Jestr
Journal of Engineering Science and Technology Review 8 (1) (2015) 65 - 71
Special Issue on Econophysics

JOURNAL OF
Engineering Science and
Technology Review

www.jestr.org

Conference Article

Investigating the Nonlinear Dynamics of Emerging and Developed Stock Markets

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Abstract

Financial time-series has been of interest of many statisticians and financial experts. Understanding the characteristic features of a financial-time series has posed some difficulties because of its quasi-periodic nature. Linear statistics can be applied to a periodic time series, but since financial time series is non-linear and non-stationary, analysis of its quasi periodic characteristics is not entirely possible with linear statistics. Thus, the study of financial series of stock market still remains a complex task having its specific requirements. In this paper keeping in mind the recent trends and developments in financial time series studies, we want to establish if there is any significant relationship existing between trading behavior of developing and developed markets. The study is conducted to draw conclusions on similarity or differences between developing economies, developed economies, developing-developed economy pairs. We take the leading stock market indices dataset for the past 15 years in those markets to conduct the study. First we have drawn probability distribution of the dataset to see if any graphical similarity exists. Then we perform quantitative techniques to test certain hypotheses. Then we proceed to implement the Ensemble Empirical Mode Distribution technique to draw out amplitude and phase of movement of index value each data set to compare at granular level of detail. Our findings lead us to conclude that the nonlinear dynamics of emerging markets and developed markets are not significantly different. This could mean that increasing cross market trading and involvement of global investment has resulted in narrowing the gap between emerging and developed markets. From nonlinear dynamics perspective we find no reason to distinguish markets into emerging and developed any more.

Keywords: Empirical Mode Decomposition, Emerging Market ,Nonlinear Dynamics

1. Introduction

Financial time-series has been of interest of many statisticians and financial experts. Understanding the characteristic features of a financial-time series has posed some difficulties because of its quasi-periodic nature. Linear statistics can be applied to a periodic time series, but since financial time series is non-linear and non-stationary, analysis of its quasi periodic characteristics is not entirely possible with linear statistics. Thus, the study of financial series of stock market still remains a complex task having its specific requirements.

The study of stock price movements commenced long time back. Bachelier [1] was first to formulate theory of random walk hypothesis. He showed that empirical evidence confirmed the random walk hypothesis i.e. a series of price changes are memory less, they follow a Markov process. This evidence confirms the efficient market hypothesis (EMH). Efficient market hypothesis states that the current price reflects all the available information about the security. Thus, predicting a price change is not possible, unless new information comes in. EMH has been received with much skepticism, and still the use of charts and volume data are rampant in predicting stock price movements. The main argument in disproving the effectiveness of technical analysis is the use of auto correlations. But, the use of such linear statistics may not be able to capture the complexities of non-linear patterns time series exhibits. As stated by Campbell et al. [2], "several authors signal a growing interest in technical analysis among financial academics, and so, it may become a more active research area in the near future".

Many important works have been done in this domain. For example, Dieci et al. (3) modeled the relationship between moods, beliefs and asset price. Similarly a behavioral model of asset price was worked out by Chiarella et al. (4). Pezzo and Uberti (5) worked on models for emerging equity markets. Hiller – Band and Weinzelburger (6) produced some interesting work on multi period capital asset pricing model. Marseguerra et al. (7) worked on investment timing decisions. Bo and Quingxin (8) derived the boundary prices for American contingent claims in a general continuous time market model with taking into account transaction prices. Ahmed and Abdusalam (9) proposed a modified BS equation that corresponds to telegraph equation. Tang et al. [10] addressed the hedging

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ISSN: 1791-2377

problem of American Contingents Claims (ACCs) in the framework of continuous-time Itoˆ models for financial markets. Cajuerio and Tabak [11] worked on relative efficiency and suggested that Asian equity markets showed greater inefficiency than those of Latin America (with the exception of Chile), and that developed markets ranked first in terms of efficiency. Batten et al. [12] investigated the sensitivity of the long-term return anomaly observed on the Nikkei stock index to sample and method bias. Strozzi and Comenges [13] proposed a new trading strategy based on state space reconstruction techniques.

In this paper keeping in mind the recent trends and developments in financial time series studies, we want to establish if there is any significant relationship existing between trading behavior of developing and developed markets. We then apply a new technique for analysing the periodicity and properties of time series. Many ‘‘paradoxes’’ exist in standard decomposition of time signals. To avoid them, Huang et al. (1998)[14] have developed a method, termed the Hilbert view, for studying non-stationary and nonlinear data in nonlinear dynamics. This method uses the empirical mode decomposition technique to generate finite number of Intrinsic Mode Functions (IMFs) that assume well behaved Huang–Hilbert Transform [14)]. The results obtained from this technique can be further analysed to reveal more details about the time series. Guhathakurta et al. (2008) [15] uses this technique to a good effect to compare two financial time series.

The study is conducted to draw conclusions on similarity or differences between developing economies, developed economies, developing-developed economy pairs. We take the leading stock market indices dataset for the past 15 years in those markets to conduct the study. First we have drawn probability distribution of the dataset to see if any graphical similarity exists. Then we perform quantitative techniques to test certain hypotheses. Then we proceed to implement the Ensemble Empirical Mode Distribution (EEMD) technique to draw out amplitude and phase of movement of index value each data set to compare at granular level of detail. The EEMD technique was developed by Wu and Huang (2009)[16]. This new approach consists of sifting an ensemble of white noise-added signal and treats the mean as the final true result. The effect of the added white noise is to provide a uniform reference frame in the time-frequency space; therefore, the added noise collates the portion of the signal of comparable scale in one IMF. The rest of the paper is arranged in the following way- section 2 gives details about the data followed by section 3 elaborating the methodology and approach. We present the analysis of the results in section 4 followed by the conclusions in section 5.

2. Data

The series studied in this analysis include nine emerging stock market indices, BUX (Hungary), CSI 300(China), IBOVESPA (Brazil), IPSA (Chile), KLSE (Malaysia), KOSPI (Korea), MXX-IPC (Mexico), S&P CNX Nifty (India) and TWII (Taiwan) and seven developed stock market indices, AORD (Australia), DAX (Germany), FCHI (France), FTSE 100 (UK), HANGSENG (Hong Kong), NIKKEI (Japan), NZE 50 (New Zealand) at daily frequencies. The market classification into developed and emerging is based on Morgan Stanley Capital International (MSCI). The MSCI market classification scheme depends on the following three criteria: economic development, size and liquidity, and market accessibility. A market is classified as developed if: i) the country's Gross National Income per capita is 25% above the World Bank high income threshold for 3 consecutive years; ii) there is a minimum number of companies satisfying minimum size and liquidity requirements; and iii) there is a high openness to foreign ownership, ease of capital inflows/outflows, high efficiency of the operational framework and stability of the institutional framework. To be included in the emerging market category, a market is characterized by size, liquidity and market accessibility criteria that are less tight than those for the developed markets.

3. Design, Methodology and Approach

The approach can be summarized in the following steps:

- Find out the IMF's of the given market returns using Empirical Mode Decomposition
- Apply Hilbert's transform to the IMF's to get the instantaneous phase and amplitudes
- Plot the probability distributions of phase and amplitudes of IMF's
- Compare the probability distributions calculated above of various market indices

The first step is find out the IMF's of various returns using EMD Empirical Mode Decomposition (EMD) is designed primarily for obtaining representations which are oscillatory, possibly non stationary or generated by a nonlinear system, in some automatic, fully data-driven way. We first decomposed the data into slow and high frequency parts. The slow frequency part was again decomposed into further slow and high frequency parts. The process was continued till series was deemed to be as fully decomposed.

An IMF is defined as a function that satisfies the following requirements:

1. In the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ at most by one.
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero

The procedure of extracting an IMF is called sifting. The sifting process is as follows:

1. Identify all the local extrema in the test data.
2. Connect all the local maxima by interpolation as the upper envelope.
3. Repeat the procedure for the local minima to produce the lower envelope.

The upper and lower envelopes should cover all the data between them. Their mean is m_1. The difference between the data and m_1 is the first component h_1:

$$X(t) - m_1 = h_1 \quad (1)$$

Ideally, h_1 should satisfy the definition of an IMF, for the construction of h_1 described above should have made it symmetric and having all maxima positive and all minima negative. After the first round of sifting, a crest may become a local maximum. New extrema generated in this way actually reveal the proper modes lost in the initial examination. In the subsequent sifting process, h_1 can only be treated as a proto-IMF. In the next step, it is treated as the data, then

$$h_1 - m_{11} = h_{11} \quad (2)$$

After repeated sifting up to k times, h_1 becomes an IMF, that is

$$h_{1(k-1)} - m_{1k} = h_{1k} \quad (3)$$

Then, it is designated as the first IMF component from the data:

$$c_1 = h_{1k} \quad (4)$$

Overall, c_1 should contain the finest scale or the shortest period component of the signal. We can, then, separate c_1 from the rest of the data by$X(t) - c_1 = r_1$. Since the residue, r_1, still contains longer period variations in the data, it is treated as the new data and subjected to the same sifting process as described above.

This procedure can be repeated to all the subsequent r_j's, and the result is

$$r_{n-1} - c_n = r_n \quad (5)$$

The sifting process stops finally when the residue, r_n, becomes a monotonic function from which no more IMF can be extracted. From the above equations, we can induce that

$$X(t) = \sum_{j=1}^{n} c_j + r_n \quad (6)$$

Thus, a decomposition of the data into n-empirical modes is achieved.

A Hilbert-transform can be applied to an IMF to get the instantaneous phase and amplitudes. To get the Hilbert transform on each IMF component, the original data can be expressed as the real part, Real, in the following form:

$$X(t) = Real \sum_{j=1}^{n} a_j(t)\, e^{if\omega_j(t)dt} \quad (7)$$

The probability distributions of instantaneous phase and amplitudes of the phase and amplitudes is then calculated for each IMF's and compared across the stock market incides.

4. Analysis and Findings

Looking at the Empirical Mode Decompositions of the respective data sets representing the different time series (Appendix-1) we do not find any significant difference between them. If we look at the number of IMFs which is an indication of the degree of nonlinearity in the data (Appendix- 1), we find that the number hovers between 11 and 12, while for the developing countries; it is also between 11 and 12. In case of emerging markets we expected a lot more nonlinearity and therefore, a significant increase in the number of constituent IMFs. However, we find that is not the case.

We looked at the distribution of the IMF values and found that while there are differences between countries there is no significant difference between emerging and developed countries. This is evident once we analyse the correlation matrix for the IMF values of the Empirical Mode Decompositions of the respective stock index time series of the Developed and Emerging countries. (Appendix-2). We can see that the correlation of the 1st IMF values between the Developed countries and those between the Emerging countries are not significantly different from those between the Emerging and developed countries). In the same way, we compared the results of 2nd IMF and came to the same conclusion as evident from Table 1, 2 & 3 of Appendix-2. This clearly indicates that the dynamics as revealed by the empirical mode decomposition is not very dissimilar in case of developed and emerging countries.

To confirm our findings we also computed the frequency distribution of the instantaneous phase and amplitude of the 1st IMF s of the different time series under study. These would reveal the difference in characteristics of the dynamics of the data series at a finer level. If the time series exhibit entirely different characteristics in terms of nonlinearity then the frequency distribution of two different IMF phase and amplitude will be entirely different from each other. We expect to discover major differences between the emerging and developed data sets at least. Looking at the frequency distribution of 1st IMF s of the empirical mode decomposition of the different stock index time series (Appendix 3, Fig 6-8), we do not find any significant difference between the two sets of data. We find that the distributions follow similar pattern in case of both the developed and emerging market data. If we further extend our analysis to the distribution of the instantaneous phases of the different stock market data (Appendix 4, Fig 9-12), we find the same picture. We cannot significantly distinguish between emerging and developed country data. We find that the essential dynamics as revealed by empirical mode decomposition are same for developed and so called emerging markets.

5. Conclusions and Research Implications

Empirical Mode Decomposition is a method that helps decompose a time series into several constituent series, which, if added, will lead to the original time series. The number and nature of such constituent series called the intrinsic mode function (IMF) depend on the nonlinear dynamic properties of the original data set itself. Thus by looking at the number and properties of such IMFs one can compare two or more time series effectively. If the time series have similar nonlinear dynamic properties the number and nature of the IMFs will also be approximately same. We use this property of EMD to good effect by studying different financial time series from multiple markets grouped under developed and emerging markets. Our findings lead us to conclude that the nonlinear dynamics of emerging markets and developed markets are not significantly different. This could mean that with increasing cross market trading and involvement of global investment has resulted in narrowing the gap between emerging and developed markets. From nonlinear dynamics perspective we find no reason to distinguish markets into emerging and developed any more. In this respect it is interesting to note that the findings of Guhathakurta et al. (2012)[18], which tested the long memory properties of the same markets also came to similar conclusions in terms of memory characteristics of the two different market groups.

Further studies may look at other investigations like the phase space evolution and recurrence analysis of the time series to try and find out whether it is time to conclude that there is essentially no difference between developed and emerging stock markets any more.

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APPENDIX 1: Empirical Mode decomposition of some of the stock market data

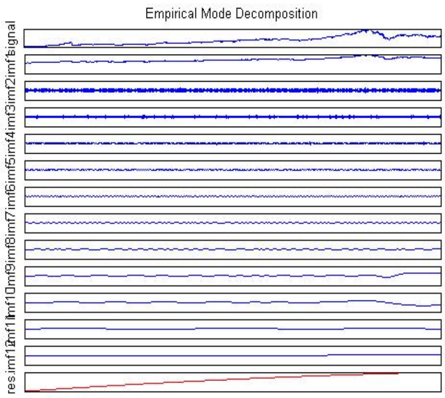

Fig 1 Empirical Mode decomposition of AORD

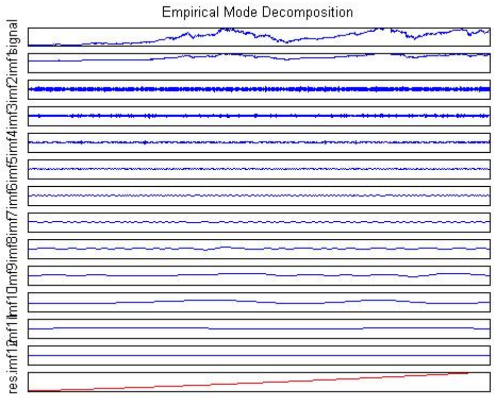

Fig 2 Empirical Mode decomposition of DAX

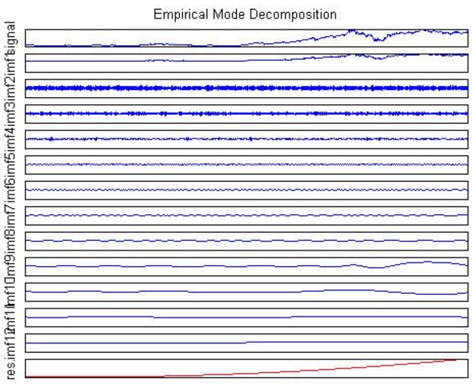

Fig 3 Empirical Mode decomposition of NIFTY

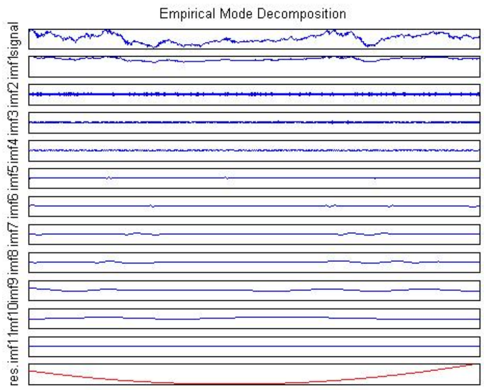

Fig 4 Empirical Mode decomposition of TWII

Appendix 2: Correlation between 1st & 2nd IMFs

Table 1: Correlation between 2nd IMFs of Emerging Country data

	BUX	CSI	IBOVESPA	IPSA	KLSE	KOSPI	MXX	NIFTY	TWII
BUX	1.000	0.076	-0.022	-0.026	0.056	0.010	-0.011	-0.029	0.014
CSI		1.000	0.018	0.003	-0.004	0.071	-0.096	-0.020	0.062
IBOVESPA			1.000	-0.040	0.023	-0.066	-0.027	0.013	0.026
IPSA				1.000	-0.006	0.006	-0.012	-0.042	0.053
KLSE					1.000	0.014	0.003	-0.065	0.015
KOSPI						1.000	-0.052	-0.039	0.001
MXX							1.000	0.026	0.017
NIFTY								1.000	-0.016
TWII								-	1.000

Table 2: Correlation between 2nd IMFs of Developed country data

	AORD	DAX	FCHI	FTSE	Hangseng	Nikkei	NZX
AORD	1.000	0.027	-0.004	-0.003	-0.001	-0.011	-0.013
DAX		1.000	-0.013	-0.026	-0.006	-0.021	0.031
FCHI			1.000	0.000	0.030	-0.016	-0.012
FTSE				1.000	-0.005	0.015	-0.043
Hangseng					1.000	-0.009	0.036
Nikkei						1.000	-0.025
NZX							1.000

Table 3: Correlation between 1st IMFs of Developed & Emerging country data

	AORD	DAX	FCHI	FTSE	Hangseng	Nikkei	NZX
BUX	0.009	-0.017	-0.044	0.000	0.016	-0.024	0.025
CSI	-0.023	-0.053	0.014	-0.047	0.001	0.021	0.009
IBOVESPA	0.004	0.008	0.019	0.003	-0.001	0.022	0.015
IPSA	-0.019	-0.007	0.004	-0.011	0.024	0.028	0.033
KLSE	0.005	0.030	0.004	-0.032	0.033	0.024	0.019
KOSPI	-0.008	0.002	-0.021	-0.018	0.017	0.000	0.011
MXX	-0.001	-0.011	0.014	-0.007	0.019	0.012	-0.026
NIFTY	0.011	0.014	0.005	0.012	-0.001	-0.002	0.040
TWAII	-0.020	0.008	0.027	0.023	0.002	0.017	-0.007

Appendix 3: Frequency distribution of instantaneous amplitude of 1st IMF of some stock markets

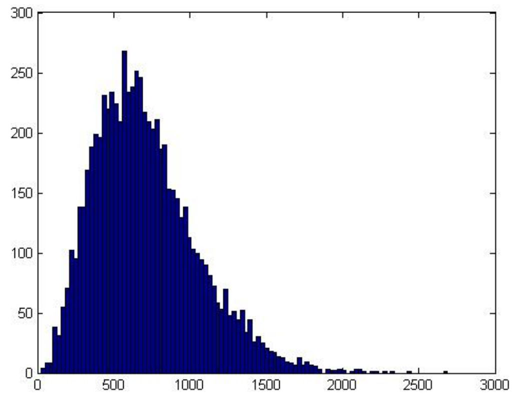

Fig 5 AORD (Australia)

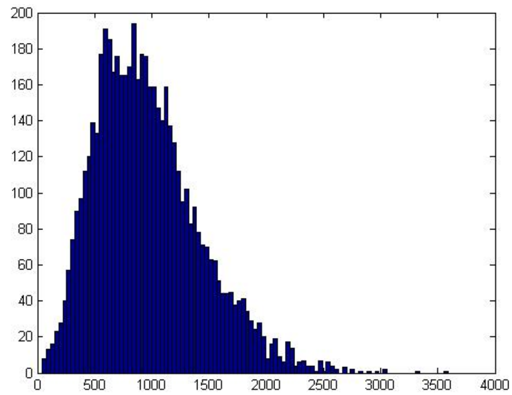

Fig 6 DAX (Germany), DJA (USA),

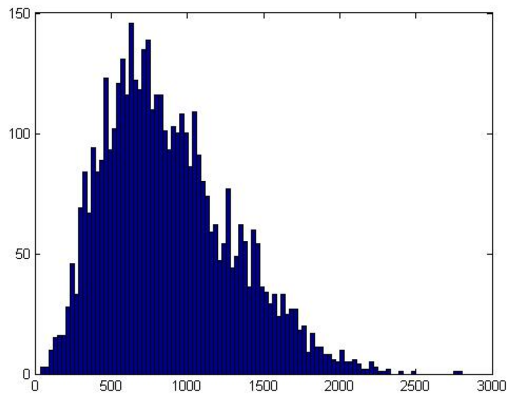

Fig 7 NIFTY

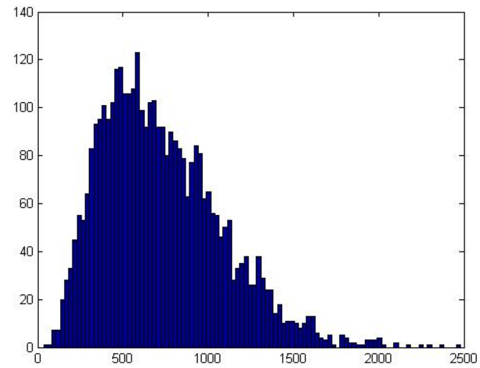

Fig 8 TWII

Appendix 4: Frequency distribution of instantaneous phase of 1st IMF

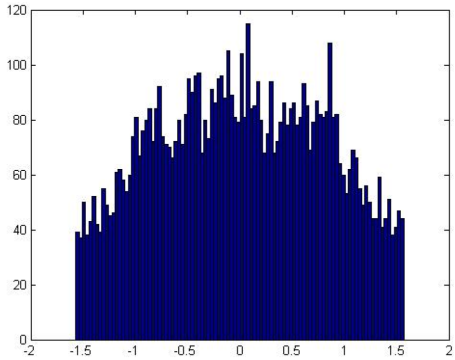

Fig 9 AORD

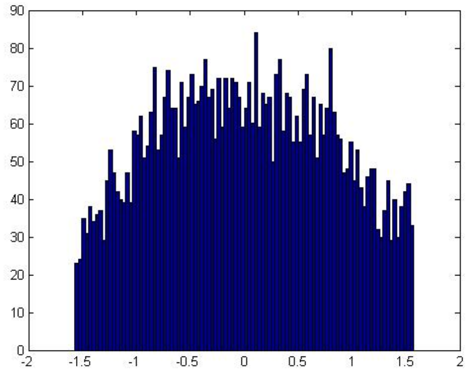

Fig 10 DAX

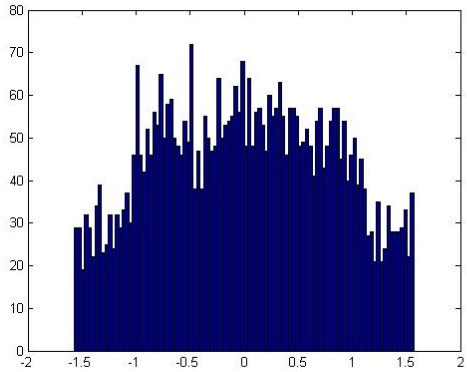

Fig 11 NIFTY

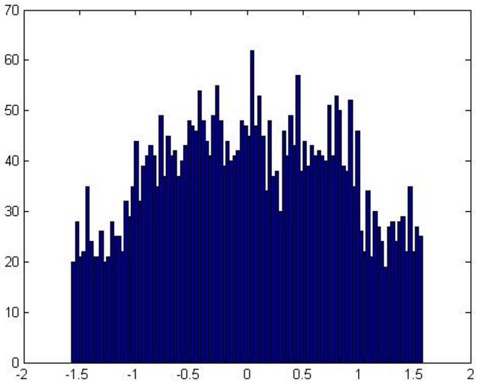

Fig 12 TWII