high-adaptive decomposition of a variable into various intrinsic mode functions with different average scales ranging from high frequency (short-run) to low frequency (long-run) components. Each of the derived IMFs reflects the dynamics of the

time-series at a well specific time scale which enable to analyze the fine structure of variables studied.

Our results over a weekly period from January 1999 to July 2015 provide evidence of a significant causality running from Chinese stock market to Brazilian, Russian, Indian and South African equity markets. These spillovers do not appear uniform. In particular, Brazil, Russia and India (in this hierarchy) suffered more than South Africa from the current China's slowdown. The fact that South Africa appears less influenced has been mainly attributed to its market position in terms of regulation and securities exchanges, its developed financial system and the gold's role as safe haven.

The paper proceeds as follows. In Section 2, we discuss the methodology used. In Section 3, we provide a brief data overview. In Section 4, we report the empirical results. The last section draws conclusions and some portfolio implications.

2. Methodology

2.1. Causality testing-based Empirical Mode Decomposition

Data from natural phenomena are often non-stationary due to their transient behaviors. According to Huang et al. (1998), the conventional signal approaches (such as Fourier transform and Wavelets) might lead to distorted or inaccurate information about non-stationary variables, like for instance ground motion recording. To reach clearer and complete information from signals that might be hidden when employing standard econometric techniques, the Empirical mode decomposition (EMD) method may be very useful. It is a part of more general procedure known as Hilbert–Huang transformation (HHT) and by its nature resembles both Fourier decomposition and wavelet transformation. EMD is suited to extract mono-component and symmetric components, known as Intrinsic mode function (IMF), from wide bands of signals (Huang et al. 1998, Altaf et al. 2007, Rilling et al. 2007; Tanaka and Mandic 2007, Zhang 2008, Yu et al. 2015). The IMF denotes an oscillatory mode of a simple function with varying amplitude and frequency. It satisfies at least two requirements. The first one relies on the fact that functions should have the same numbers of extrema and zero-crossings or differ at the most by one. The second one consists in the need of symmetrical functions with respect to local zero mean. By exploring data intrinsic modes, the EMD helps display possible hidden features in the data, and aims indeed at transforming the studied time series to hierarchical structure by means of the scaling transformations It

provides effective frequency information evolving over time and quantifies the changeability captured via the oscillation under different scales and locations. In brief, the IMFs have well defined instantaneous frequencies, which give an idea about the instantaneous energy and frequency content of signals.

Determining the dependence between BRICS markets over uncertainty surrounding China's slowdown using EMD consists of (1) decomposing original time series into different intrinsic mode functions (IMFs) and one residue among different time scales, from high to low frequencies, and (2) utilizing nonlinear causality test to analyze whether a significant causality occurs across China-BRICS equities among matched modes and thus over different time-horizons. Figure 1 depicts the proposed analysis approach. In particular two main steps are involved:

Step 1: Signal decomposition

As previously mentioned, the EMD technique is used to decompose the original time series data into matched modes on various time-scales, corresponding to possible hidden features. In practice, the intrinsic mode functions are derived by determining the maxima and minima of time series $x(t)$, generating then its upper and lower envelopes ($e_{\min}(t)$ and $e_{\max}(t)$), with cubic spline interpolation.

To start, we measure the mean ($m(t)$) from upper and lower envelopes:

$$m(t) = (e_{\min}(t) + e_{\max}(t))/2 \tag{1}$$

Then, we decompose $m(t)$ of the time series to determine the difference $d(t)$:

$$d(t) = m(t) - x(t) \tag{2}$$

where $d(t)$ is presented as the ith IMF , by replacing $x(t)$ with the residual $r(t) = x(t) - d(t)$.

Then, we connect the local maxima with the upper envelope and the minima with the lower one. This step allows us to determine the first component through the difference between the data and the local mean of the two envelopes. When residue successfully meets the conditions that the number of zero- crossings and extrema do not differ by more than one as mentioned above and the sifting process can be fully achieved if the total number of IMFs is limited to log2*N* (*N* denotes the length of a data series) or when the residue (*r*) becomes a

monotonic function and data cannot be extracted into further intrinsic mode functions (Huang et al. 2003), the original time series can be expressed as the sum of some IMFs and a residue:

$$X(t) = \sum_{j=1}^{N} c_j(t) + r\ (t) \tag{3}$$

In the sifting process, the first component contains the shortest period component of the time series. The residue after extracting the quickly fluctuating component corresponds to the longer period fluctuations in the data. Thus, the mode functions are extracted from high frequency to low frequency bands. Empirical mode decomposition is carried out here as a filter to separate high frequency (fluctuating process) and low frequency (slowing varying component) modes. Basically, this procedure corresponds to high-pass filtering by adding fastest oscillations (i.e., IMFs with smaller index) to slowest oscillations (i.e., IMFs with larger index), consisting of: (1) Computing the mean of the sum of c_i for each component (except for the residue); (2) Employing t-test to obtain for which j the mean departs from zero; (3) Once j is determined as a relevant change point, partial reconstruction with IMFs from this to the end is considered as the slow-varying component and the partial reconstruction with other IMFs is identified as the high frequency component.

Step 2: Scale-on-scale causality testing

After disentangling data variables into a set of different components by employing EMD, such that each component corresponds to a range of frequencies, a second step consists on testing the nonlinear causality on a scale-on-scale basis (i.e., depending to IMFs variations). We should mention here that a relatively little number of studies have focused on the assessment of large-scale causalities (Yu et al. 2015).To this end, a general causality test-based on a Taylor expansion (Péguin Feissolle and Teräsvirta 1999) has been employed.

$$y_t = f^*(y_{t-1},\ldots,y_{t-q},x_{t-1},\ldots,x_{t-n},\theta^*) + \varepsilon_t \tag{4}$$

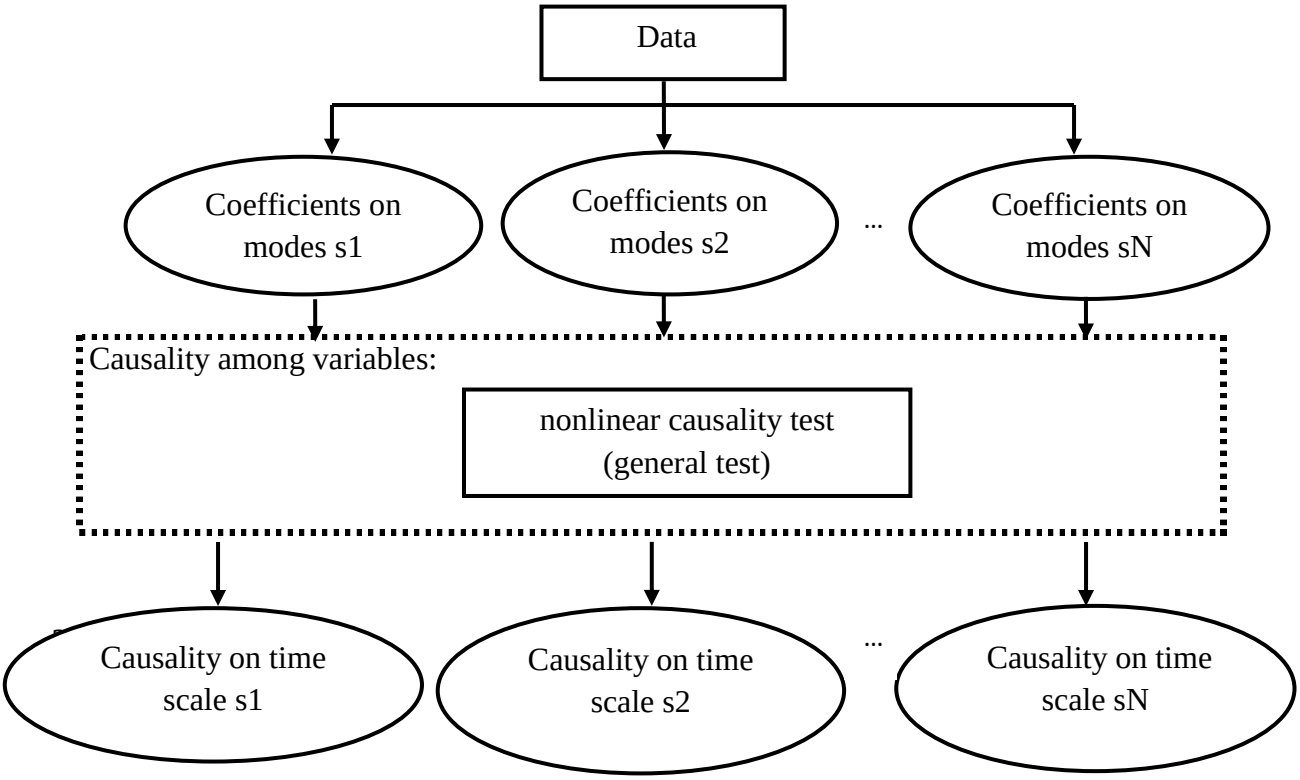
where θ^* is a parameter vector and $\varepsilon_t \sim nid(0,\sigma^2)$; the functional form of f^* is unknown but we assume that is adequately represents the causal relationship between x_t and y_t. To test noncausality hypothesis, we start by the fact that x_t does not cause y_t if the past values of x_t does not contain any information about y_t that is already contained in the past values of y_t itself.

$$y_t = f\left(y_{t-1},\ldots,y_{t-q},\theta\right)+\varepsilon_t. \tag{5}$$

To test (5) against (4), we linearize f^* in (4) by expanding the function into a *k*-order Taylor series around an arbitrary fixed point in the sample space. We obtain:

$$\begin{aligned} y_t = {} & \beta_0 + \sum_{j=1}^{q}\beta_j y_{t-j} + \sum_{j=1}^{n}\gamma_j x_{t-j} + \sum_{j_1=1}^{q}\sum_{j_2=j_1}^{q}\beta_{j_1 j_2} y_{t-j_1} y_{t-j_2} + \sum_{j_1=1}^{q}\sum_{j_2=1}^{n}\delta_{j_1 j_2} y_{t-j_1} x_{t-j_2} \\ & + \sum_{j_1=1}^{n}\sum_{j_2=j_1}^{n}\gamma_{j_1 j_2} x_{t-j_1} x_{t-j_2} + \ldots + \sum_{j_1=1}^{q}\sum_{j_2=j_1}^{q}\ldots\sum_{j_k=j_k-1}^{q}\beta_{j_1\ldots j_k} y_{t-j_1}\ldots y_{t-j_k} \\ & + \ldots + \sum_{j_1=1}^{n}\sum_{j_2=j_1}^{n}\ldots\sum_{j_k=j_k-1}^{n}\gamma_{j_1\ldots j_k} x_{t-j_1}\ldots x_{t-j_k} + \varepsilon_t^* \end{aligned} \tag{6}$$

Figure 1. Framework of scale-on-scale causality testing



2.2. The frequency domain causality

As an attempt to ascertain the robustness of our results, we apply a frequency domain causality recently developed by Breitung and Calderon (2006). Use of this approach allows identifying the cyclical properties of data, and thus if the predictive power is concentrated at the quickly fluctuating components (short-run) or at the slowly fluctuating components (long-run). Decomposing data variables into various frequencies may help markets participants in their decisions making.

To define the frequency causality test, we first consider $z_t = [x_t, y_t]$ as a two-dimensional time series vector with t = 1… T. It is supposed that z_t has a finite-order VAR representation $\theta(L)z_t = \varepsilon_t$ where $\theta(L)z_t = 1 - \theta_1 L - ... - \theta_p L^p$ is a 2 × 2 lag polynomial with $L^k z_t = z_{t \to k}$. It is assumed that the vector ε_t is white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t') = \Sigma$, $E(\varepsilon_t \varepsilon_t') = \sum$ where $\sum$ is a positive definite matrix. The system is stationary expressed as:

$$z_t = \phi(L)\varepsilon_t = \begin{pmatrix} \phi_{11}(L)\phi_{12}(L) \\ \phi_{21}(L)\phi_{22}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{12} \\ \varepsilon_{21} \end{pmatrix} \tag{7}$$

$$= \Psi(L)\upsilon_t = \begin{pmatrix} \psi_{11}(L)\psi_{12}(L) \\ \psi_{21}(L)\psi_{22}(L) \end{pmatrix} \begin{pmatrix} \eta_{12} \\ \eta_{21} \end{pmatrix}$$

The spectral density can be derived from the previous matrix and expressed as follows:

$$f_x(w) = \frac{1}{2\pi} \left\{ \left|\psi_{11}(e^{-iw})\right|^2 + \left|\psi_{12}(e^{-iw})\right|^2 \right\} \tag{8}$$

The Granger causality test-based frequency domain allows deriving the distributional properties of time series. Let x_t and y_t (the variables of interest) be stationary variables of length *T*. The main goal of this study is to test whether x_t Granger cause y_t , at a given frequency λ, conditioning upon Z_t (additional control variables). Accordingly, Geweke (1982) proposed a measure of causality denoted as:

$$M_{x \to y/Z}(w) = \log\left[1 + \frac{\left|\psi_{12}(e^{-iw})\right|^2}{\left|\psi_{11}(e^{-iw})\right|^2} \right] \tag{9}$$

As $\left|\psi_{12}(e^{-iw})\right|^2$ is a complex function of VAR parameters, Breitung and Candelon (2006) and in order to resolve this drawback argued that the hypothesis $M_{x\rightarrow y/Z}(\omega) = 0$ corresponds to a linear restriction on the VAR coefficients.

$$H_0 : R(\omega)\phi(L) = 0 \tag{10}$$

where $R(\omega) = \begin{bmatrix} \cos(\omega)\cos(2\omega)...\cos(p\omega) \\ \sin(\omega)\sin(2\omega)...\sin(p\omega) \end{bmatrix}$

The significance of the causal relationship can be tested by a standard F-test or by comparing the causality measure for $\omega \in [0, \pi]$ with the critical value of a χ^2 distribution with 2 degrees of freedom, which is 5.99.

3. Data and summary statistics

This study uses weekly data for the stock market indices growth (STR)[2] of Brazil's BOVESPA, China's Shanghai SEA index, Russia's RTS index, India's BSE and South Africa's FTSE/JSE over the period from January 1999 to July 2015[3], with a total of 760 observations. For comparison purpose, we analyze two sub-periods: the first is the Chinese rapid growth period between January 1999 to December 2010 (i.e., 576 observations) and the second is the slowdown period from January 2011 and July 2015 (i.e., 184 observations). The data were collected from Datastream database and quandl website. We prefer use weekly instead of daily data, given that we hoped to properly characterize the underlying dependence structure. Daily or high-frequency data may be heavily influenced by drifts and noise that could mask or did not reflect appropriately the dependence between the investigated variables and thus complicate modeling of the marginal distributions via non-stationary variances, long memory processes and sudden jumps. This research examines also the sensitivity of the dependence between BRICS stock markets to global economic and financial factors including the gold price (gold) and the implied volatility of stock returns (or VIX). Gold has been largely served as a hedging tool against sudden stocks and as a safe haven during extreme

[2] The stock return (STR) is calculated by considering the ratio stock price (in log) at time t and the lagged stock price (in log).

[3] The period of the study is motivated by the availability of the Brazilian and South African data and the fact that we required a common sample period for all the BRICS countries.

stock market movements (Baur and McDermott 2010). We chose the gold price as potential exogenous variable since BRICS countries include the world's major consumers of gold (China and India), and also one of the strongest producers (South Africa). In addition to gold, the finance literature has been frequently relied on proxies of uncertainty such as VIX index that plays profoundly on asset allocation and portfolio strategies (Hood and Malik 2013, Balcilar et al. 2014, Mensi et al. 2015)[4]. All these variables have been transformed by taking natural logarithms to correct for potential heteroskedasticity and dimensional differences among time series.

The descriptive statistics of variables (by log levels) for the two concerned periods are reported in Table 1(Panels A and B). The sample mean of STR is positive for all the countries studied. The skewness of stock market returns is negative and positive among the considered countries. The Kurtosis seems above 3 for all cases, implying that the distribution is more flattened than the Gaussian distribution; there are fat tails within density function comparing to the density of the Gaussian distribution N (0, 1). Besides, statistics of Jarque Bera test suggest that neither BRICS stock returns series nor the supplementary control variables are normally distributed.

Table 1. Descriptive statistics

Panel A: Period of rapid China's growth							
	STR_China	STR_Brazil	STR_Russia	STR_India	STR_South Africa	VIX	gold
Mean	0.047	0.051	0.043	0.005	0.011	3.273	1.798
Median	0.022	0.033	0.035	0.000	-0.008	3.983	1.766
Maximum	0.997	0.909	1.656	0.551	0.311	5.025	2.156
Minimum	-0.327	-0.919	-0.297	-0.592	-0.283	-2.739	1.669
Std. Dev.	0.204	0.339	0.543	0.185	0.087	1.851	0.148
Skewness	1.615	-2.222	0.238	-0.104	0.240	-1.633	1.402
Kurtosis	8.507	9.564	3.973	5.158	5.321	5.136	3.972
Jarque-Bera	11.722	15.632	3.378	13.525	16.166	43.827	4.404
Panel B: Period of China's slowdown							
Mean	0.081	0.064	0.051	0.013	0.010	4.459	2.305
Median	0.036	0.052	0.047	0.006	-0.015	4.417	2.560
Maximum	1.107	1.134	2.312	0.667	0.413	4.839	3.063
Minimum	-0.456	-0.871	-0.354	-0.389	-0.195	4.138	-1.136
Std. Dev.	0.369	0.421	0.676	0.211	0.096	0.237	1.119
Skewness	2.038	1.105	0.513	-0.117	0.455	0.280	-2.680
Kurtosis	9.276	7.398	4.225	6.312	6.808	1.833	8.919
Jarque-Bera	23.451	21.303	7.108	22.167	19.35	31.887	11.897

[4] Further control variables have been accounted for without fundamentally changing our findings. These variables include oil and iron prices. The results are available upon request.

4. Empirical results

4.1. Standard techniques findings

We start our analysis by employing some standard techniques (VECM and standard Granger causality test) for the two investigated periods: period of China's rapid growth and in the wake of China's economic slowdown. The idea here is to have a case of benchmarking to compare the VECM and the Granger causality results with the new methods (in particular, causality testing-based EMD and frequency domain causality test). To proceed, we have, first, applied Ng-Perron (Ng-Perron 2001) unit root test to examine whether the variables are stationary in the level or first difference form. The obtained outcomes indicate that almost all the considered variables show unit root behavior at level and appear stationary at 1st difference with intercept and trend (Table A.1, Appendices). Due not having information about structural breaks stemming in the time series, Ng-Perron unit root findings may be biased. To solve this limit, we carry out de-trended Zivot and Andrews (1992)'s structural break unit test to determine the integrating orders of the variables in the presence of structural breaks. We note that, for the two periods investigated, all the variables are stationary at specific levels showing structural breaks (Table A.1, Panels A and B, Appendices). Then, we use VECM model and standard Granger causality test in order to test if China's slowdown exacerbates uncertainty spillovers among BRICS equities.

Using VECM, we show that both short- and long-term linkages among BRICS equities are statistically significant prior to the Chinese crisis (Table 2, Panel A). This result remains supported for the second period (Table 2, Panel B). A sharp heterogeneity is found with respect to BRICS stock markets reactions over China's rapid growth period. In particular, the relationship is strong for Brazil, followed by Russia and India and finally South Africa. Similar hierarchy is found during the China's slowdown period, but the linkage appears stronger compared to the period before the onset of Chinese crisis.

Table 2. VECM: The dependence between China and BRICS stock market returns

	Panel A: Period of China rapid growth				Panel B: Period of China's slowdown			
	STR_Brazil	STR_Russia	STR_India	STR_SA	STR_Brazil	STR_Russia	STR_India	STR_SA
D(STR_China$_{t-1}$)	0.201** (0.0032)	0.149* (0.0617)	0.117*** (0.0006)	0.042** (0.0058)	0.241** (0.0022)	0.151** (0.0039)	0.138** (0.0014)	0.065*** (0.0000)
D(gold$_{t-1}$)	-0.038* (0.0124)	0.048*** (0.0001)	-0.047* (0.0110)	0.151 (0.8755)	-0.135* (0.0421)	-0.414 (0.6213)	0.142 (0.9518)	0.049 (0.3762)
D(VIX$_{t-1}$)	0.003 (0.7651)	-0.029* (0.0341)	0.236 (0.5592)	0.019 (0.6157)	-0.056* (0.0133)	0.245 (0.8950)	0.009** (0.0781)	-0.075** (0.0823)
STR_China$_{t-1}$	0.317** (0.0056)	0.269*** (0.0000)	0.141** (0.0018)	0.098*** (0.0003)	0.421*** (0.0000)	0.289* (0.0126)	0.203** (0.0011)	0.104*** (0.0009)
gold$_{t-1}$	0.115* (0.0904)	-0.091 (0.2456)	-0.806 (0.5389)	0.145** (0.0049)	0.276*** (0.0000)	-0.607 (0.2536)	-0.256 (0.3841)	0.094** (0.0045)
VIX$_{t-1}$	-0.038** (-2.161)	-0.113* (-1.907)	-0.046** (-2.357)	-1.267 (-1.238)	-0.042* (-2.159)	-0.158*** (-3.556)	-0.404 (-0.893)	-0.102* (-1.967)
ECT$_{t-1}$	-0.033 (0.5512)	-0.087*** (0.0000)	-0.113*** (0.0005)	-0.100** (0.0092)	-0.093*** (0.0002)	-0.111*** (0.0000)	-0.098 (0.4876)	-0.137 (0.5629)
R-squared	0.67	0.65	0.72	0.43	0.62	0.71	0.55	0.41
Adj. R-squared	0.51	0.59	0.66	0.29	0.49	0.63	0.40	0.32

Note: SA corresponds to South Africa; (.): p-value; p-value<0.01: ***; p-value<0.05: **; p-value<0.

The results of standard Granger causality test (Table 3, Panels A and B) go in the same direction. We will return later on the arguments explaining these results. But we must clarify that the results obtained through these methods, so-called "classic", may be erroneous since they provide averages which do not satisfactorily account for the problems of non-stationarity and nonlinearity. The question here is beyond whether there exist or not significant relationships between the Chinese market and the stock returns of Brazil, Russia, India and South Africa since we know yet that these markets are inter-linked. Rather, our focus in this study is to identify how these BRICS spillovers vary from one mode to another. Hence, a scale-on-scale analysis will be used in the following to uncover how exactly moves the relationship China-BRICS equities over different components, which can hardly be visible from VECM and Granger causality test (Bouoiyour et al. 2015 b).

Table 3. Standard Granger causality tests: The dependence between China and BRICS stock market returns

	Panel A: Period of China rapid growth				Panel B: Period of China's slowdown			
	STR_Brazil	STR_Russia	STR_India	STR_SA	STR_Brazil	STR_Russia	STR_India	STR_SA
STR_China	0.0001***	0.0056**	0.0013**	0.0124*	0.0000***	0.0019**	0.0008***	0.0041**

Note: SA corresponds to South Africa; (.): the p-value; p-value<0.01: ***; p-value<0.05: **; p-value<0.1

4.2. EMD findings

Figure A.1 (Panel A, Appendices) shows that, via EMD, the BRICS stock returns are decomposed into eight IMFs plus one residue for the first period (prior to China's slowdown). All the IMFs are listed from high (short-run) to low frequency (long-run), and the last one is the residue. We note that as the frequency changes from high to low, the amplitudes of the IMFs become wider. The residue varies slightly around the long-term mean. In the wake of Chinese economic downturn (Panel B, Figure A.1, Appendices), the focal stock returns are decomposed into only six IMFs[5] plus one residue. From highest to lowest frequency components, the amplitudes appear not the same with any harmonic; for example, the IMF1 and IMF2 amplitudes appear smaller than IMF5 and IMF6. The residue remains following a long-term average. Throughout the rest of our study, we discuss three scaling components: short-run, medium-run and long-run. Table 4 presents the time scale interpretation of empirical mode decomposition for the period of rapid Chinese growth and the period of slowdown.

Table 4. Interpretation of scales-based on EMD

<table>
<tr><th>modes</th><th>Panel A: Period of rapid China's growth</th><th>Panel B: Period of China's slowdown</th></tr>
<tr><td>IMF1</td><td rowspan="3">Short-run: less than 8 weeks</td><td rowspan="2">Short-run: less than 6 weeks</td></tr>
<tr><td>IMF2</td></tr>
<tr><td>IMF3</td><td rowspan="2">Medium-run: above 6 weeks and less than 30 weeks</td></tr>
<tr><td>IMF4</td><td rowspan="2">Medium-run: above 8 weeks and less than 45 weeks</td></tr>
<tr><td>IMF5</td><td rowspan="2">Long-run: above one year</td></tr>
<tr><td>IMF6</td><td rowspan="3">Long-run: above one year</td></tr>
<tr><td>IMF7</td><td>—</td></tr>
<tr><td>IMF8</td><td>—</td></tr>
</table>

On various time-scales, distinct modes may behave differently, owing to inner factors driving the focal equities. Table 5 reports some measures which are given to assess IMFs features: mean period of each IMF, correlation between each IMF and the original data series and the variance percentage of each IMF. The mean period corresponds to the value derived by dividing the total number of points by the number of peaks for each IMF. Two correlation coefficients, Pearson correlation and Kendall rank correlation coefficients are employed here to measure the relationships between IMFs and the original data. Because IMFs are

[5] We have not the same number of IMFs for the two investigated periods due to the fact that the EMD technique generates itself the modes depending to data and the sample length.

intrinsically independent, it is possible to sum up the variances and use the percentage of variance to determine the contribution of each IMF to the total volatility of the original data. Together, these measures reveal interesting insights. In particular, for the period of rapid growth (Panel A, Table 5), we can distinguish two groups of countries: (1) China, Brazil and Russia which are driven by long term factors (IMFs6–8; above one year) that may be a reflect of the great dependence of these spillovers to market fundamentals; (2) India and South Africa which appear to be sensitive to rapid oscillations (IMFs1–3; within one to eight weeks). This result can be attributed to the fact that emotions determine the stock market price evolution. Accurately, a great optimism may drive prices up and a heavier pessimism may drive prices down. Besides, stock markets can be buoyed by sudden market-changing events, making the stock market behavior very hard to be effectively predicted. Moreover, the residues display a strong correlation with the central original series. The continuing rising trend can be explained by the growing attention to BRICS stock markets due to their rapid growth and substantial trade and investment integration with the most developed economies in, and their position as a promising era for international portfolio diversification (Bouoiyour and Selmi 2015 b).The results change marginally by moving from the first period (Table 5, Panel A) to the second period (Table 5, Panel B). While Chinese, Brazilian, and Russian equities remain determined by the same driving forces, Indian stock market appears highly driven by high frequency components. We note that South Africa joined the group of China, Brazil and Russia and hence becomes predominantly determined by low frequency components.

Table 5. IMFs features

	Panel A: Period of rapid China's growth				Panel B: Period of China's slowdown			
	Mean period	Pearson correlation	Kendall correlation	variance as % of the sum of (IMFs+residue)	Mean period	Pearson correlation	Kendall correlation	variance as % of the sum of (IMFs+residue)
China								
IMF1	1.08	0.109**	0.098*	4.56%	1.5	0.054	0.038	5.94%
IMF2	1.42	0.056	0.040	0.68%	3.72	0.046	0.042	1.56%
IMF3	1.97	0.074**	0.061	1.12%	5.56	0.115**	0.100**	4.65%
IMF4	3.24	0.088**	0.073***	2.98%	6.07	0.271**	0.245*	26.16%
IMF5	4.55	0.079*	0.062	2.73%	19.25	0.304***	0.273**	31.67%
IMF6	23.45	0.295***	0.274**	24.13%	21.13	0.104*	0.086**	7.13%
IMF7	25.10	0.346**	0.325**	39.75%	—	—	—	—
IMF8	32.46	0.092*	0.067***	3.65%	—	—	—	—

Residue		0.234**	0.230***	20.15%		0.296***	0.253***	22.89%
Brazil								
IMF1	1.25	0.110***	0.099***	1.86%	1.63	0.103*	0.095*	2.19%
IMF2	1.79	0.065	0.066**	2.12%	3.48	0.194*	0.166**	9.13%
IMF3	4.52	0.059*	0.032	1.98%	3.97	0.086	0.080*	1.00%
IMF4	8.97	0.176	0.158*	8.07%	5.05	0.021	0.017	0.14%
IMF5	11.23	0.123**	0.117**	1.01%	18.11	0.167**	0.148***	26.21%
IMF6	28.46	0.476***	0.454**	30.11%	26.79	0.235***	0.211***	38.68%
IMF7	35.15	0.362**	0.324*	19.79%	—	—	—	—
IMF8	37.06	0.313**	0.307*	23.52%	—	—	—	—
Residue		0.197***	0.192**	11.54%		0.193**	0.188**	22.65%
Russia								
IMF1	2.15	0.054	0.039	0.97%	1.96	0.112**	0.103	11.73%
IMF2	4.63	0.066*	0.050	1.12%	3.55	0.100*	0.088**	6.56%
IMF3	4.75	0.095**	0.082*	1.89%	8.19	0.098*	0.076**	4.31%
IMF4	5.11	0.271**	0.264**	11.85%	9.86	0.065***	0.069	2.45%
IMF5	14.38	0.294***	0.287*	16.76%	26.94	0.179***	0.165**	23.65%
IMF6	16.29	0.221*	0.218**	18.59%	30.12	0.186*	0.173***	29.95%
IMF7	23.45	0.354***	0.339**	21.16%	—	—	—	—
IMF8	25.00	0.187*	0.159**	16.10%	—	—	—	—
Residue		0.165*	0.147**	10.52%		0.205*	0.193**	21.35%
India								
IMF1	4.32	0.212*	0.186***	16.93%	3.62	0.195***	0.167***	19.23%
IMF2	7.69	0.277**	0.259**	44.11%	7.94	0.262***	0.199**	30.97%
IMF3	8.16	0.218***	0.204***	3.46%	8.39	0.112**	0.099*	6.68%
IMF4	9.24	0.117*	0.108**	8.63%	11.02	0.109**	0.076	3.56%
IMF5	11.35	0.102***	0.094***	0.51%	11.93	0.086	0.054	4.12%
IMF6	13.18	0.096**	0.075***	1.27%	25.04	0.131**	0.116**	7.14%
IMF7	38.25	0.113*	0.089**	1.18%	—	—	—	—
IMF8	49.67	0.145***	0.137**	1.87%	—	—	—	—
Residue		0.183*	0.175**	21.99%		0.256*	0.234**	28.15%
South Africa								
IMF1	2.57	0.156*	0.151*	34.81%	1.20	0.121***	0.117**	3.18%
IMF2	2.34	0.310***	0.287**	26.73%	1.48	0.096**	0.088**	0.20%
IMF3	2.78	0.242**	0.169***	18.96%	6.56	0.123***	0.101**	8.15%
IMF4	4.09	0.099*	0.095*	0.70%	7.32	0.078**	0.065**	0.22%
IMF5	8.23	0.134**	0.121***	3.95%	15.78	0.154*	0.132***	7.58%
IMF6	12.75	0.091***	0.065	1.01%	28.99	0.292*	0.289**	61.65%
IMF7	25.89	0.072*	0.068**	1.12%	—	—	—	—
IMF8	36.29	0.054***	0.047**	0.87%	—	—	—	—
Residue		0.192*	0.184**	11.78%		0.216**	0.204*	19.00 %

Note: *, **, ***: Correlations are significant at the levels of 0.01, 0.05 and 0.1, respectively (2-tailed).

Table 6 gives more accurate information about the three mono-components yet identified and confirmed the previous findings regarding the potential contributors of BRICS stock markets.

Table 6. Correlations and variance of components

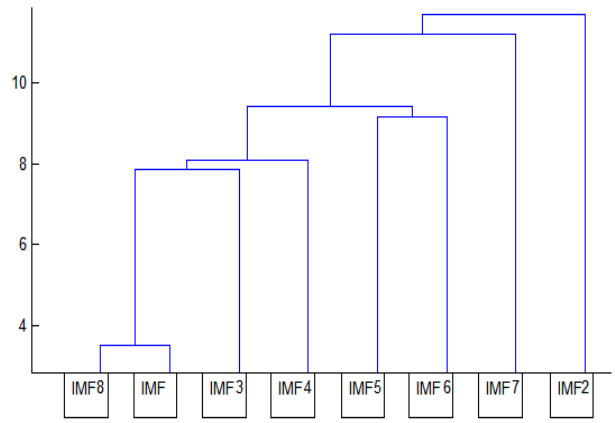
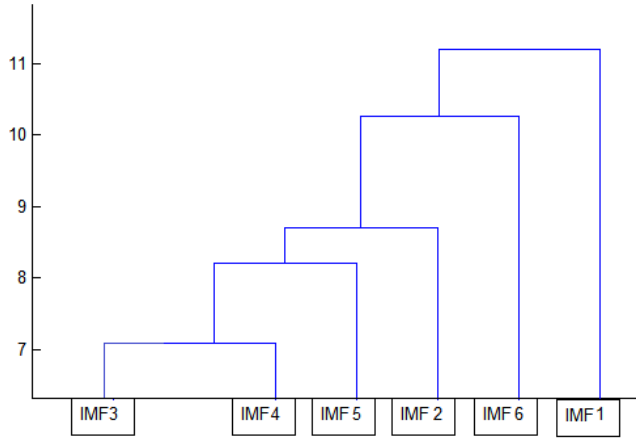
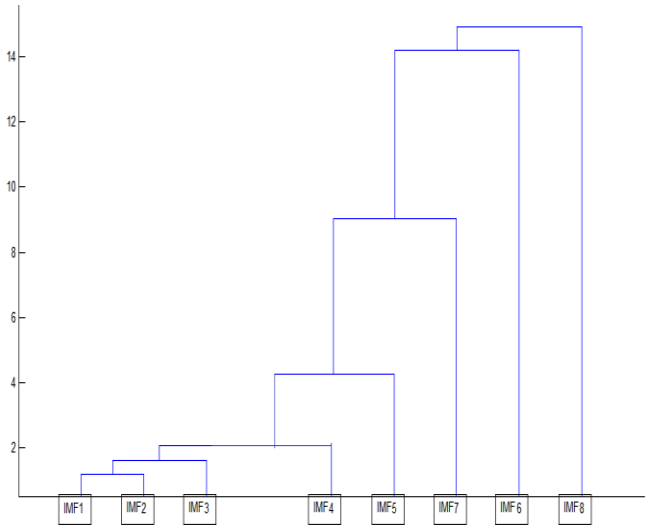
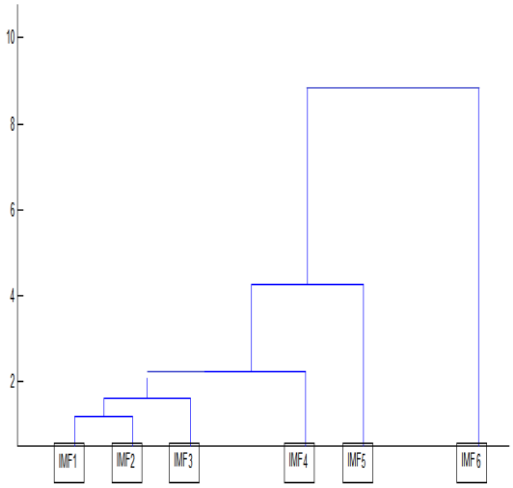
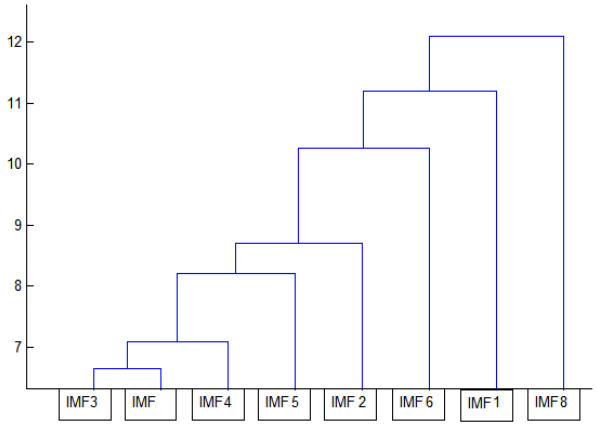
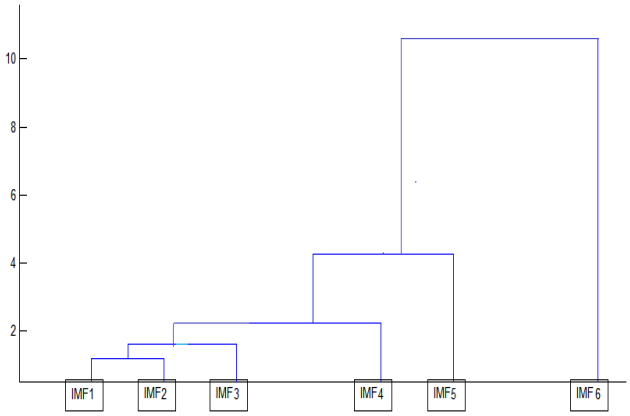
	Panel A: Period of rapid China's growth			Panel B: Period of China's slowdown		
	Pearson correlation	Kendall correlation	variance as % of the sum of IMFs	Pearson correlation	Kendall correlation	variance as % of the sum of IMFs
China						
High frequency component	0.219*	0.165***	6.36%	0.114**	0.102*	12.15%
Low Frequency component	0.498**	0.465***	67.53%	0.268**	0.223***	64.96%
Trend component	0.386***	0.322**	20.15%	0.222***	0.198*	22.89%
Brazil						
High frequency component	0.097*	0.065	5.99%	0.154**	0.141**	12.32%
Low Frequency component	0.357**	0.299**	73.42%	0.279***	0.255**	64.89%
Trend component	0.190*	0.154**	11.54%	0.266***	0.241***	22.65%
Russia						
High frequency component	0.257**	0.242***	3.98%	0.157**	0.124**	18.29%
Low Frequency component	0.384*	0.359**	55.85%	0.321*	0.291***	53.60%
Trend component	0.321**	0.318***	10.52%	0.215**	0.206**	21.35%
India						
High frequency component	0.723*	0.698***	54.50%	0.479***	0.436**	50.20%
Low Frequency component	0.171**	0.119**	24.44%	0.078*	0.065	11.26%
Trend component	0.452***	0.414*	21.99%	0.194**	0.185**	28.15%
South Africa						
High frequency component	0.789***	0.725*	80.50%	0.104*	0.092*	3.38%
Low Frequency component	0.316**	0.238**	3.00%	0.351**	0.336***	69.23%
Trend component	0.427***	0.354**	11.78%	0.210*	0.199*	19.00%

Note: *, **, ***: Correlations are significant at the levels of 0.01, 0.05 and 0.1, respectively (2-tailed)

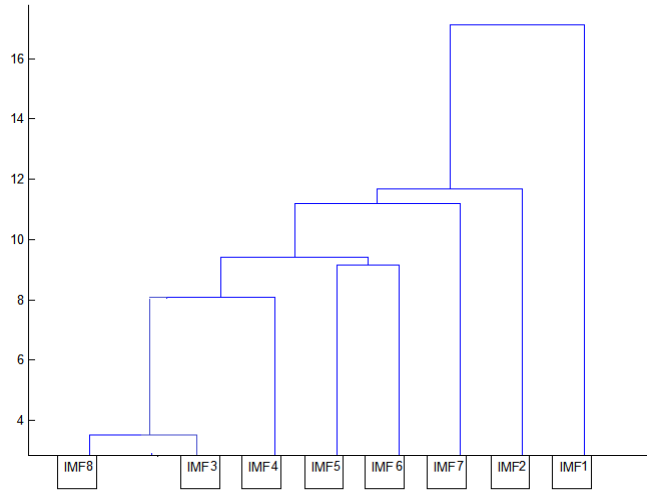
After providing the decomposition findings of stock returns of China, Brazil, Russia, India and South Africa and the basic analysis of the different IMFs, the hierarchical clustering analysis was carried out. To do so, we have employed the "pdist" function[6] to compute the Euclidean distance between pairs of IMFs, or the IMFs and the residue in order to create a hierarchical cluster tree using the smallest distance principle and to generate a dendrogram plot of the hierarchical cluster tree. Figure 2 reports the clustering outcomes for the two concerned periods. For the period of Chinese rapid growth, the eight IMFs may be grouped into three categories (as indicated in Table 4). Regarding the mean periods, the partial reconstruction with IMF1, IMF2 and IMF3 can be recognized as the shortest scales, IMF4 and IMF5 as the medium term scaling components, whereas the partial reconstruction with IMF6, IMF7 and IMF8 can be treated as the longest time-scales (Figure 2, Panel A). The short scales correspond to the Euclidean distance smaller than four weeks; the medium scaling components represent the Euclidean distance within four weeks and less than eight weeks; the longest scales correspond to the distance more than 14 weeks. The clustering findings, for the period before China's economic slow-moving (Figure 2, Panel B), confirm the previous results by often distinguishing the same two groups (i.e., whose determined by longer scale factors (China, Brazil and Russia), and whose driven by short-run factors (India and South Africa). Nevertheless, for the period of China's slowdown, the results change considerably. Unlike India which appears the only country among BRICS driven by high frequency components (IMF1), South Africa joined China, Brazil and Russia and become significantly sensitive to slowly fluctuating components (IMFs 5–6).

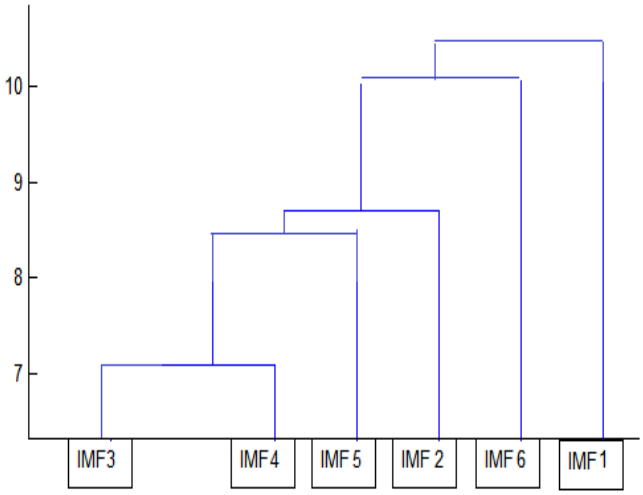
[6] The hierarchical clustering investigation was also implemented in the Matlab R2015a software package.

Figure 2. The Euclidean distance via hierarchical clustering method

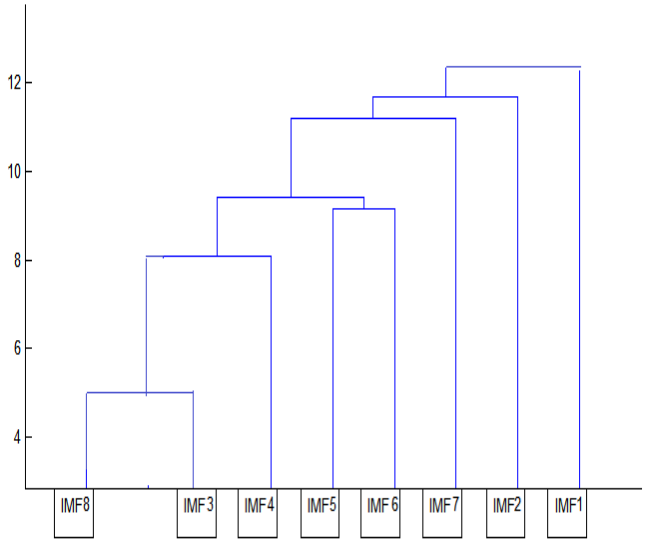
Panel A: Period of rapid China's growth	Panel B: Period of China's slowdown
China	
	
Brazil	
	
Russia	
	

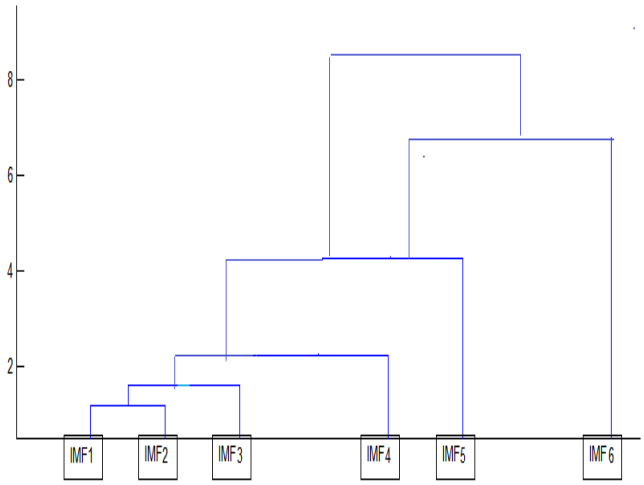
India





South Africa





Despite the importance of analyzing the dynamics of the investigated variables, these results remain insufficient to reach complete picture about the central issue. The most important for us is to determine the strength of China's slowdown spillover effects and what drive the linkage China- BRICS stock returns over a period of great uncertainty surrounding the China's economic downturn, and not what determine the equity market returns of each country independently. Thus, we try in the following to test the causality between Chinese and BRICS (Brazil, Russia, India and South Africa) financial markets as alternative to modes (or frequencies).

4.3. Causality testing-based EMD findings

A nonlinear Granger causality test (i.e., general test) is conducted to analyze causal linkages between the Chinese market and the BRICS stock market returns at different modes by rigorous means of EMD. We show sharp variations in findings which are not congruent with earlier studies. Table 7 reports the corresponding results in which the p-values are listed.

As previously, the investigated countries can be categorized as follows: The first group includes Brazil and Russia where a strong causality is supported (scale above one year; IMF6, IMF7 and IMF8). The second group includes India and South Africa where causality is validated at short-run horizons (within one to eight weeks, IMF1, IMF2 and IMF3). Also, the residues of Chinese stock returns significantly cause the BRICS equities at a longest time-scale of about 150 weeks (Table 7.1). By accounting for gold price and the VIX index (Table 7.2, Panel A), we note some differences among countries with respect to their responses to the current slowdown of China. This signals the sensitivity of the spillovers among BRICS to the global and financial factors. In the wake of China economic downturn (Table 7.2, Panel B), the scale length becomes longer for all the cases. In particular, we note a stronger influence on Brazilian and Russian equities (IMFs 6-8). Indian and South African markets appear less influenced (short and medium term effect at the range IMFs 1-5). In sum, we support evidences that (i) the faltering pace of China's growth has intensified the uncertainty spillovers among BRICS markets; (ii) The Chinese slowdown affects dissimilarly BRICS financial markets. While India and South Africa appear less influenced by the potent anxiety over slowing growth in the world's second-largest economy, Brazil and Russia seem the biggest losers.

Table 7. Scale-by-scale causality among China and BRICS stock returns

Panel A: Period of rapid China's growth					Panel B: Period of China's slowdown				
Time-scales	Brazil	Russia	India	South Africa	Time-scales	Brazil	Russia	India	South Africa
7.1. Unconditional analysis									
Short scales					Short scales				
IMF1	0.6785	0.6934	0.0345*	0.0411*	IMF1	0.7645	0.6245	0.0057**	0.0086**
IMF2	0.2459	0.2345	0.0089**	0.0096**	IMF2	0.5234	0.7542	0.0130*	0.0171*
IMF3	0.3872	0.9510	0.2345	0.4308					
Medium scales					Medium scales				
IMF4	0.5274	0.4663	0.5582	0.8156	IMF3	0.5484	0.4785	0.0413*	0.0023**
IMF5	0.6178	0.7102	0.7239	0.6723	IMF4	0.2297	0.7213	0.0059**	0.2159
Long scales					Long scales				
IMF6	0.0036**	0.0513*	0.9568	0.3908	IMF5	0.0014**	0.5437	0.7312	0.8261
IMF7	0.0219*	0.4567	0.7635	0.3156	IMF6	0.0213*	0.0006***	0.6273	0.3345
IMF8	0.5062	0.3351	0.3061	0.6126					
Residue	0.0013**	0.0404*	0.0065**	0.4867	Residue	0.0035**	0.0000***	0.0156*	0.0094**
7.2. Conditional analysis									
Short scales					Short scales				
IMF1	0.3211	0.3286	0.2345	0.0234*	IMF1	0.9124	0.3219	0.0035**	0.0154*
IMF2	0.2879	0.5081	0.0039**	0.0045**	IMF2	0.6754	0.1092	0.0184*	0.0068**
IMF3	0.5672	0.5672	0.0004***	0.9515					
Medium scales					Medium scales				
IMF4	0.3891	0.7100	0.4138	0.2216	IMF3	0.2563	0.6789	0.0251*	0.0073**
IMF5	0.5023	0.2879	0.2545	0.5004	IMF4	0.8954	0.6430	0.0574*	0.0216*
Long scales					Long scales				
IMF6	0.0114*	0.4567	0.3561	0.3456	IMF5	0.0000***	0.0022**	0.5671	0.8467
IMF7	0.0076**	0.0012**	0.3867	0.3267	IMF6	0.0011**	0.0008***	0.4498	0.6524
IMF8	0.0032**	0.0048**	0.2961	0.1876					
Residue	0.0010**	0.0000***	0.0156*	0.0515*	Residue	0.0000***	0.0029**	0.0004***	0.0121*

Note: The table reports the p-values; *, ** or *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

4.4. Frequency domain causality findings

To ascertain the robustness of our results, we re-tested whether the recent Chinese crisis exacerbates risk spillovers among China and the four BRICS (Brazil, Russia, India and South Africa), using a frequency domain causality test[7]. The focus of the use of this frequency approach is on detecting cycles in the intensity of spillovers. It is vital for investors seeking to diversify their portfolios to track the cyclicality of spillovers.

Figure 4 depicts the evolution of the spillovers among the variables of interest conditioning upon gold price and VIX index[8]. The figure contains the test statistics with their 5 percent critical values for the different frequency bands involved (solid line) over the interval [0, π]. The frequency (ω) on the horizontal axis can be translated into a cycle or periodicity of T weeks by $T = (2\pi / \omega)$ where T is the period. Notably, the interactions between China and the four BRICS equities become more intense over the period of China's slowdown.

The findings of Granger causality running from Chinese stock market to Brazilian and Russian stock returns show that for the rapid growth period (period 1, Figure 3.1), STR_China Granger-cause STR_Brazil at level of frequencies reflecting long-term business cycle, when $\omega \in [0.01\pi - 0.76\pi]$, corresponding to a cycle length above six weeks. When During the period of uncertainty surrounding the recent crisis of China (period 2, Figure 3.1), the results remain solid while the cycle expands. In particular, we note that there is a significant causality when $\omega \in [0.01\pi - 1.08\pi]$, corresponding to a cycle superior to eight weeks. For India, the causality is validated at short-term horizons, $\omega \in [2..70\pi - 2.92\pi]$or a cycle between 2.1 and 2.3 weeks (period 1, Figure 3.3). In the wake of Chinese crisis, the link becomes stronger, i.e., when $\omega \in [1.95\pi - 2.60\pi] \cup [2.70\pi - 3.03\pi]$ corresponding to a cycle between 2.3and 3.2 weeks (period 2, Figure 3.3). Almost like India, a short-run causal relationship is observed from China to South Africa's stock returns. The cycle becomes lengthy with the onset of Chinese crisis; if for the period 1 (Figure 3.4), such causality is supported for a cycle of 2.4 weeks ($\omega \in [2.60\pi - 3.03\pi]$), for period 2, it is observed when $\omega \in [1.30\pi - 1.95\pi]$, corresponding to a cycle between 3.2 and 4.8 weeks.

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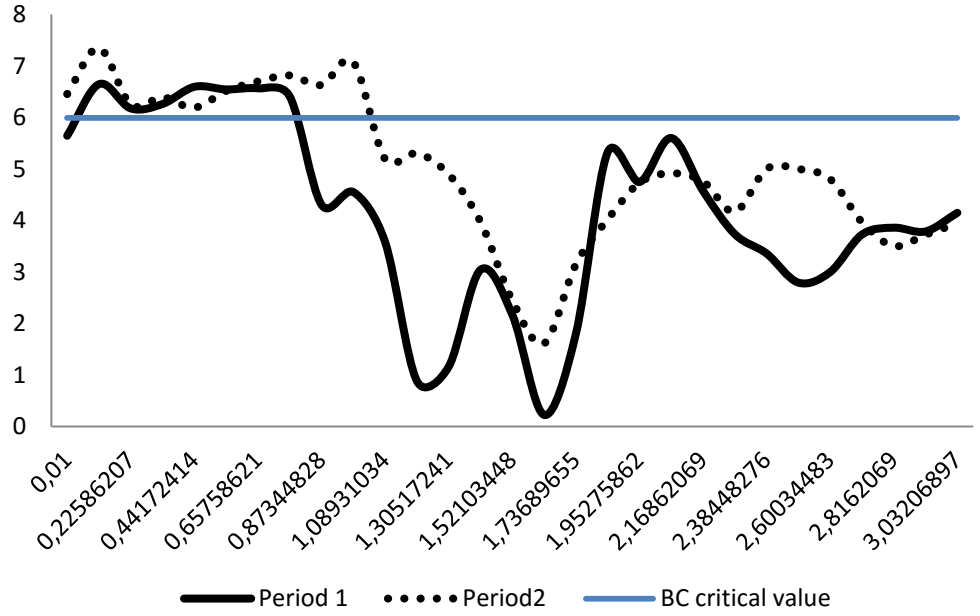
[7] Although EMD is performed within a discrete time framework, the frequency domain causality has a spectral content across a continuous range. The frequency domain causality test provides clearer cycle information almost in real time, whereas business cycles cannot be identified before a cycle has been completed.

[8] For simplicity reasons, we have not given the results of unconditional analysis (i.e., without considering control variables) that may be obtained upon request.

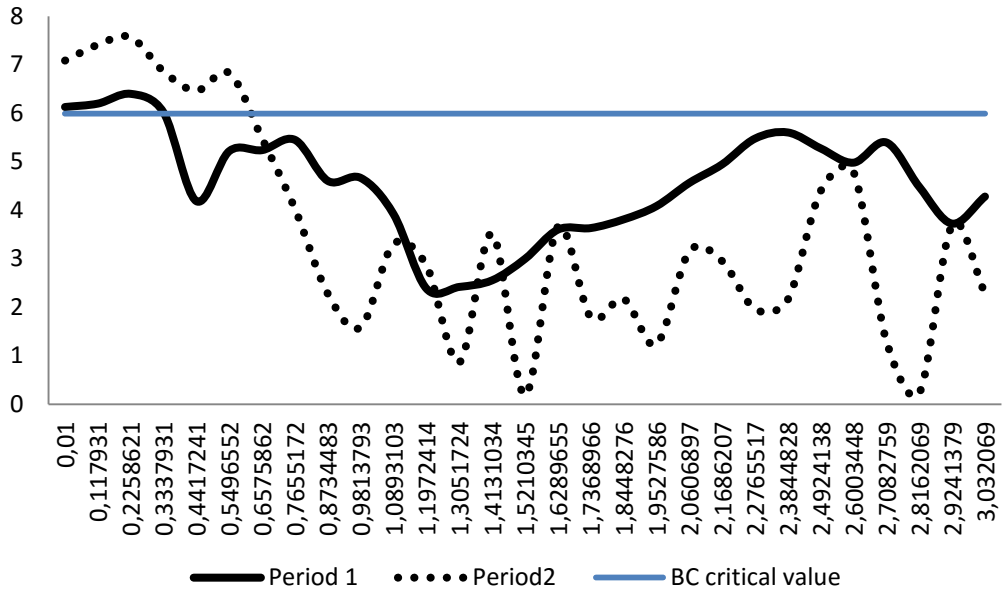
In sum, we sustain two interesting points: (1) we usually distinguish two groups of countries: the first is formed by Brazil and Russia driven by long term inner factors, whereas the second includes India and South Africa determined by short and medium-run features, and (2) our interpolation procedure has influenced the strength of Granger-causality since the cycle becomes stronger for the period of China's slowdown.

Figure 3. The frequency domain causality between China and BRICS stock returns

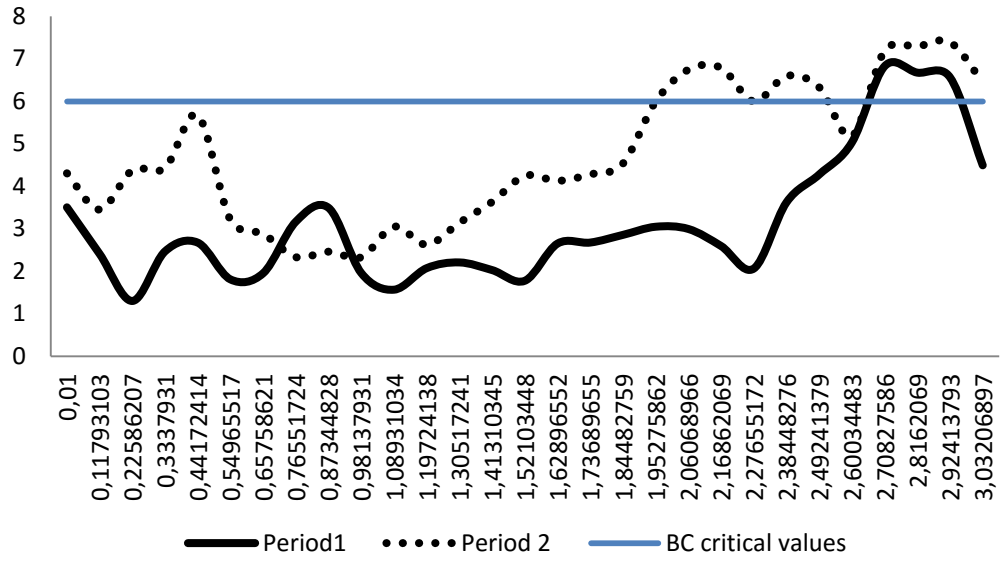
3.1. STR_China and STR_Brazil



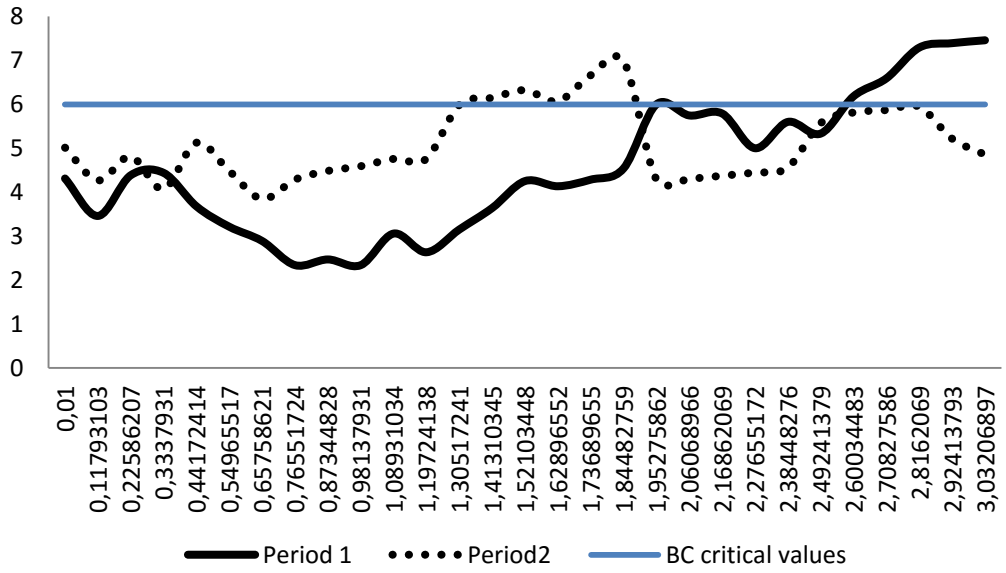
3.2.STR_China and STR_Russia



3.3.STR_China and STR_India



3.4.STR_China and STR_South Africa



Note: The horizontal line represents the 5% critical value of the null hypothesis test of no Granger causality at frequency *w*; period 1: corresponds to the Chinese rapid growth period; period 2: the China's slowdown period.

Despite some computational differences, causality testing-based EMD and frequency domain causality test findings are likely to be complementary; all suggesting that China's slowdown does not affect uniformly BRICS financial markets. Summing up, we note the occurrence of a "complex" multi-scale behavior of the causality between the Chinese stock market and the equities of the four BRICS (Brazil, Russia, India, and South Africa) over the China's slowdown period. The causality testing-based EMD appears likely to correctly reflect the actual situation distinguished by heavier uncertainty. We deduce also the usefulness and the functionality of frequency domain causality test in this exercise.

5. Conclusions and some portfolio implications

China's economy is weakening; in 2013, it grew by 7.7 percent, its worst rate since 1999. Because of the increasing speed of globalization, liberalization of capital movements and securitization of stock markets, traders, investors and regulators all over the world are very anxious about the impact of the recent China's slowdown on the rest of word. BRICS region is no exception in this respect. This study uses a multi-scale causality analysis to investigate the uncertainty spillovers within BRICS over China's slowdown period from a new perspective.

We show that the severity of China's downturn influence is not uniform across BRICS equities. In particular, the Chinese crisis threatened Brazil, Russia and India (in this order) more than South Africa. These results appear intuitive since we respect the same hierarchy when considering the intensity of trade and foreign direct investment relationships. Figure A.2 (Appendices) reports the statistics of the average annual exports to China and imports from China to the rest of BRICS from 2000 to 2014. Over this 15 years period, Brazilian exports to China averaged 59.34 USD billion, followed by Russia (47.12 USD billion), then India (31.91 USD billion) and finally South Africa (8.92 USD billion). It is also well noticeable that Russia (40.58 USD billion) and Brazil (36.68 USD billion) are the biggest importers of Chinese goods, followed by India and South Africa (20.91 USD billion and 20.52 USD billion, respectively). With respect to Chinese foreign direct investments (FDI) into BRICS countries, Brazil (13.3 USD billion) and Russia (11.11 USD) billion appear better positioned than India (9.69 USD billion) and South Africa (Figure A.3, Appendices). Nevertheless, for South Africa, the level of China's investment is relatively weaker. China accounted for around 0.21 percent (reaching 0.97 USD billion as average 2000-2014) of global FDI inflows. We keep the same hierarchy when considering the BRICS FDI into China, while the investment level in this case seems smallest. This sharp consistency (in terms of countries' position) underscore that our results are neither unusual nor striking.

But it must be recalled that the current China's slowdown has played a significant role in exacerbating the spillovers within BRICS equities. It has long been well documented that investors react to bad news rather than good news (i.e., asymmetric response). Indeed, the sizable volatility, the potent uncertainty and the panic over the faltering pace of Chinese economic growth would undoubtedly reduce the incentive to invest, and investors would become more pessimistic, responding more strongly to bad than good news content. Further, the quantitative easing (or QE) and cheap money pushed money out of safe investments and

into risky areas (Bernanke 2012). Generally, with the aftermath of negative shocks (or bad news), investors will be forced into relatively riskier investments to find higher yields or a return.

We shouldn't ignore the problem of sincerity of the Chinese data on economic growth. In this context, some recent researches have doubts about these statistics (for example, Arthus and Virad 2016), but we leave this scrupulous debate aside. To this we must add the findings of Bouoiyour et al. (2015 b) which argued that the effect of stock returns on real economic activity wasn't uniform across BRICS countries. Indeed, the authors suggested that South African and Indian equities are better positioned regarding the predictability power for output growth. For China and Russia, the equity returns seem unable to satisfactorily predict the real activity. This last finding may be generally due to the lack of transparency in market transactions and the practices of corporate governance in these countries. Given these elements, these elements, we need to be careful in interpreting our results.

What appears more interesting from our multi-scale causality outcomes is the heterogeneity in terms of the intensity of spillovers. Even though China's slowdown exerts a widest influence (long-run) on Brazilian and Russian markets, its impact on Indian and South African equities seems supported in the short-run. Whatever the models used (causality testing-based EMD and frequency domain causality test) and whatever the periods investigated (China's rapid growth or China's slowdown), the findings remain fairly robust, with slight changes in terms of intensity. Precisely, the Chinese crisis has intensified the risk spillovers among BRICS (except for South Africa where the causality becomes less strong when using frequency domain causality). This sustains our evidence that South Africa behaves differently to the current uncertain situation. Some potential elements can explain this dissimilarity. First, compared to Brazil, Russia and India, Chinese and South African companies are still in the early stages of learning how to operate in each other's economies (Gupta and Wang 2009). Second, the position of South Africa in terms of regulation of securities exchanges and financial system development may play a powerful role in mitigating the adverse effects of China's slowdown on the performance of its stock market (Ferhani and Sayeh 2008, Bouoiyour et al. 2015 b). South Africa is recently ranked by the World Economic Forum's Global Competitiveness Survey (2015) as the first position out of 144 emerging countries in terms of regulation of securities exchanges and financial market sophistication. The survey classified South Africa third in terms of its ability to raise finance via the local equity market, third in the effectiveness of corporate boards and fourth in

protecting the rights of minority shareholder. Further, considering gold as a highly liquid asset that can be accessed any time, South Africa -the fifth largest gold producer in the world- can suffer less since investors turn to gold under turbulent times and over periods of financial stress. We must recall that gold possesses no credit risk and cannot turn worthless even though economic crisis (Baur and Lucey 2010, Baur and McDermott 2010). Indeed, over uncertain period, when investors attempt to get rid of their risky investments, they relocate their finances into the less risky assets such as gold. In brief, this yellow metal can provide great protection against losses when South African stock market experienced drops due to China's current upheaval.

Moreover, by looking at the obtained findings and the statistics reported in Table A.2 (Appendices), we can deduce that the stock prices of the companies belonging more to cyclical industries are more sensitive to China's slowdown. Dissimilar to Brazil and Russia, the stock market price indices of India and South Africa which appear less influenced by the Chinese downturn are more based on defensive industries[9].

Last but not least, profitable investment strategies can be built on the basis of this article' outcomes. The evidence that the reactions of BRICS equities to Chinese economic downturn change markedly from quickly to slowly fluctuating components may have profound consequences for portfolios that trade with various rebalancing horizons. Holding diversified portfolio could play a significant role in palliating risk management, by allocating investments among various BRICS equities that reacts each differently to China downturn. Although it does not guarantee against loss, portfolio diversification remains the most useful tool of ensuring long-range financial objectives and lightening the adverse risks.

Even though it is a challenging task to carry out signal processing techniques for non-stationary and noisy signals (Lin and Hongbing 2009), this study highlights the effectiveness EMD for capturing inner features that may drive asset markets. Combined with some other methods, this signal approach allows finding more accurate and comprehensive insights into a complex issue. This makes causality testing-based EMD a promising new addition to the existing toolboxes for non-stationary and nonlinear signals. Likewise, the frequency domain causality has also proved its usefulness in this exercise.

[9] The defensive or non-cyclical industries are those that do well in turbulent times, since the demand continue to grow regardless of whether there is certain or uncertain situation. Accordingly, Damodaron (2014) argued that, over unstable context, cyclical companies see generally their earnings go up and down, providing excessive volatility.

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Appendices

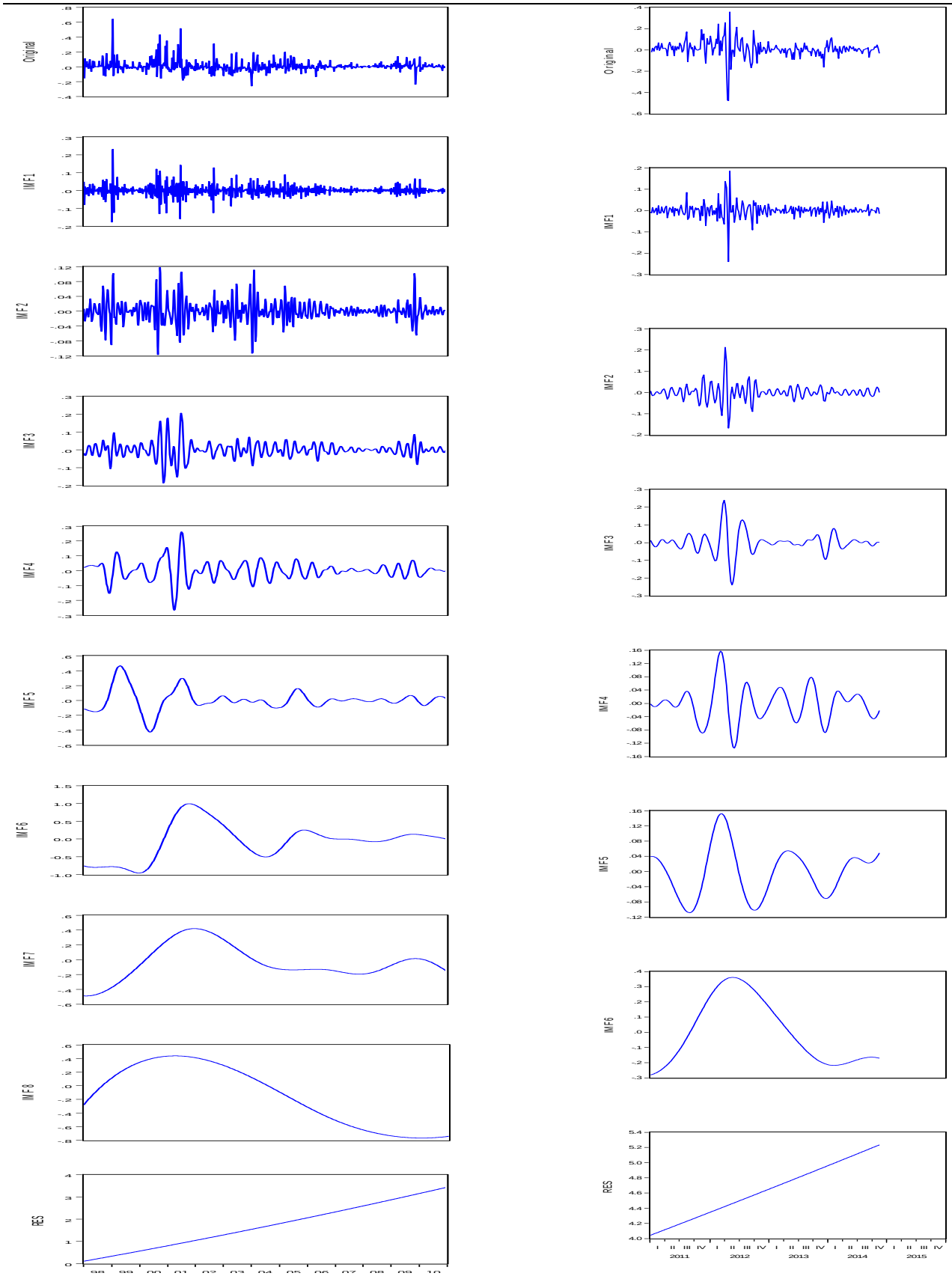
Table A.1. Unit Root Analysis

	Panel A: Period of rapid China's growth				Panel B: Period of China's slowdown			
	Ng-Perron Unit Root Test							
Variable	MZa	MZt	MSB	MPT	MZa	MZt	MSB	MPT
STR_China	-13.04(1)	-2.65	0.23	7.65	-11.26(1)	-2.65	0.23	7.65
STR_Brazil	-14.62(1)	-2.66	0.57	6.57	-10.78(1)	-2.66	0.57	6.57
STR_Russia	-10.58(1)	-3.07	0.76	6.50	-10.13(1)	-3.07	0.76	6.50
STR_India	-9.83(2)	-4.12	0.92	7.02	-10.54(1)	-4.12	0.92	7.02
STR_SA	-13.15(1)	-2.76	0.61	6.42	-11.76(1)	-2.76	0.61	6.42
gold	-10.38(1)	-3.26	0.54	6.83	-10.92(1)	-3.26	0.54	6.83
VIX	-12.05(1)	-4.25	0.63	8.12	-11.08(1)	-4.25	0.63	8.12
Variable	ZA at Level		ZA at 1st Difference		ZA at Level		ZA at 1st Difference	
	T-statistic	Time Break	T-statistic	Time Break	T-statistic	Time Break	T-statistic	Time Break
STR_China	-3.91(2)	2009	-11.06(1)*	2003	-4.15(1)	2011	-13.18(2)*	2011
STR_Brazil	-7.83(4)*	2004	-7.85(2)*	2008	-9.06(2)*	2011	-11.97(2)*	2011
STR_Russia	-4.51(2)*	2001	-3.90(3)*	2011	-9.21(2)*	2011	-9.76(2)*	2011
STR_India	-4.12(1)*	2008	-3.61(2)*	2009	-8.89(2)*	2011	-9.43(2)*	2011
STR_SA	-4.22(2)*	2009	-4.00(1)*	2008	-8.17(2)*	2012	-6.04(1)*	2011
gold	-5.38(1)*	2009	-5.11(2)*	2010	-6.42(1)*	2009	-5.72(1)*	2009
VIX	-5.38(1)*	2010	-6.71(2)*	2011	-7.39(2)*	2012	-9.94(2)*	2011

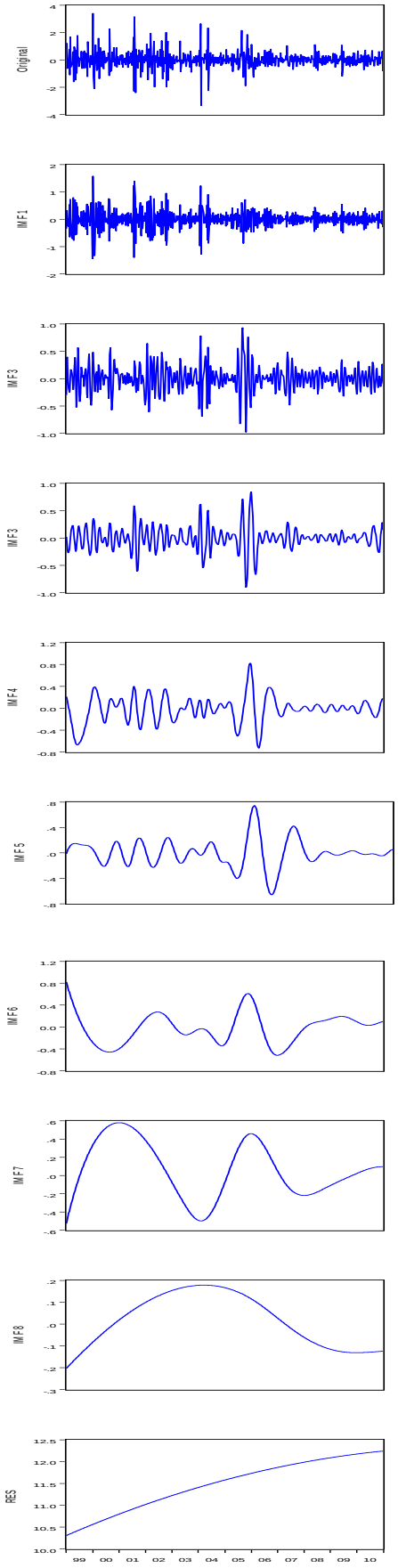
Notes: * represent significant at 1 per cent level of significance. Lag order is shown in parenthesis.

Figure A.1. IMFs and Residue derived from EMD

Panel A: Period of rapid China's growth	Panel B: Period of China's slowdown
China	



Brazil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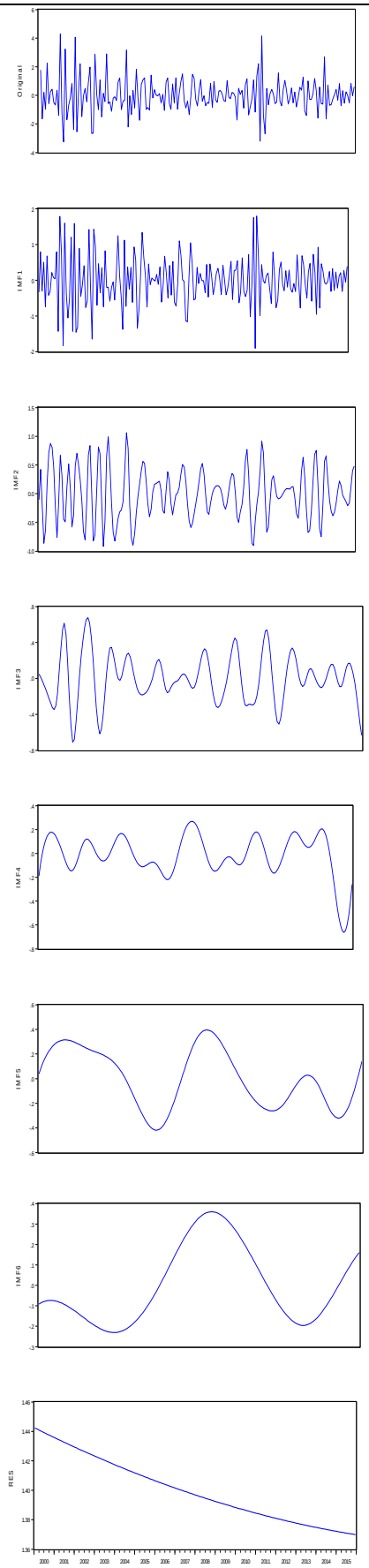
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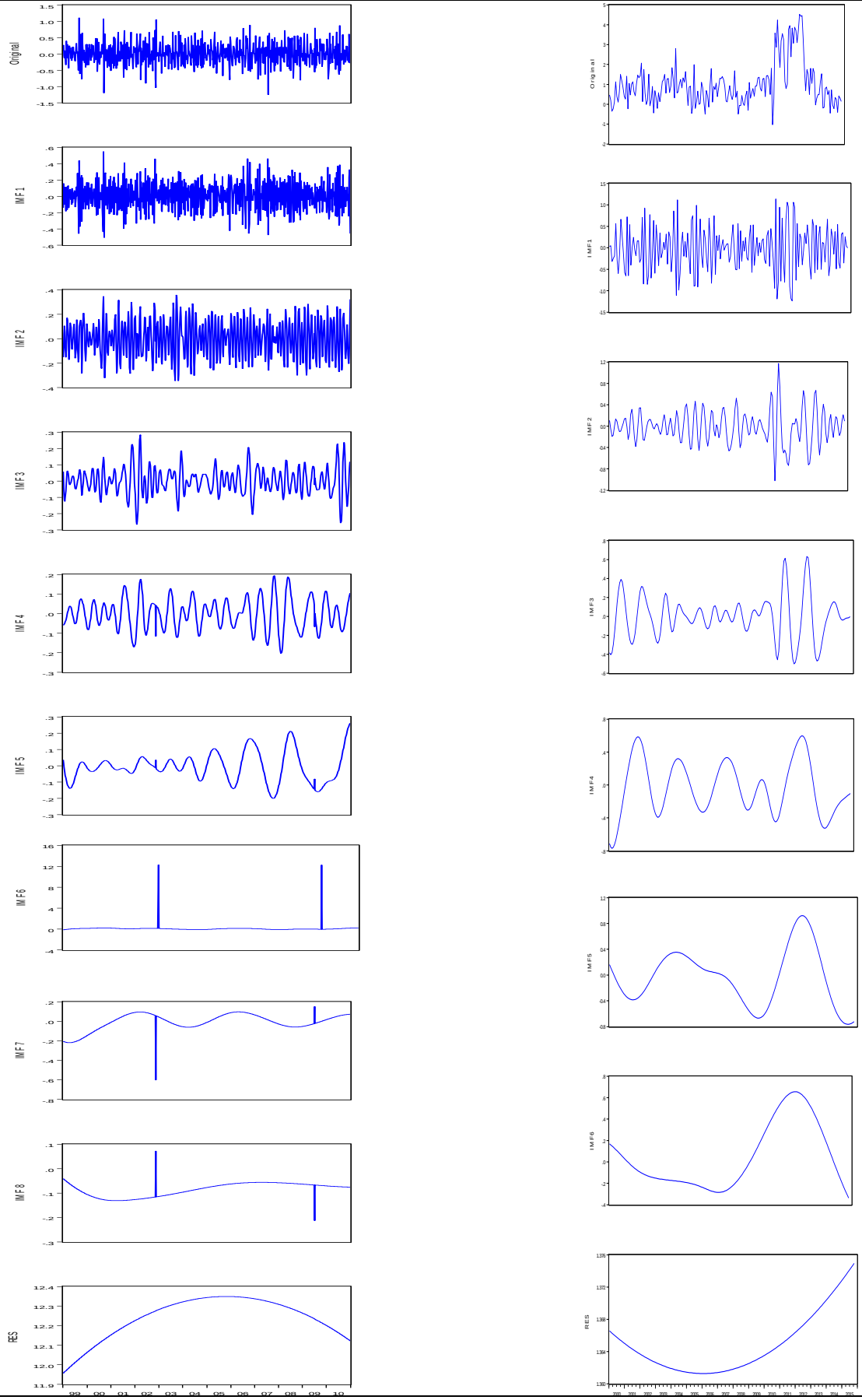
Russia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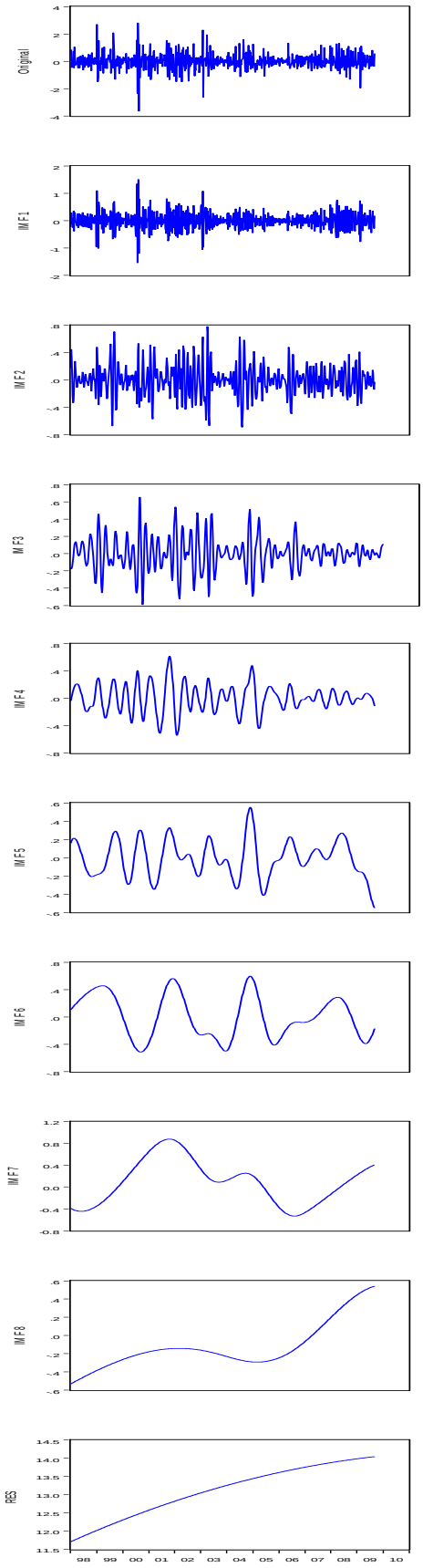
India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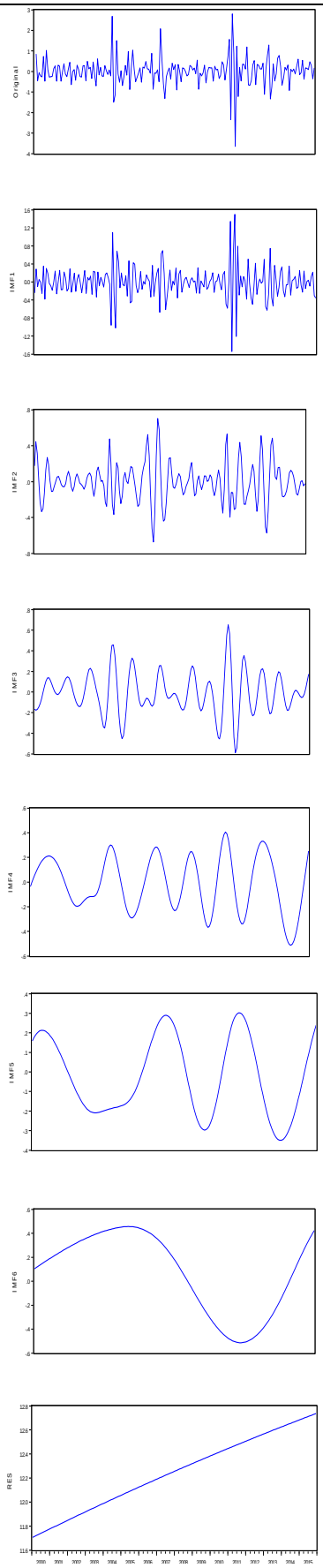
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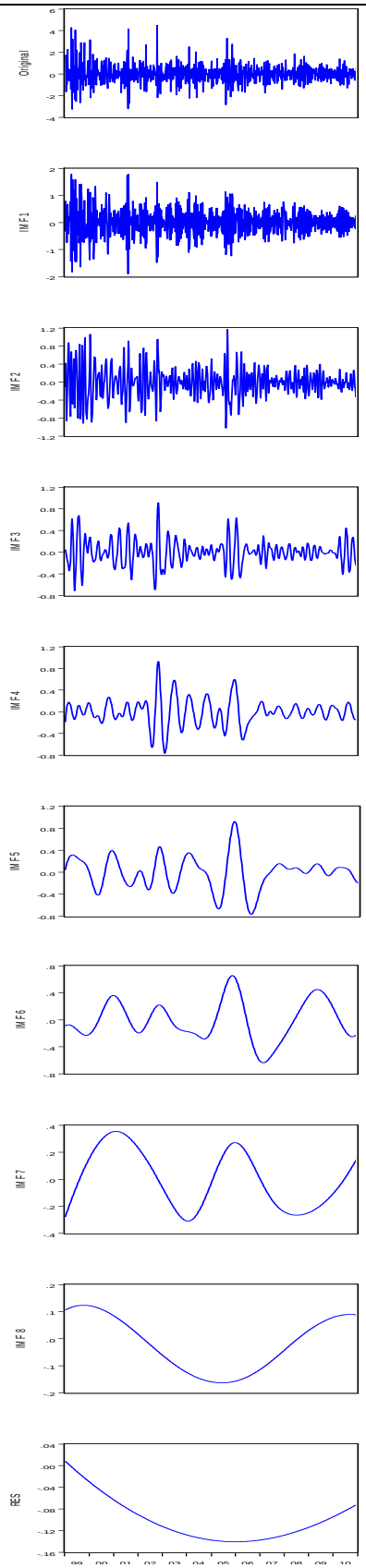
South Africa



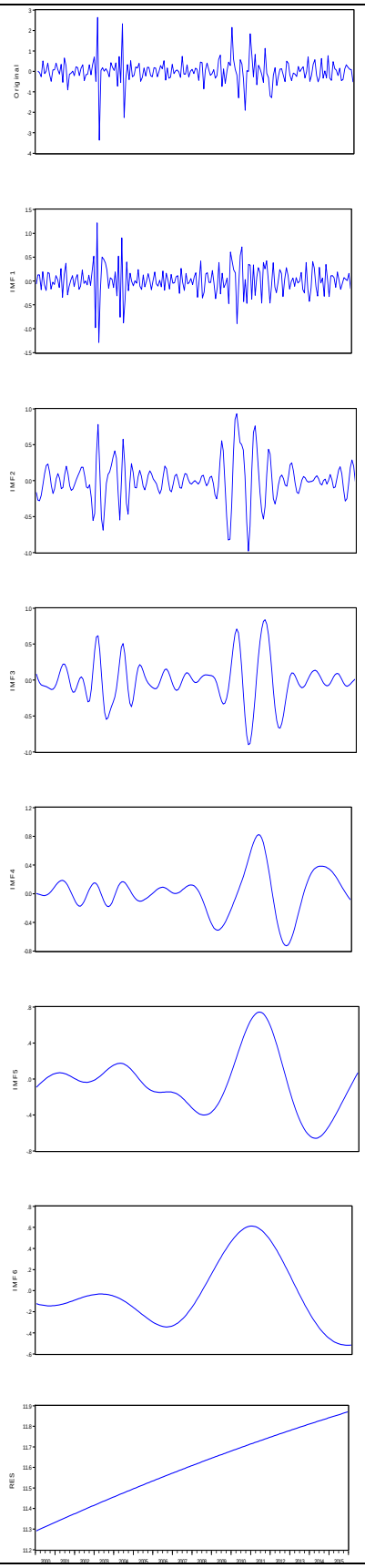
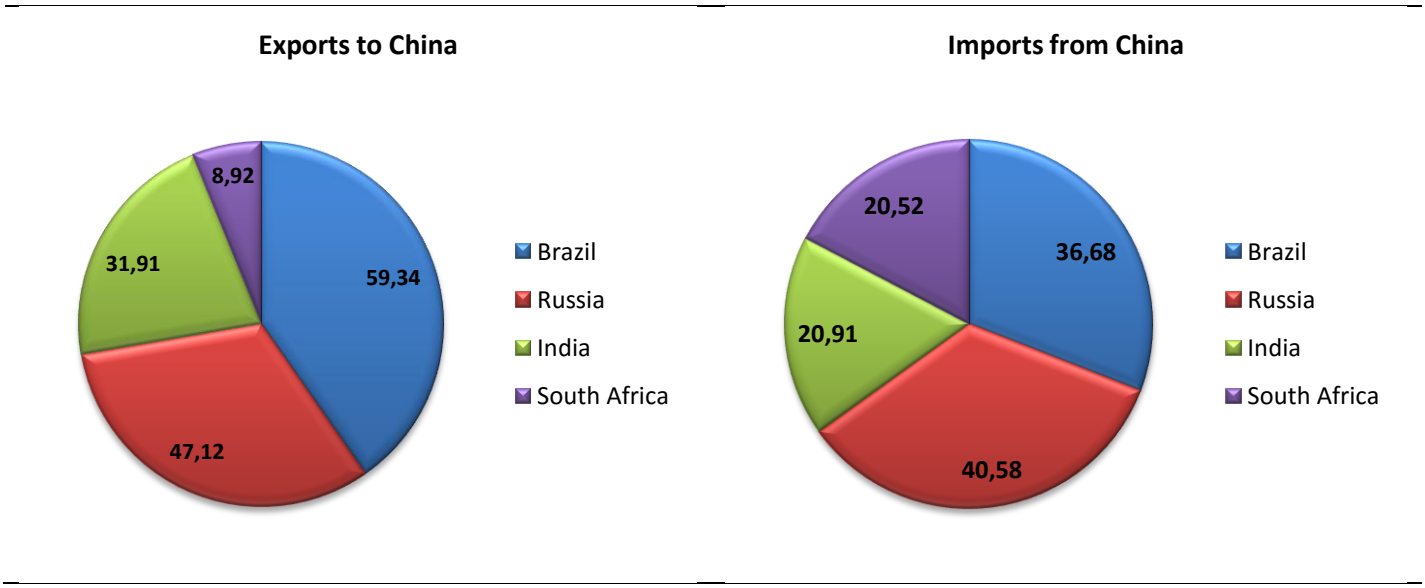
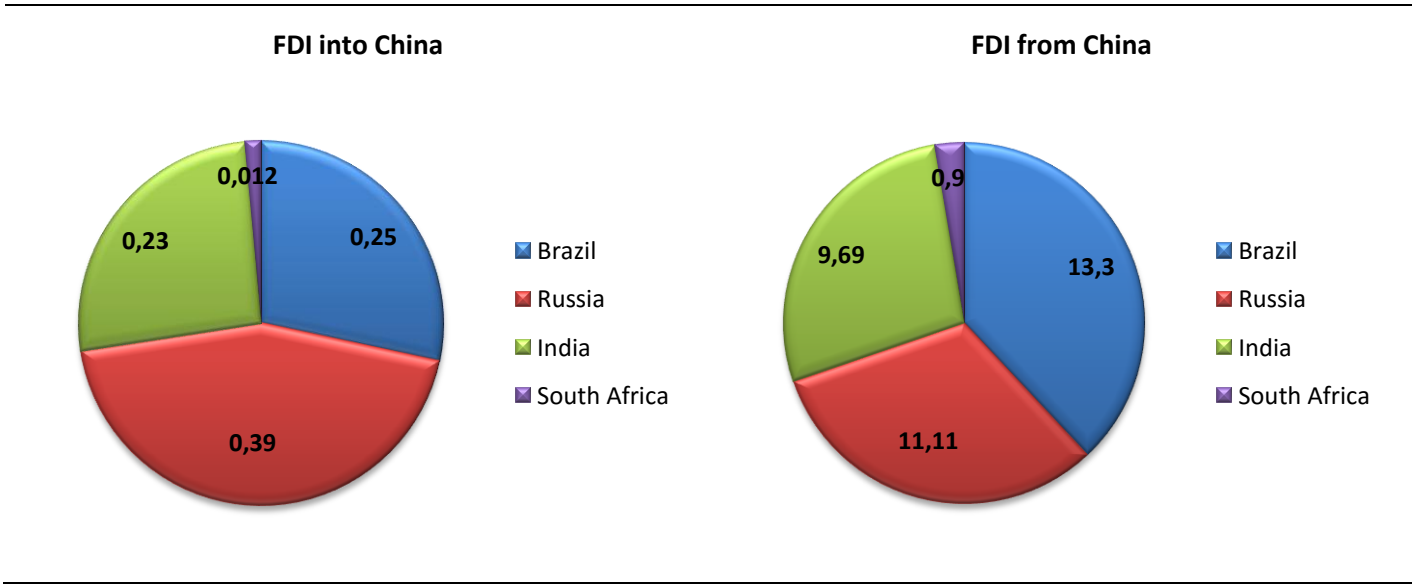


Figure A.2. Bilateral Trade Relationship in billion USD (as average 2000-2014)



Source: The Observatory of Economic Complexity (OEC).

Figure A.3. Bilateral Investment Relationship in billion USD (as average 2000-2014)



Source: UNCTAD.

Table A.2. Sectoral distribution of the BRICS stock market indices (in percent)

Sectors	Brazil	Russia	India	South Africa
Cyclical sectors				
-Oil and raw materials	50.2	60.2	1.4	2.0
-Financials and Banks	21.9	9.7	2.6	46.0
-Industrial and manufacturing	6.3	6.1	9.1	8.3
-Information technology	-	3.2	47.0	2.9
Total	78.4	79.2	60.1	59.2
Non-cyclical sectors				
-Consumer goods	9.5	11.2	6.8	9.8
-Telecommunications	4.3	4.1	10.4	7.0
-Others	7.8	6.4	22.7	21.8
Total	21.6	20.8	39.9	39.8

Sources: CME group, Bloomberg India-infoline (IIFL) websites.