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China's "New Normal": Will China's growth slowdown derail the BRICS stock markets?[1]

Abstract: After four decades of impressive performance, China's economic expansion has begun to slow. Considering the growing China's integration in global financial, we examine the effect of heightened uncertainty surrounding the China's transition to the new growth model on the remaining BRICS (in particular, Brazil, Russia, India and South Africa) stock markets. This analysis is novel in its methodological approach, which is conducted to pinpoint the dynamic spillover effects as alternative to the time and frequency. The impact of China's growth slowdown is found to be heterogeneous across the BRICS stock markets, suggesting that this crisis does not affect return dynamics in these markets in a uniform way. More specifically, South Africa hasn't been rattled as badly as Brazil, Russia and India. The intensity of bilateral trade and investment relationships, the position of market in terms of regulation and securities exchanges, the financial system efficiency and the ability of counter-cyclical policies to cope with the severe downturn have been put forward to explain the heterogeneous responses of BRICS equities.

Keywords: China's growth slowdown; BRICS stock markets; scale-on-scale analysis.
JEL codes : F36 ; G11 ; G15.

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1. Introduction

China’s real GDP growth is slowing sharply from an average of about 10 percent between 1980 and 2013 to 7 percent between 2014 and 2016.In the past, China largely benefited from an increasing workforce, which stimulated GDP especially because younger workers tend to be more productive than older ones. However, since 2012 the working-age population started to shrink, the inevitable outcome of the “one child” policy, which was approved in 1979. The noticeable drop in growth rates is partly due to this demographic winnowing. Increasing wages pose another potential challenge. Chinese wages now exceed those of most other emerging market economies, making China a less attractive destination for foreign investors. And this growth slowdown is widening and that is likely to continue, amid recent trade tensions with the United States.

A decline in domestic demand in China can harmfully affect the world economy and slow down global economic growth. The United States is one of the countries that is likely to be adversely influenced by the Chinese economy’s downturn. China is the U.S. biggest import partner whose imports were approximately $505.5 billion as of 2017 or nearly22% of the total imports of the United States. In light of these considerations, the future performance of the Chinese economy can bring about huge spillovers to other systemic economies as well as its potential trading partners. Given the emergence of China as a key driver of the global economy and its power in the world, it is highly expected 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 risk spillovers among other BRICS (i.e., Brazil, Russia, India, and South Africa[2]) stock markets. The existing investigations are likely to be qualitative

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

and/or descriptive, for example, reports by International Monetary Fund (2015) and IMF Asia and Pacific Department Regional Economic Outlooks (2014).

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(inter alia: Fama 1990, Galliger 1994, Mauro 2000, Kim 2003, Chen and Chen 2011,Croux and Reusens 2013, Bouoiyour and Selmi 2018).Notably, most of the studies has investigated the stock returns-real activity relationship for developed countries (for example, Canova and Nicolo 1995, Croux and Reusens 2013, Chen and Chen 2011). Because of the increasing speed of globalization, liberalization of capital movements, securitization of stock markets and the emergence of new equities, particularly in the Asian region, traders, investors and regulators become more interested by the responses of output growth to stock returns in emerging countries (see, for instance, Christoffersen and Sløk 2000, Maysami et al. 2004, Chen et al. 2006, Deb and Mukherjee 2008, Tsouma 2009, Bouoiyour et al. 2015, among others). It must be stressed that the stock market capitalization of the BRICS has totalled 7.6 USD billion in 2013 compared to 1.1 USD billion in 2000.

Moreover, assessing 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. While a growing number of studies have been devoted to the interdependence between stock markets, the empirical literature has shown mixed findings with respect the linkage between these variables, 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), OLS, standard

Granger causality test or multivariate GARCH models (Levy and Sarnat 1970, Solnik 1974, Masih and Masih 2001, Sharkasi et al. 2004 and Phuan et al. 2009, etc.). Other studies on this issue have conducted bivariate and multivariate cointegration models (Taylor and Tonks 1989, Kasa 1992) to distinguish between long-run and short-run dynamics. Even though these kinds of works offered prominent contributions, the insights regarding the precise horizons for stock markets characteristics are rather limited. Overall, the information derived from these techniques turn out to be insufficient for risk managers and investors who have a specific time horizon in mind when managing their portfolios. The examination of the interconnectedness of stock markets is of paramount prominence for the understanding of a crisis and its propagation mechanism. Although spillover effects in equity markets have been extensively evaluated in the extant literature (for example, Diebold and Yilmaz 2009, Engle et al. 2013), a limited research has tried to differentiate the short-term and long-term correlations between stock markets using more sophisticated techniques (for instance, Fernandez 2005, Rua and Nones 2009, Raghavan 2010, Shah et al. 2014, Wang et al. 2017, Yang et al. 2018). Wang et al. (2017) use wavelet approach to explore the relationship between stocks in the U.S. market over distinct time horizons from a network perspective. Besides, Yang et al. (2017) carry out a wavelet-based quntile regression to assess the interdependence between six Chinese stock markets and the international financial market including possible safe haven assets and global economic factors under several market states and investment horizons. Their findings provide fresh and very useful insights for participants in financial markets, especially for investors or hedgers who have various investment or hedging horizons.

Certainly, the wavelet approach is able to address investment, hedging and diversification opportunities through a proper decomposition of the stock market features for different time spans at a specific point in time. However, when applying a wavelet approach it is sometimes very difficult to identify local frequency changes, as the spectrum is generated by stepping through various predetermined frequency components yielding generally to blurred findings. The wavelet method presents problems of shift variance. More accurately, when the start point varies by, for example, dropping the initial point, the wavelet transform can reveal distinct outcomes. Hence the paramount importance to account for scales that are free from rigid mathematical constraints and that are driven to reflect inherent movements embedded in data without a priori knowledge. In this way, the Empirical Mode Decomposition (EMD) has proven effective when applied to a broad range of applications for extracting signals from data generated through noisy nonlinear and non-stationary processes (Huang et al. 1998, 2003, Huang and Attoh-Okine 2005). Recently, a special attention has been given to EMD, given its ability to decompose signals into scale components, to manage non-stationary data and to provide an alternative representation of the relationship between time series on a scale-by-scale basis. Since actors across various stock markets operate heterogeneously, it seems required to carry out elaborate econometric techniques that control for the time varying dynamics in time series. In this way, the EMD is appealing as the behavior of stock markets usually seem to go through different phases.

Our results provide robust 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, but seem more pronounced with the increased uncertainty over China economic downturn. In particular, Brazil, Russia and India (in this order) suffered more than South Africa from the China's growth slowdown.

The outline of the paper is as follows. Section 2 presents a literature review on. In Section 3, we discuss the conducted methodology, and describe the data. Section 4 reports the empirical results. Section 5 concludes and provides some relevant portfolio implications.

2. Literature review

Over the last decades there has been a large strand of literature focused on the relationship among asset markets in developed and emerging markets. The theory suggests that large benefits can be derived through international portfolio diversification if the returns of distinct financial markets are not perfectly correlated. According to Choudhry et al. (2007), a statistically significant correlation among stock markets means that there is a common force that brings these markets together, implying then that the benefit of diversification is limited. As a result, investors started to invest in distinct stock markets wherever they can earn more benefits. Nonetheless, the evidence from crisis events such as the global financial crisis underscores that market co-movements yield to contagion and then to strong correlations lessening the diversification opportunities. In this ground, a rigorous estimation of correlations between markets is of paramount importance to efficaciously capture changes in risk (Engle 2009). Since the dynamic correlations depict the historical linkages among different assets, investors and risk managers usually focus on correlation to frame expectations for how an investment portfolio may perform (Longin et al. 2001; Solnik 2002). Several researches have been carried out to examine the interdependence between distinct equity markets. In general, equities are said to be integrated when significant correlation exists between markets. Nevertheless, the studies on this issue provided mixed outcomes (Hilliard 1979; Aggarwal et. al. 2003; Chi et al. 2006; Abbas and Chancharat 2008, among others). The earliest empirical research on stock markets relationships consider the interdependence among markets as effects of the conditional means of the return of one country onto the conditional means of chronologically succeeding returns of another country. They have concentrated on the analysis of short-term benefits of international portfolio diversification (for example, Levy and Sarnat 1970; Solnik 1974). Other works have analyzed the interdependence between stock markets via the covariance of excess returns (for instance, Phylaktis 1999). Another strand of literature has assessed the linkages across stock markets using bivariate (Taylor and Tonks 1989) or multivariate cointegration methodology (Kasa 1992).

Apart from examining the dynamic relations between stock markets, many investigations have focused on the effect of major events such as global financial collapse on the stock market interdependencies (for example, Lim and McAleer 2004, Aggarwal et. al. 2008, Ansari 2009, Joe et al. 2012, Wang 2014). Ansari (2009) argued that the synchronization across the stock markets has changed sharply after the globalization. Joe et al. (2012) examined the contemporaneous co-movements and lead/lag relationships among different Asian stock markets over the period 2001– 2011 and showed that the synchronization among the markets decreases during this period. Nevertheless, Wang (2014) evaluated the linkages between the U.S. stock market and six Asian stock markets and deduced that the global financial collapse has reinforced the linkages among these markets. By conducting a network analysis for fourteen Asian stock markets, Aswani (2017) documented that the interdependence between these stock markets rises markedly during the crisis period rather than the pre-crisis or the post-crisis period.

More recently, Bouoiyour et al. (2019) tried to address whether or not the stock market of China is integrated with that of the US prior to and post 2016 U.S. presidential elections. They used a Copula-quantile-on-quantile regression to examine the dependence structure between the quantile of US stock return on the quantile of China stock return. This technique is useful for risk managers working on portfolio optimization, asset pricing and the assessment of systemic risk. The results reveal a gradual transitioning feature in the correlation going from the centrally located quantiles (normal state) to the tail quantiles (bull and bear states). Specifically, a negative correlation is found when the China's market is improving and the US market is heading into decline, and also when the two markets are functioning around the normal circumstances.

The present research complements the existing literature by analyzing the role that may play the uncertainty over China's growth slowdown in exacerbating the risk spillovers among the China stock market and the remaining BRICS stock returns. We investigate the dynamic spillover effects prior to and after the China economic downturn. In times of heightened uncertainty, an effective defense is to be well informed about the correlation between different stock markets at distinct points of time. From a risk management perspective, accounting for nonlinearity (i.e., a multi-scale causality) is very beneficial for market participants (in particular, traders, investors and risk managers) as they would allow them to effectively protect against unforeseen shocks and rising uncertainties. Such a fine analysis could help investors in adjusting the portfolio composition to better match the desired portfolio risk profile

3. Methodology and data

To effectively control the risks that they face, portfolio managers generally need to consider the dependence between different equities in times of market distress or rising uncertainty. Because the co-movement or the causality between stock markets during high risk episodes may mask the irregularities we would like to identify, it is important to use techniques for decomposing a time series into a number of components. This would allow pinpointing the dynamic interconnectedness among different markets. For investors wishing to use the stock market hedging and diversification features to deal with uncertain exposure, it is relevant to have information about whether the linkages between the stock markets under study are consistent over time, or concentrated in specific times. Accordingly, this study uses a relatively new technique, called Empirical Mode Decomposition (EMD), based on the sequential extraction of energy associated with distinct frequencies ranging from highly fluctuating components (short-run) to less fluctuating modes (long-run).

3.1. 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 using 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 stock markets in times of heightened uncertainty surrounding China growth'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 test whether a significant causality occurs across China-BRICS stock returns among matched modes and thus over different time-horizons. Figure 1 depicts the proposed analysis approach. Specifically, two main steps are involved:

Step 1: Signal decomposition

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:

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

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

$$d(t) = m(t) - x(t) \quad (2)$$

where $d(t)$ is presented as the i^{th} 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 log2N (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:

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

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. The EMD 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). In particular, a general causality test- based on a Taylor expansion (PéguinFeissolle and Teräsvirta 1999) has been performed.

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

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.

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

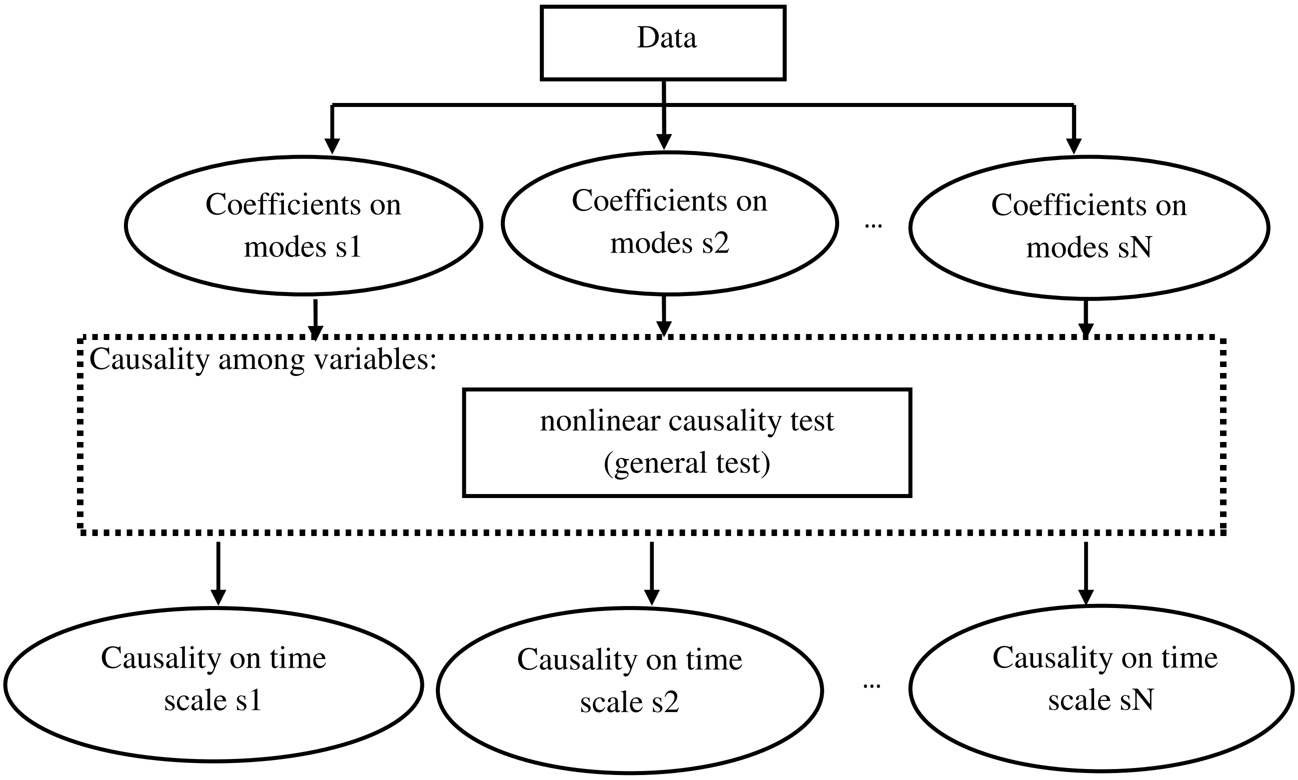
To test (5) against (4), we linearize f^* in (4) by expanding the function into a *k*-order Taylor series around an arbitrary fixed point in the sample space. We obtain:

$$y_t = \beta_0 + \sum_{j=1}^{q}\beta_j y_{t-j} + \sum_{j=1}^{n}\gamma_j x_{t-j} + \sum_{j_1=1}^{q}\sum_{j_2=j_1}^{q}\beta_{j_1 j_2} y_{t-j_1} y_{t-j_2} + \sum_{j_1=1}^{q}\sum_{j_2=1}^{n}\delta_{j_1 j_2} y_{t-j_1} x_{t-j_2}$$

$$+\sum_{j_1=1}^{n}\sum_{j_2=j_1}^{n}\gamma_{j_1 j_2} x_{t-j_1} x_{t-j_2} + \dots + \sum_{j_1=1}^{q}\sum_{j_2=j_1}^{q}\dots\sum_{j_k=j_k-1}^{q}\beta_{j_1\dots j_k} y_{t-j_1}\dots y_{t-j_k}$$

$$+\dots+\sum_{j_1=1}^{n}\sum_{j_2=j_1}^{n}\dots\sum_{j_k=j_k-1}^{n}\gamma_{j_1\dots j_k} x_{t-j_1}\dots x_{t-j_k} + \varepsilon_t^* \qquad (6)$$

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



3.2. Data and descriptive statistics

This study uses daily data for the stock market indices growth (STR)[3] 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 20, 1999 to March 05, 20184,. For comparison purpose, we analyze two sub-periods: the first is the Chinese rapid growth period between January, 20 1999 to December 31, 2010, and the second is the slowdown period from January 01, 2011 and March 05, 2018. The data were collected from Datastream database.

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

4The 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.

The use of daily data enables to take into account the exact moment of each policy announcement and to assess the immediate market response to that particular news. With high frequency data, we can set a sufficiently narrow time window around each policy announcement and each untoward shock to assess if the markets respond to specific news. Measuring the surprise in a limited time horizon ignores the noise owing to other events. However, if we use weekly, monthly or quarterly data, the measurement of the immediate impacts of unforeseen shocks or events will be more complicated (Selmi et al. 2018). Indeed, the occurrence of events is followed by investors who form or revise their expectations based on the results of these events. The informational efficiency hypothesis states that markets absorb news into asset prices in anticipation of an event' outcomes. By using daily data, we are able to account for the exact moment of each policy announcement and to assess the immediate market response to that particular news. In short, the use of daily data appears more appropriate for our purpose of characterizing the dynamic spillovers across stock markets especially in period of rising uncertainty.

We incorporate in the following gold prices and the Chicago Board Options Exchange Volatility Index (largely known by VIX) to check whether the results are still robust after the inclusion of global economic and financial factors. VIX measures the stock market expectations of the volatility implied by S&P 500 Gold has been largely served as a hedging tool against sudden stocks and as a safe haven during extreme 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 biggest producers (South Africa). In addition to gold, the finance literature has been frequently relied on proxies of uncertainty such as VIX index that plays an important role in asset allocation and portfolio strategies (Hood and Malik 2013, Balcilar et al. 2014, Mensi et al. 2015)[5]. The data for gold prices, which are measured in USD per ounce, were downloaded from the website of the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/GOLDAMGBD228NLBM); Likewise for the VIX index (https://fred.stlouisfed.org/series/VIXCLS).Table 1 provides the descriptive statistics of the daily returns for the period of rapid China's growth (Panel A, Table 1) and the period of China's growth slowdown (Panel B, Table 1). We clearly show that the average returns are positive for all the return series over the two periods under study. Importantly, all the stock markets in question become much more volatile during the period of China economic downturn. The greatest volatility of the different BRICS equities is confirmed by Figure A.1. (Appendix). The skewness coefficients are negative and the kurtosis coefficients are above three for all return series and over the two periods, indicating that the probability distributions of the return series under study are skewed and leptokurtic, thereby rejecting normality which is also confirmed by the Jarque-Bera statistics (J-B).

Table 1. Descriptive statistics of return series

	STR_China	STR_Brazil	STR_Russia	STR_India	STR_South Africa	VIX	gold
Panel A: Period of rapid China's growth							
Mean	0.061	0.073	0.019	0.013	0.031	0.178	0.149
Median	0.027	0.041	0.027	0.003	0.018	0.323	0.301
Std. Dev.	0.327	0.471	0.311	0.298	0.169	4.526	1.883
Skewness	-0.932	-1.319	-0.654	-3.264	-0.707	-0.250	-0.347
Kurtosis	3.214	5.072	3.628	8.787	6.314	9.656	8.873
Jarque-Bera	13.094	12.404	9.106	20.071	11.802	61.97	43.861
Panel B: Period of China's slowdown							
Mean	0.052	0.038	0.009	0.006	0.008	0.1165	0.1537
Median	-0.004	-0.003	-0.001	0.000	-0.005	0.3457	0.3669
Std. Dev.	1.736	1.563	1.629	1.625	1.078	6.225	1.404
Skewness	-0.615	-1.088	-0.973	-2.314	-1.774	-0.571	-1.289
Kurtosis	9.246	7.939	6.977	19.267	12.489	5.373	10.124
Jarque-Bera	91.713	44.935	29.745	43.386	15.569	25.06	20.94

[5] 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 findings

4.1. Standard techniques findings

We begin 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 causality testing-based Wavelet decomposition[6]). 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, Appendix). 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, Appendix). Then, we apply the VECM model and the standard Granger causality test in order to test if China's slowdown exacerbates risk 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 linkages seem strong for Brazil, followed by Russia and India and finally South

[6] We thank the Reviewer for the very careful review of our paper and for pointing out helpful comments and insightful remarks. A major revision of the paper has been carried out to take all of them into account.

Africa. Similar hierarchy is found during the China's slowdown period, but these links appear more pronounced compared to the period prior to the onset of Chinese crisis.

Table 2. VECM: The dependence structure between China and the remaining BRICS markets

	Panel A: Period of China rapid growth				*Panel B: Period of China's slowdown*			
	STR_Brazil	STR_Russia	STR_India	STR_South Africa	STR_Brazil	STR_Russia	STR_India	STR_South Africa
D(STR_China$_{t-1}$)	0.234*** (0.0000)	0.168** (0.0043)	0.110*** (0.0000)	0.051*** (0.0004)	0.304*** (0.0000)	0.162*** (0.0002)	0.142*** (0.0009)	0.094** (0.0032)
D(gold$_{t-1}$)	-0.054** (0.0092)	0.039*** (0.0000)	-0.062*** (0.0000)	0.008* (0.0415)	-0.163** (0.0093)	-0.041* (0.0311)	0.083 (0.2452)	-0.061* (0.0981)
D(VIX$_{t-1}$)	-0.018* (0.067)	-0.023** (0.0051)	-0.064** (0.0081)	-0.023 (0.5412)	-0.049* (0.0105)	-0.092** (0.0067)	-0.078* (0.0513)	-0.063** (0.0091)
STR_China$_{t-1}$	0.431** (0.0056)	0.303** (0.0018)	0.276*** (0.0007)	0.184** (0.0011)	0.509*** (0.0006)	0.411*** (0.0008)	0.336** (0.0010)	0.229** (0.0014)
gold$_{t-1}$	0.111** (0.0041)	-0.076* (0.0818)	-0.065** (0.0053)	0.102*** (0.0000)	-0.171** (0.0023)	-0.109* (0.0813)	0.147 (0.2061)	0.094 (0.1542)
VIX$_{t-1}$	-0.064** (0.0091)	-0.096* (0.0510))	-0.055*** (0.0004)	0.082 (0.1356)	-0.051** (0.0067)	-0.087** (0.0016)	-0.059* (-0.0410)	-0.088* (0.0514)
ECT$_{t-1}$	-0.026* (0.0504)	-0.039** (0.0010)	-0.091*** (0.0000)	-0.100*** (0.0004)	-0.081*** (0.0000)	-0.088*** (0.0000)	-0.073** (0.0019)	-0.065** (0.0026)
R-squared Adj. R-squared	0.73 0.68	0.67 0.54	0.71 0.69	0.64 0.52	0.69 0.51	0.68 0.64	0.59 0.38	0.46 0.39

Note: (.): 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 "standard" methods, may be erroneous since they provide averages which do not satisfactorily account for the problems of asymmetry 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 time-scale to another. Hence, a multi-scale analysis is conducted 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).

Table 3. Standard Granger causality test: The dependence structure between China and the remaining BRICS markets

	Panel A: Period of China rapidgrowth				*Panel B: Period of China'sslowdown*			
	STR_Brazil	STR_Russia	STR_India	STR_SouthAfrica	STR_Brazil	STR_Russia	STR_India	STR_SouthAfrica
STR_China	0.0014**	0.0003***	0.0000***	0.0002***	0.0010**	0.0027**	0.0014**	0.0009***

Note: (.): the p-value; p-value<0.01: ***; p-value<0.05: **; p-value<0.1

4.2. EMD findings

This paper attempts the dynamic spillovers across China and the remaining BRICS markets over different time-scales. Our main objective is to show how dividing variables into intrinsic mode functions can be useful in assessing the financial spillovers in periods of China's rapid growth and China economic downturn. By performing EMD, the dependent and independent variables were divided into several IMFs and one residue (the time-scale decomposition results are available for interested readers upon request). Asthe number of IMFs is limited and restricted to log2N where N is the length of data[7], sifting processes produced eight IMFs for each variable over period of rapid China's growth (Panel A, Table 4), and only six IMFs for the period of China growth's slowdown. All of the derived IMFs are listed from high to the low frequency components and the last one is the residue. Throughout the rest of our study, we discuss three frequency components for the first period (Panel A): short-run (IMF1, IMF2 and IMF3), medium-run (IMF4 and IMF5) and long-run (IMF6, IMF7 and IMF8)[8]. Fig. 2 presents our time scale interpretation of EMD. We adopt another grouping for the second period (Panel B): short-term (IMF1 and IMF2), medium-term (IMF3), and long-term (IMF 5 and IMF6). But this does not fundamentally change our results.

[7]The EMD technique generates modes depending on the data used. For more information on the data extraction method used, please refer to Huang et al. (2003).

[8]We adopt another grouping for the second period (Panel B): short-term (IMF1 and IMF2), medium-term (IMF3), and long-term (IMF 5 and IMF5). This does not fundamentally change our results.

Table 4. Interpretation of scales-based on EMD

modes	Panel A: Period of rapid China's growth	Panel B: Period of China's slowdown
IMF1	Short-run: less than two months (60 days)	Short-run: less than two months (60 days)
IMF2		
IMF3		Medium-run: above two months (60 days) and less than one year (365 days)
IMF4	Medium-run: above two months (60 days) and less than one year (365 days)	
IMF5		Long-run: above one year (365 days)
IMF6	Long-run: above one year (365 days)	
IMF7		—
IMF8		—

On various time-scales, distinct modes may behave differently, due to hidden factors driving the focal stock markets. 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 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 365 days) 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; less than 60 days). 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. The results change marginally by moving from the first period (Panel A, Table 5) to the second period (Panel B, Table 5). 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	0.93	0.111*	0.078**	5.01%	0.96	0.051	0.026	1.36%
IMF2	0.99	0.061	0.052	1.34%	1.93	0.072	0.070*	1.56%
IMF3	1.15	0.081*	0.059	1.11%	3.48	0.098***	0.83**	2.65%
IMF4	4.34	0.094***	0.080***	2.06%	6.68	0.173***	0.148**	24.16%
IMF5	9.11	0.069**	0.051	3.19%	13.71	0.232**	0.209***	31.67%
IMF6	16.07	0.206*	0.196***	16.14%	17.91	0.189**	0.176**	15.13%
IMF7	21.38	0.292***	0.284***	28.29%	—	—	—	—
IMF8	26.72	0.115**	0.092**	18.18%	—	—	—	—
Residue		0.251***	0.244***	23.91%		0.311**	0.268**	23.41%
				Brazil				
IMF1	1.03	0.126***	0.085**	1.91%	1.42	0.111**	0.107**	4.56%
IMF2	2.11	0.091*	0.081**	2.55%	2.72	0.188**	0.132**	11.42%
IMF3	5.32	0.059*	0.032	2.42%	4.15	0.046	0.031	2.91%
IMF4	8.91	0.168***	0.149**	9.11%	8.42	0.060*	0.042	2.52%
IMF5	12.24	0.171***	0.162***	11.23%	16.79	0.183***	0.172**	16.93%
IMF6	19.86	0.328***	0.311***	18.72%	24.83	0.252**	0.238**	42.11%
IMF7	24.10	0.251**	0.242***	17.73%	—	—	—	—
IMF8	27.16	0.229**	0.217**	19.91%	—	—	—	—
Residue		0.183***	0.176***	16.41%		0.186***	0.174**	20.98%
				Russia				
IMF1	1.51	0.071*	0.059*	0.88%	1.23	0.091*	0.072*	7.73%
IMF2	1.76	0.088*	0.043	0.94%	1.83	0.072*	0.066	6.11%
IMF3	6.09	0.082*	0.036	0.91%	6.71	0.104**	0.088*	8.92%
IMF4	14.38	0.178**	0.159*	14.89%	8.52	0.092**	0.083**	5.11%
IMF5	16.09	0.283**	0.261**	17.06%	13.91	0.181***	0.172***	18.32%
IMF6	18.32	0.206***	0.183**	16.91%	19.27	0.236***	0.214**	23.34%
IMF7	25.11	0.410***	0.379***	21.34%	—	—	—	—
IMF8	27.36	0.196**	0.177**	18.02%	—	—	—	—

Residue		0.171**	0.132*	9.05%		0.189**	0.177**	22.72%
India								
IMF1	3.59	0.311***	0.246***	31.27%	2.09	0.172**	0.155*	16.78%
IMF2	6.10	0.258**	0.231***	27.16%	3.56	0.311**	0.249***	29.04%
IMF3	7.94	0.197**	0.188**	11.24%	7.91	0.187***	0.121**	12.35%
IMF4	10.03	0.141*	0.095*	8.13%	9.83	0.095**	0.076*	4.01%
IMF5	12.14	0.100***	0.088*	0.88%	13.42	0.093*	0.081*	3.21%
IMF6	12.68	0.076*	0.053	0.45%	21.67	0.104*	0.097*	5.51%
IMF7	17.91	0.091*	0.066*	0.51%	—	—	—	—
IMF8	23.48	0.062	0.041	1.18%	—	—	—	—
Residue		0.211***	0.199***	19.18%		0.231***	0.199***	29.09%
South Africa								
IMF1	1.94	0.272**	0.264**	24.56%	1.41	0.113**	0.100**	4.11%
IMF2	2.61	0.404***	0.384**	28.19%	2.68	0.086**	0.072*	1.92%
IMF3	2.88	0.189**	0.177*	12.31%	4.51	0.134**	0.121***	8.71%
IMF4	4.19	0.105*	0.083**	3.42%	8.32	0.061	0.042	6.39%
IMF5	8.33	0.116***	0.100**	6.41%	14.93	0.217**	0.194**	25.16%
IMF6	12.08	0.084*	0.077*	1.31%	25.18	0.334***	0.276***	40.18%
IMF7	25.24	0.069*	0.051	0.92%	—	—	—	—
IMF8	28.91	0.044	0.023	0.75%	—	—	—	—
Residue		0.211***	0.195**	16.72%		0.248**	0.233**	18.23 %

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 each of the BRICS stock markets over the period of China rapid growth and the period of China's slowdown (Panels A and B, respectively).

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	0.178**	0.159**	7.46%	0.133***	0.127**	2.92%
Low Frequency component	0.511***	0.492***	62.61%	0.361**	0.324**	46.8%
Trend component	0.412**	0.386***	23.91%	0.303***	0.256**	23.41%
Brazil						
High frequency component	0.087*	0.079*	6.88%	0.156***	0.141**	15.98%
Low Frequency component	0.421***	0.389***	56.36%	0.324***	0.278***	59.04%
Trend component	0.176**	0.161**	16.41%	0.194**	0.186**	20.98%

Russia						
High frequency component	0.249***	0.206*	2.73%	0.181***	0.162***	13.84%
Low Frequency component	0.326***	0.301***	55.31%	0.406***	0.362***	41.66%
Trend component	0.218**	0.173*	9.05%	0.189**	0.173*	22.72%
India						
High frequency component	0.518***	0.499**	69.67%	0.479***	0.381***	45.82%
Low Frequency component	0.138*	0.110*	2.14%	0.139**	0.089*	8.72%
Trend component	0.392***	0.365***	19.18%	0.215***	0.194**	29.09%
South Africa						
High frequency component	0.606**	0.551***	65.06%	0.097**	0.088*	12.06%
Low Frequency component	0.097*	0.061	2.98%	0.281***	0.253**	65.34%
Trend component	0.162**	0.149**	16.72%	0.192***	0.177**	18.23%

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[9] 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 two months (60 days); the medium scaling components represent the Euclidean distance within two months (60 days) and less than eight months (240 days); the longest scales correspond to the distance more than 12 months or one

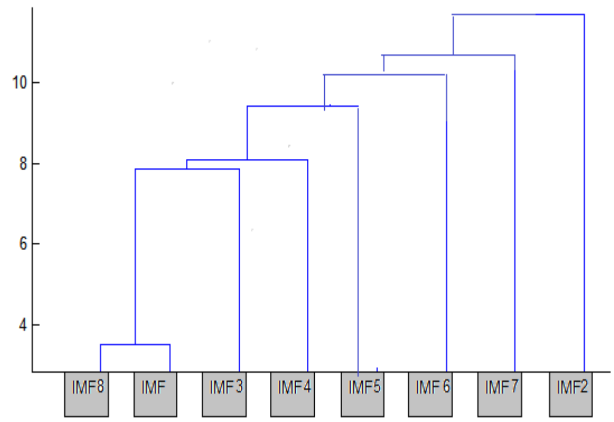
[9]The hierarchical clustering investigation was also implemented in the Matlab R2015a software package.

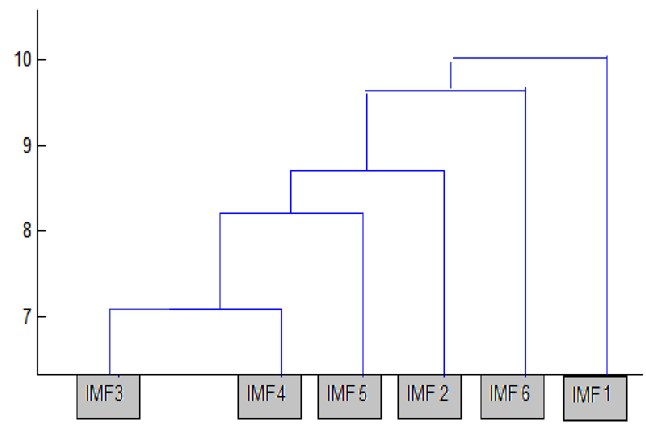
year (365 days). The clustering findings, over the period prior to China's economic slow-moving (Panel B, Figure 2), confirm the previous results by often distinguishing the same two groups (i.e., whose determined by longer scale factors (China, Brazil and Russia), and whose driven by short-run factors (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).

Figure 2. The Euclidean distance via hierarchical clustering method

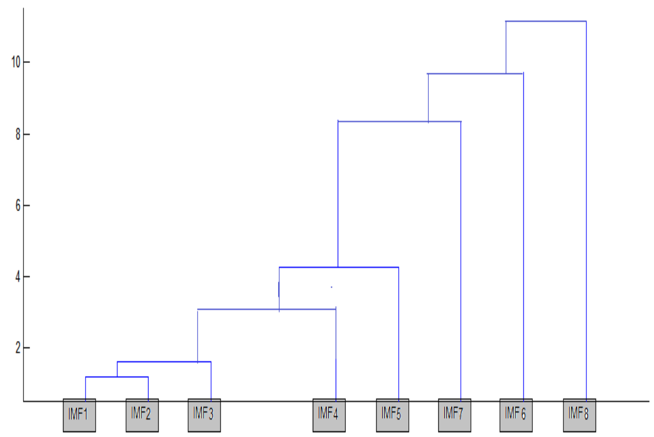
Panel A: Period of rapid China's growth	Panel B: Period of China's slowdown

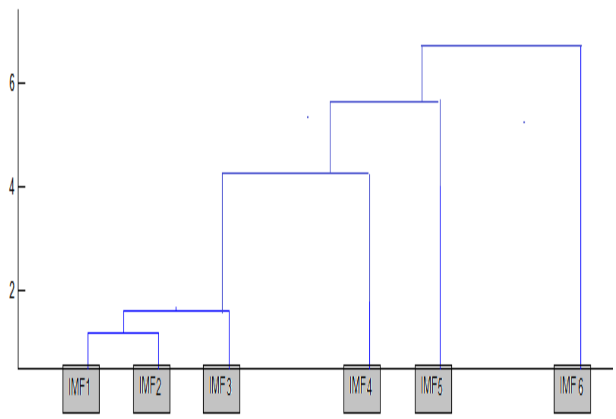
China



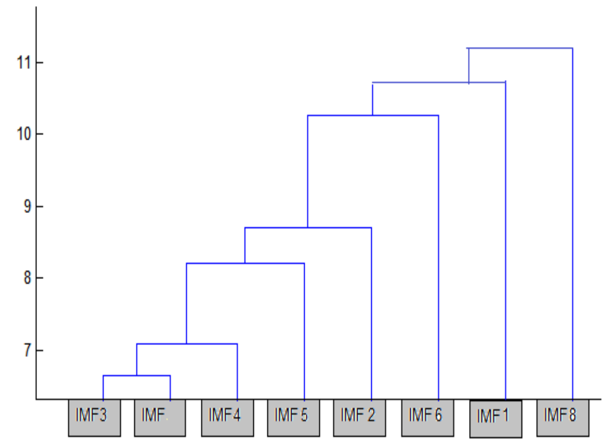


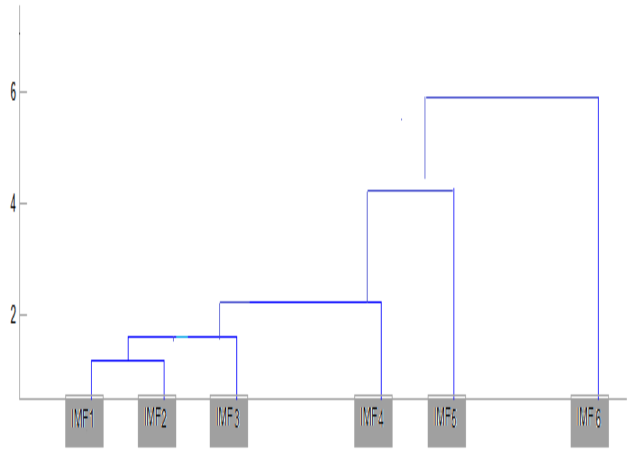
Brazil



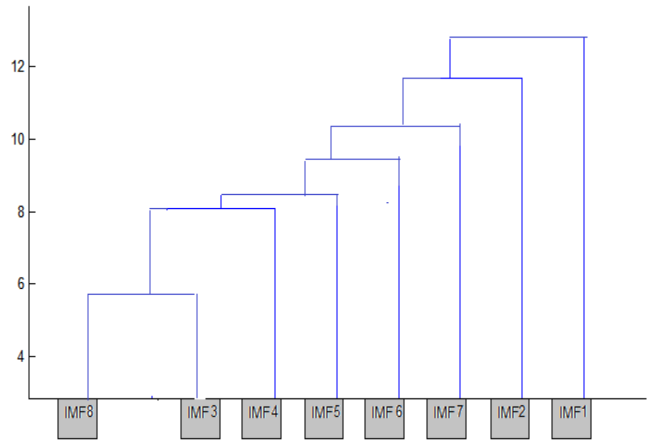


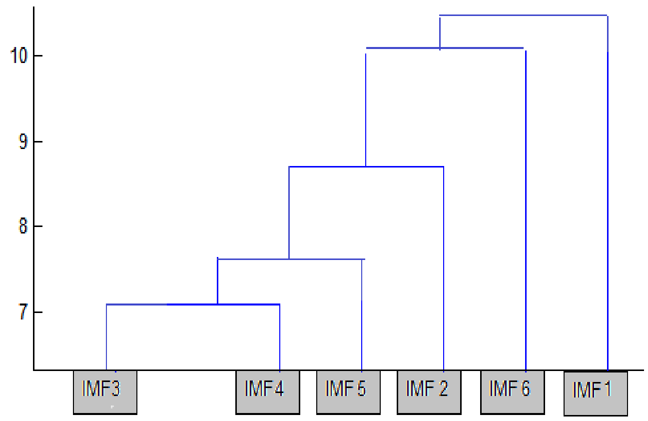
Russia



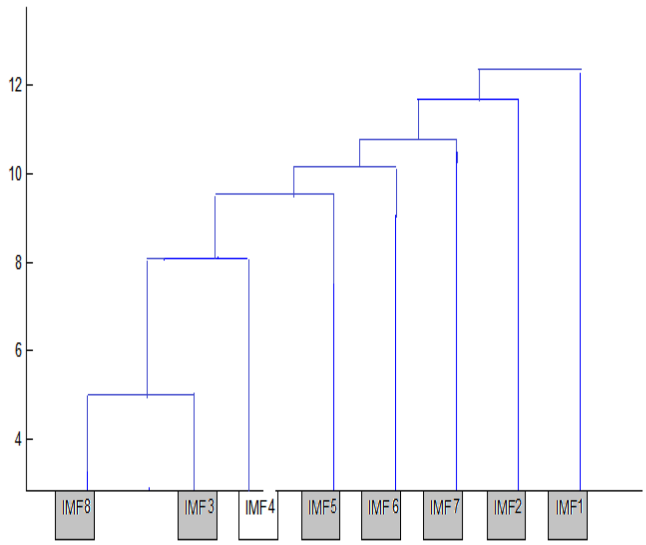


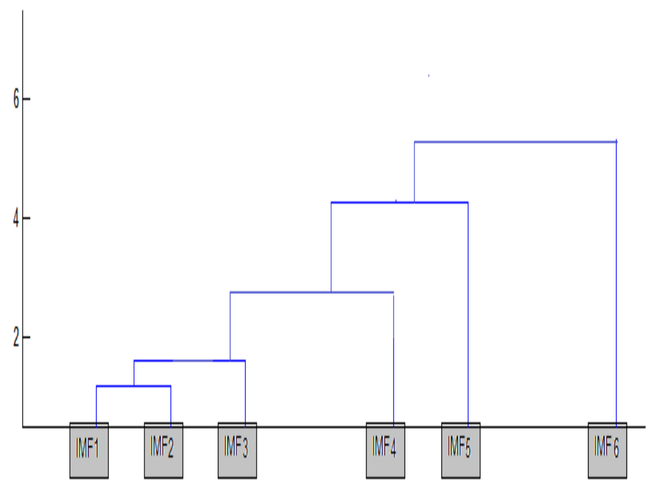
India





South Africa





Regardless of 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 dynamic risk spillover effects of China growth's slowdown and what drives the linkages China- BRICS stock returns over a period of great uncertainty surrounding the China crisis, and not what determine the equity market returns of each country independently. Thus, we try in the following to test the causality between China stock return and the remaining BRICS stock returns as alternative to various time-scales.

4.3. Causality testing-based EMD findings

A nonlinear Granger causality test is conducted to analyze causal linkages between the Chinese market and the remaining 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 in the long-term (scale above 365 days; IMF6, IMF7 and IMF8). The second group includes India and South Africa where causality is validated at short-run horizons (less than 60 days, IMF1, IMF2 and IMF3). Also, the residues of Chinese stock returns significantly cause the BRICS stock returns in the long-term (Table 7.1). By accounting for gold price and the VIX index (Panels A and B, Table 7.2), 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 (Panel B, Table 7.2), the scale length becomes longer for all the cases. In particular, we note a stronger influence on Brazilian and Russian equities (IMFs 6-8: above 365 days). Indian and South African markets appear less influenced (short and medium term effect at the range IMFs 1-5: less than one year).

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	0.3981	0.5119	0.1462	0.0043**	IMF1	0.4321	0.3146	0.0013**	0.0138*
IMF2	0.2276	0.2081	0.0003***	0.0018**	IMF2	0.4015	0.2275	0.0029**	0.1014
IMF3	0.2451	0.3410	0.0012**	0.0009***					
Medium scales					Medium scales				
IMF4	0.6134	0.2344	0.2289	0.1567	IMF3	0.3210	0.1963	0.0162*	0.0111*
IMF5	0.5542	0.5203	0.3016	0.1810	IMF4	0.2072	0.2048	0.0303*	0.0048**
Long scales					Long scales				
IMF6	0.0000***	0.0068**	0.3651	0.2867	IMF5	0.1093	0.0091**	0.8012	0.4985
IMF7	0.0003***	0.0073**	0.4218	0.4155	IMF6	0.0046*	0.0068**	0.7146	0.6371
IMF8	0.0016**	0.0107	0.2910	0.3762					
Residue	0.0001***	0.0039**	0.0017**	0.1483	Residue	0.0001***	0.0026**	0.0044**	0.0015**
7.2. Conditional analysis									
Short scales					Short scales				
IMF1	0.1968	0.2671	0.0019**	0.1335	IMF1	0.6134	0.2678	0.0135*	0.0067**
IMF2	0.4031	0.1342	0.0018**	0.0167*	IMF2	0.5592	0.1432	0.0108*	0.0013**
IMF3	0.2264	0.2053	0.0000***	0.0098**					
Medium scales					Medium scales				
IMF4	0.1051	0.2627	0.3358	0.2156	IMF3	0.2981	0.4267	0.0118*	0.0029**
IMF5	0.0918*	0.3178	0.2094	0.2378	IMF4	0.3415	0.5039	0.0092**	0.0034**
Long scales					Long scales				
IMF6	0.1263	0.4567	0.5011	0.9172	IMF5	0.0023**	0.0003***	0.1652	0.4360
IMF7	0.1029	0.0006**	0.4327	0.5429	IMF6	0.0046**	0.1012	0.1832	0.3782
IMF8	0.0114*	0.0000**	0.2289	0.6039					
Residue	0.0003***	0.0001***	0.0073**	0.0061**	Residue	0.0002***	0.0000***	0.0010**	0.0017**

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. Robustness checks

We now investigate how various econometric specifications and data may change our estimates. We first use an alternative time-frequency approach, namely wavelet decomposition (WD). A number of time-frequency transformations able to effectively describe signals with time-varying features have surfaced in the literature, though two have gained large popularity in the analysis of complex systems: the wavelet transform and the empirical mode decomposition. It is important to point out the appropriateness of both techniques for the analysis of nonstationary and nonlinear signals. Accordingly, Kijewski-Correa and Kareem (2006, 2007) affirmed the capability of the Empirical Mode Decomposition and the Wavelet decomposition (WD) to properly detect the instantaneous frequency of signals of constant and time-varying frequency in the presence of noise. Given this consideration, We utilize the WD as an alternative technique to ascertain the robustness of the EMD results. Using WD, we separate data into various frequency components, and then we examine each component with resolution matched to its time-scale. With wavelet transform, one selects a set of basis signal components and thereafter determines the parameters for each of these signals such that their aggregate will compose the original signal. Nonetheless, the empirical mode decomposition makes no assumptions a priori about the composition of the signal.[10] Instead, it employs spline interpolation between maxima and minima to repeatedly traces out the IMFs. Each IMF will be a single periodic oscillator, and the number of IMFs cannot be anticipated prior to the decomposition; please see Appendix A for more details about the wavelet transform. Comparing the scale on scale causality based WD findings (see Table 8) with those of the causality based EMD (Table 7), we robustly find the faltering pace of China's growth has intensified the risk spillovers across China and the remaining BRICS markets. In addition, we consistently show that the Chinese slowdown affects heterogeneously BRICS stock markets. While India and South Africa appear moderately affected by the great anxiety over slowing growth in the world's second-largest economy (i.e. the causality is driven by short-term hidden factors), Brazil and Russia seem the

[10] For more details about wavelet decomposition, you can refer to Appendix B.

biggest losers (i.e. a causality supported in the long-term: above 240 days). This holds true for both the unconditional and conditional analyses (Tables 8.1 and 8.2, respectively).

Table 8. Wavelet decomposition results: 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
8.1. Unconditional analysis									
Short scales					Short scales				
WD1	0.2871	0.2136	0.0010**	0.0004***	WD1	0.1158	0.1972	0.0107*	0.0092**
WD2	0.1543	0.1852	0.0006***	0.0010**	WD2	0.1264	0.2341	0.0068**	0.0188*
Medium scales					Medium scales				
WD3	0.3451	0.2575	0.2289	0.1726	WD3	0.1874	0.2431	0.0093**	0.1142
WD4	0.4872	0.2914	0.2095	0.1193	WD4	0.1932	0.2185	0.0061**	0.0032**
Long scales					Long scales				
WD5	0.0000***	0.0001***	0.1568	0.1952	WD5	0.0012**	0.0007***	0.4415	0.2093
8.2. Conditional analysis									
Short scales					Short scales				
WD1	0.1546	0.1542	0.0003***	0.0110*	WD1	0.3255	0.2411	0.0093**	0.0134*
WD2	0.2029	0.1098	0.0000***	0.0091**	WD2	0.2091	0.2356	0.0214*	0.1142
Medium scales					Medium scales				
WD3	0.1164	0.3110	0.1146	0.4561	WD3	0.1022	0.1092	0.0008***	0.0113*
WD4	0.0711*	0.3452	0.1283	0.4781	WD4	0.3154	0.1076	0.0001***	0.0034**
Long scales					Long scales				
WD5	0.0024**	0.0013**	0.4177	0.3015	WD5	0.0001***	0.0014**	0.4155	0.3890

Notes: WD1: less than 30 days; WD2: within 30 and 60 days; WD3: within 60 and 120 days; WD4: within 120 and 240 days; WD5: more than 240 days; The table reports the p-values; *, ** or *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Also and as a robustness analysis, we re-run the exercise using weekly data to test whether a change in the frequency data may lead to some changes in our findings. The conducted unconditional and conditional investigations (Tables 9.1 and 9.2, respectively) confirm the previous results.

Table 9. Scale-by-scale causality among China and BRICS stock returns (weekly data)

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
9.1. 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**
9.2. 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.

Overall, even though it seems a challenging task to carry out signal processing techniques for non-stationary and noisy signals (Lin and Hongbing 2009), this study highlights the efficacy of the EMD for capturing hidden factors that may drive the dynamic spillovers across stock markets especially in times of ongoing volatility. Combined with some other methods, this signal approach allowed finding fresh and precise insights into complex issues. This makes causality testing-based EMD a promising new addition to the existing toolboxes for non-stationary and nonlinear signals. Likewise, the wavelet decomposition has also proved its usefulness and relevance in this exercise.

5. Conclusions and some portfolio implications

Several Years of rapid economic growth have notably increased China's standing in the world. Over the last decade, it accounted for a fifth of the total growth in global exports and imports, and played a potential role in supporting demand during times of distress including the eurozone's financial crisis. Given the emergence of China as a key driver of the global economy, the China's slowing economy is sending shock waves through its trading partners around the world. The present research attempts to assess whether the deepening Chinese slowdown intensifies uncertainty spillovers among China and the remaining BRICS (Brazil, Russia, India, and South Africa) stock markets. Since the co-movement or the causality between stock markets during times of rising uncertainty may mask the irregularities we want to identify, we carry out flexible econometric techniques that are designed to extract essential hidden features from data. This sets our study apart from other literature on the issue. Specifically, we conduct a multi-scale analysis based on empirical mode decomposition and wavelet approach.

What appears interesting from the obtained results is the heterogeneity in terms of the significance of risk spillovers. Even though China's slowdown exerts wider influence (long-run) on Brazilian and Russian markets, its impact on Indian and South African equities seems relatively moderate (i.e., supported in the short-run). Whatever the models used (causality testing-based EMD or wavelets) and whatever the periods investigated (China's rapid growth or China's slowdown), these findings remain fairly robust, with modest changes in terms of significance. These results seem intuitive since we respect the same hierarchy when considering the intensity of trade and foreign direct investment relationships. Figure C.1

(Appendix) reports the statistics of the average annual exports to China and imports from China to the rest of BRICS from 2000 to 2018. Over this 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 and Brazil are the major importers of Chinese goods, followed by India and South Africa. Regarding Chinese foreign direct investments (FDI) into BRICS countries, Brazil and Russia appear better positioned than India and South Africa (see Figure C.2, Appendix). Nevertheless, for South Africa, the level of China's investment is relatively weak. We keep the same hierarchy when considering the BRICS FDI into China. This consistency in terms of countries' position deeply underscore that our findings are neither unusual nor striking.

In addition, 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). 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 summarizing in Table C.2 (Appendix), we can deduce that the stock prices of the companies belonging more to cyclical industries are more sensitive to China growth's slowdown. Unlike 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[11].

We shouldn't neglect 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 debate aside. To this we must add the findings of Bouoiyour et al. (2015) which argued that the effect of stock returns on real economic activity wasn't uniform across BRICS countries. More specifically, the authors suggested that South African and Indian stocks are better positioned regarding the predictability power for output growth. For China and Russia, the stock 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, we need to be careful in interpreting our results. Importantly, profitable investment strategies can be built on the basis of our results. The evidence that the reactions of BRICS equities to Chinese economic downturn change sharply from quickly to slowly fluctuating components may have profound consequences for portfolios that trade with

[11]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, in times of turmoil, cyclical companies see generally their earnings go up and down, providing excessive volatility.

various rebalancing horizons. Holding diversified portfolio could play a significant role in palliating risk management and lightening the adverse risks, by allocating investments among distinct BRICS stocks that respond heterogeneously to China's growth slowdown.

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Appendix

Figure A.1. Time evolution of BRICS stock price indices

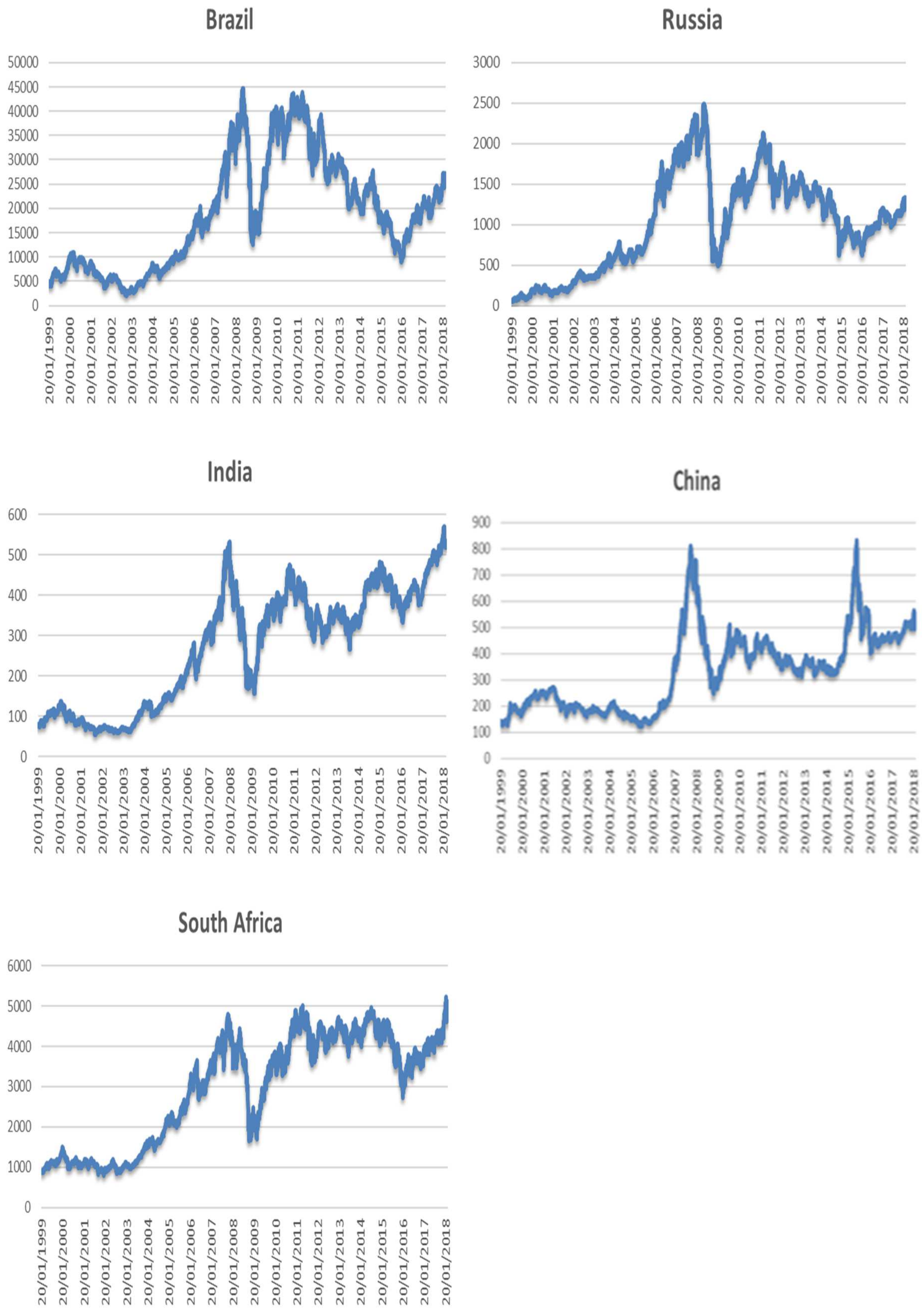


Table A.1. Unit Root Analysis

	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	-16.04(1)	-2.65	0.23	7.65	-15.61(1)	-2.65	0.23	7.65
STR_Brazil	-16.71(1)	-2.66	0.57	6.57	-13.04(1)	-2.66	0.57	6.57
STR_Russia	-13.48(2)	-3.07	0.76	6.50	-13.15(1)	-3.07	0.76	6.50
STR_India	-12.89(1)	-4.12	0.92	7.02	-13.24 (1)	-4.12	0.92	7.02
STR_SA	-11.76(1)	-2.76	0.61	6.42	-12.69(1)	-2.76	0.61	6.42
gold	-9.84(1)	-3.26	0.54	6.83	-12.81(1)	-3.26	0.54	6.83
VIX	-10.67(1)	-4.25	0.63	8.12	-12.72(1)	-4.25	0.63	8.12
	ZA at Level		ZA at 1st Difference		ZA at Level		ZA at 1st Difference	
Variable	T-statistic	Time Break	T-statistic	Time Break	T-statistic	Time Break	T-statistic	Time Break
STR_China	-6.89(4)*	2009	-13.09(1)*	2008	-6.11(1)*	2012	-13.18(2)*	2013
STR_Brazil	-6.45(4)*	2008	-9.62(1)*	2008	-10.34(2)*	2011	-11.97(2)*	2011
STR_Russia	-5.82(2)*	2013	-7.68(2)*	2014	-9.81(2)*	2013	-9.76(2)*	2012
STR_India	-5.73(2)*	2016	-4.89(2)*	2016	-9.42(2)*	2016	-9.43(2)*	2013
STR_SA	-6.38(4)*	2010	-4.52(2)*	2008	-9.11(4)*	2012	-6.04(1)*	2014
gold	-4.76 (2)*	2016	-7.09(2)*	2014	-7.83(1)*	2009	-5.72(1)*	2009
VIX	-4.55(1)*	2016	-5.64(2)*	2016	-8.11(2)*	2016	-9.94(2)*	2016

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

Appendix B. A brief overview on the wavelet decomposition

We explore the dynamic spillovers between China market and the remaining BRICS stock markets prior to and post-China growth's slowdown. For this purpose, we use a Wavelet Transform operating on a data vector whose length is transformed into distinct vector of the same length. It is a technique that allows to properly separating data into different frequency components, and then analyzes each component with resolution matched to its time-scale. The wavelet approach aims at transforming the investigated time series to hierarchical structure by rigorous means of the wavelet transformations prompting a set of wavelet coefficients. This technique enables to simultaneously decompose a signal as a function of both time t and frequency f (period or scale a).

A wavelet series is a representation of a real or complex valued function by a specific orthonormal series generated by a wavelet transform. Using the wavelet decomposition, the function *f (x)* can be symbolized by the superposition of daughters $\psi_{a,b}$ of father wavelet ϕ mother wavelet ψ. Father wavelet represents the smooth part of the signal (or low frequency band), while the mother wavelet represents the volatile part (or high frequency), denoted as:

$$\phi(x) = \sqrt{2}\sum_{k} l_k \phi(2x - k) \quad \text{(a.1)}$$

$$\psi(x) = \sqrt{2}\sum_{k} h_k \phi(2x - k). \quad \text{(a.2)}$$

Where l_k and h_k are respectively the low-pass and high-pass filter coefficients. $l_k = \frac{1}{\sqrt{2}}\int \phi(t)\phi(2t-k)dt$; $h_k = \frac{1}{\sqrt{2}}\int \psi(t)\phi(2t-k)dt$.

A wavelet decomposition of a function $f(x)$ can be defined as a sequence of projections into father and mother wavelets $s_{J,k}, d_{J,k}, \ldots, d_{1,k}$, expressed as follows:

$$s_{J,k} \approx \int \phi_{J,k}(t) f(t) dt \quad \text{(a.3)}$$

$$d_{j,k} \approx \int \psi_{j,k}(t) f(t) dt \quad ,j=1,2.... J. \text{(a.4)}$$

where $s_{J,k}$ is the smooth behavior of the signal at a specific time scale. The coefficients $d_{j,k}$ represent deviations from the trend.

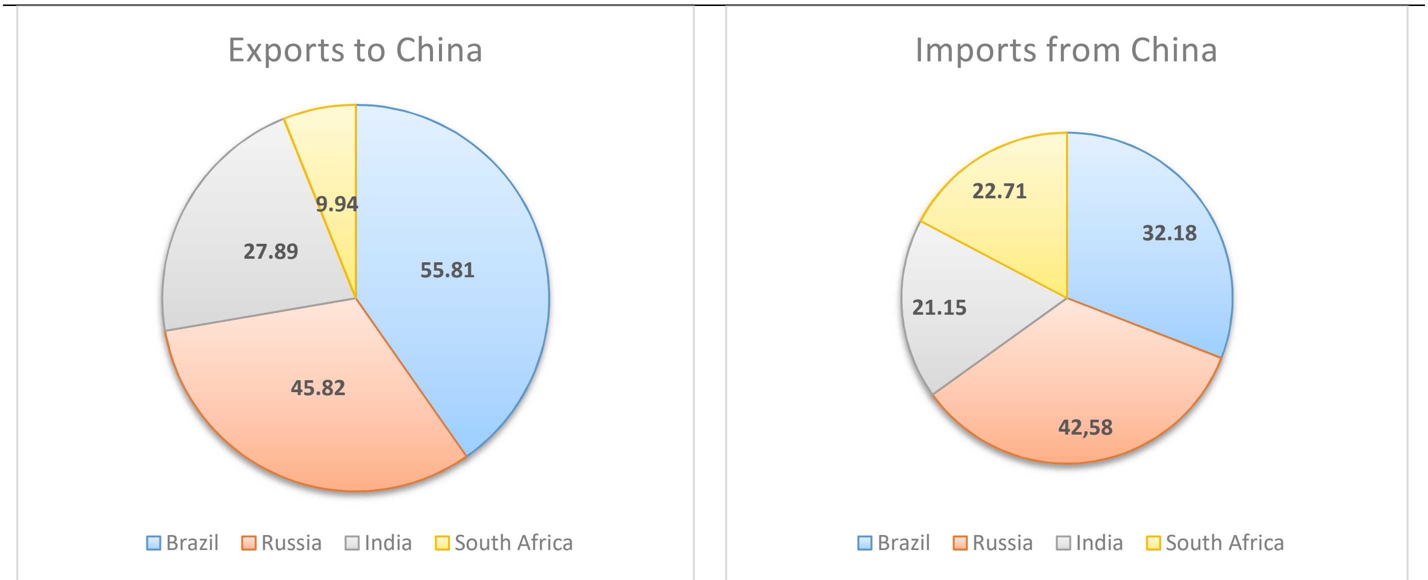
Thereafter, the wavelet decomposition can be written as following:

$$f(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + ... + \sum_k d_{1,k}\psi_{1,k}(t) \quad \text{(a.5)}$$

where J is the number of multi-resolution levels.

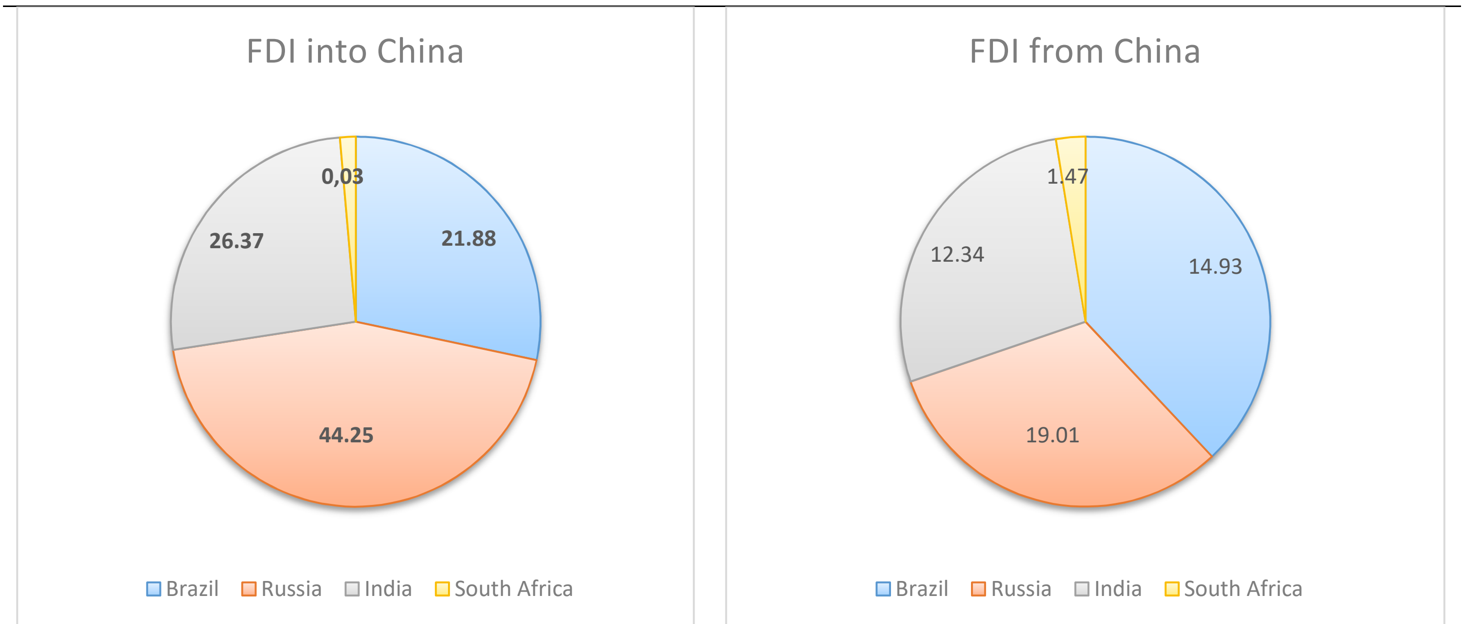
The raw signals are then used as input for the wavelet analysis in order to find the energy distribution of each wavelet coefficient. A further step consists of testing the causality of each frequency band.

Figure C.1. Bilateral Trade Relationship in billion USD (as average 2000-2018)



Source: The Observatory of Economic Complexity (OEC).

Figure C.2. Bilateral Investment Relationship in billion USD (as average 2000-2018)



Source: UNCTAD.

Table C.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.