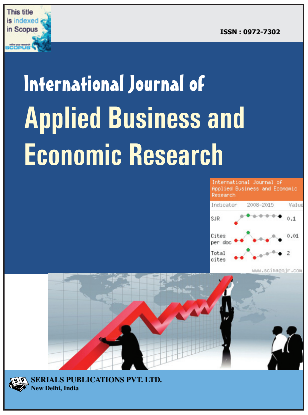

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Application of ARMA Models for Measuring Capital Market Efficiency: An Empirical Study in Selected Emerging Financial Markets

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ABSTRACT

Measuring efficiency of a financial market before investing is a preliminary step to every successful investor and there are many literatures developed by financial economists which give explanations to perform this action. But, most of the literatures are by nature descriptive rather than conclusive because they are not based on empirical investigations. The present study is an attempt to fill this research gap. The Distribution Test, Unit Root Test and ARMA Test to estimate the efficiency of financial markets has been employed in this study to test weak form efficiency in nine emerging financial markets of the world. These emerging financial markets include: Brazil, China, Greece, India, Indonesia, Malaysia, Mexico, South Korea and Taiwan. The results of the analysis reveals that under unit root test and ARMA test all the selected financial markets are not weak form efficient.

Keywords: Financial Globalization, Efficient Market Hypothesis, Emerging Financial Markets, Random Walk Model, Jarque Bera (JB) Test, Augmented Dickey Fuller (ADF) Test, Philips Perron (PP) Test, Auto Regressive Moving Average (ARMA) Models, Box-Jenkins Methodology.

1. INTRODUCTION

It was Eugene Fama who first of all talked about the Efficient Market Hypothesis (EMH) in 1970 and later on he was awarded the prestigious Nobel Prize for Economics in 2013 for his concept. The concept of EMH plays a vital role in classifying the financial markets on the basis of efficiency. Morgan Stanley which is the most trusted and reputed organization for classifying different financial markets of the world categories them as: Developed Markets, Emerging Markets and Frontier Markets (MSCI, 2015). Emerging markets seek the emergence of a market economy so that it can attain the status of a matured market

(Das, 2004). Markets like Australia, Germany, Japan, UK and USA were emerging at one point in time. Though very few of financial economists may be remembering the past state of these markets, a significant example in this connection may be of Hong Kong and Singapore which have shifted from the status of emerging markets to developed markets during the last one decade only. An efficient financial market is that which do not allow making unprecedented gains by its investors. In other words all investors can secure average returns in an efficient market and in order to have above average returns they are required to take above average risks (Malkeil, 2003). It is because stock prices follow a 'random walk' instead of becoming predictable in an efficient market. Though there are obvious arguments in opposition to EMH, attempts to test the efficiency of a financial market are still considered the preliminary step before making any investment strategy. Many researchers have tried in past to provide a solid set of literature for testing the efficiency of financial markets. But, the most accepted literatures are by nature descriptive instead of conclusive. It is because the researches are not based on empirical evidences although there are econometric tools available in this context to make empirical investigations. We have employed the Distribution Test, Unit Root Test and Auto Regressive Moving Average (ARMA) Models to estimate the efficiency of a few selected emerging financial markets of the world in this study.

2. A THEORETICAL ANALYSIS THROUGH THE REVIEW OF LITERATURE

There are many researches done in the past for measuring efficiency of financial markets and in this context the study done by Pavlov and Yang (2010) has become able to provide concrete contribution to the subject matter. In this thesis the researcher duo selected four stock markets including Ukraine, China, Russia and USA. Then they applied the Distribution test, Unit root test, Runs test, ARMA test and GARCH test for testing the efficiency of these stock markets. The results of the study revealed that the four stock markets are not weak-form efficient. Out of the various types of tests suggested by the authors ARMA test and GARCH test are generally considered as the most robust for test of efficiency and then forecasting in the world of financial economics. Green (2011) in her master's thesis used the ARIMA models with particular attention to Box-Jenkins Approach and found that ARIMA model is the most appropriate for classifications of time series data sets on the basis of their behavior. In the same line of research, Peter and Silvia (2012) conducted a study to compare ARIMA models with ARIMAX models. In order to facilitate the comparison, they took GDP per capita which is a popular macroeconomic variable and modeled the time series data set using both ARIMA and ARIMAX. On the basis of the results of the study they concluded that ARIMA models are slightly more accurate even than ARIMAX models in forecasting. Also according to Mondal et. al., (2014) ARIMA models are most preferred in time series analysis for its simplicity and wide acceptability. They took stocks from different sectors of Indian economy and employed ARIMA modeling for forecasting their prices. It has been found in the study that the prediction accuracy of ARIMA models is significant. Similarly, Paul et. al., (2013) used ARIMA models in stock indices of Bangladesh, Isenah and Olubusoye (2014) implemented ARIMA models in Nigerian Stock Market and Junior et. al., (2014) employed ARIMA models in Bovespa Stock Index of Brazil. All of them found that ARIMA is one of the most robust econometric methodologies for modeling time series data sets. And it is noteworthy here that it is not that ARIMA is suitable only for financial times series, it is also useful for modeling time series data related to the field of demand forecasting, engineering and agriculture. Williams and Hoel (2003) used ARIMA models in the field of engineering, Babazadeh and Shamsnia (2014) implemented ARIMA models in the field of agriculture and Da Viega et. al., (2014) employed ARIMA models for demand forecasting in food retail. All of them found that ARIMA models are extremely useful in understanding the behavior of time series data under consideration. Now, the research question that arises is that whether ARIMA models can be fruitfully implemented in financial time series data of stock indices and along with distribution test and unit root tests it can measure the degree of efficiency of the financial market by measuring the efficiency of stock indices under consideration or not? In order to answer this question the present study has been undertaken.

3. RESEARCH DESIGN

The broad objective of this study is to provide a conclusive literature advocating the application of econometric techniques for measuring efficiency of financial markets. For this purpose, financial time series data of stock indices are ideally most suitable and that is why data on daily closing prices of stock indices in selected financial markets has been collected. Then an extensive review of extant literature was conducted and the specific objectives of the study have been framed as:

- To profile the selected financial markets.
- To conduct Distribution Test for estimating efficiency of selected stock indices.
- To conduct Unit Root Test for estimating efficiency of selected stock indices.
- To conduct ARMA Test for estimating efficiency of selected stock indices.

The financial time series data of selected stock indices has been collected for the period starting from 01/07/1997 to 31/12/2016. The period of study is such chosen because most of the selected emerging financial markets started liberalizing in late eighties and it is assumed that about a decade time period would have been required by them to achieve a considerable level of financial sector development. Hence, if we will take data from 1997 onwards then it will be most suitable for our study and we can cover a complete twenty years period also.

The econometric techniques chosen in the present study for assessing efficiency of selected financial markets are:

1. Distribution Test
2. Unit Root Test
3. ARMA Test

Distribution Test

Before applying any kind of econometric modeling to the data, it is essential to know whether the data distribution is normal or non–normal. The present study applies Jarque–Bera (1981) test statistic to know the nature of level data series under study. It is an asymptotic joint test statistic whose formula is given below;

$$\text{JB Statistic JB} = n\left[\frac{s^2}{6} + \frac{(k-3)^2}{24}\right]$$

This test statistic follows a chi–square (χ^2) distribution with 2 degrees of freedom. The return distribution will be symmetric and normally distributed if the probability (*p*) value of the JB statistic is less than the critical '*p*' at a given significance level.

Unit Root Test

A time series that is stochastic in nature is said to be stationary if the mean and variance are constant over time and the value of the covariance between the two time periods depend only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed. A visual plot of the data is the first step to discover whether a time series is stationary or not. From the sets of data we have considered in the present study the impressions from their visual plots reveals that they are trending upwards. It means there seems to be high possibility of having nonstationarity in the time series taken into account in this study. It is because if a time series is stationary, will tend to return to its mean (called mean reversion) and fluctuations around this mean (measured by its variance) will have broadly constant amplitude. If a data set is non-stationary, it is also known popularly as a series suffering from the problem of unit root. Non stationarity and unit root in a time series data are treated as synonymous. The other step that is generally followed before the test of unit root is the calculation of descriptive statistics in order to assess the nature of time series so considered. The descriptive statistics like mean, standard deviation, skewness and kurtosis are calculated from the level data series in order to know the average performance of the sample indices and stocks over the period of the study and the nature of distribution. The formula used for the above moments are stated below:

(i) Mean $\bar{Y} = \sum_{t=1}^{n} \frac{Y_t}{n-1}$: 1st moment

(ii) Standard Deviation $(\delta) = \left[\sum_{t=1}^{n} \left(\frac{Y_t - \bar{Y}}{n-1} \right) \right]^{1/2}$: 2nd moment

(iii) Skewness $(S) = \frac{\sum_{t=1}^{n} \frac{(Y_t - \bar{Y})^3}{n} - 1}{\delta^2}$: 3rd moment

(iv) Kurtosis $(k) = \frac{\sum_{t=1}^{n} \frac{(Y_t - \bar{Y})^4}{n} - 1}{\left[\sum_{t=1}^{n} \frac{(Y_t - \bar{Y})}{n-1} \right]^2}$: 4th moment

Now after it here we introduce the unit root test of stationarity with the following model:

$$Y_t = Y_{t-1} + u_t$$

where, u_t is the stochastic error term that follows the classical assumptions; namely, it has zero mean, constant variance δ^2, and is nonautocorrelated. Such an error term is also known as a white noise error term in engineering terminology. Here, if we run the regression,

$$Y_t = \rho Y_{t-1} + u_t$$

and actually find that $\rho = 1$, then we say that the stochastic variable Y_t has a unit root. To find out if a time series Y_t is nonstationary, first we need to run the regression and find out if $\hat{\rho}$ is statistically equal to 1 or equivalently estimate the next equation as per above; then find out if $\hat{\delta} = 0$ on the basis of, say, the *t* statistic. Unfortunately, the *t* value thus obtained does not follow Student's *t* distribution even in large samples.

Under the null hypothesis that $\rho = 1$, the conventionally computed t statistic is known as the τ (tau) statistic, whose critical values have been tabulated by Dickey and Fuller on the basis of Monte Carlo simulations. In the literature the tau test is known as the Dickey – Fuller (DF) test, in honor of its discoverers. For theoretical and practical reasons, the Dickey – Fuller test is applied to regression run in the following form:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + u_t$$

where, t is the time or trend variable.

In each case the null hypothesis is that $\delta = 0$, that is, there is a unit root. If the error term u_t is autocorrelated, we can modify the equation given above as follows:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{n} \Delta Y_{t-i} + \varepsilon_t$$

Where, for example, $\Delta Y_t = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$, etc. that is, one uses lagged difference terms. When the DF test is applied in the models like the above, it is called Augmented Dickey Fuller (ADF) Test. The ADF test statistic has the same asymptotic distribution as the DF statistic, so the same critical values can be used. Now, if the time series Y_t is differenced once and the differenced series is found stationary then the original series Y_t which is random walk will be called 'integrated of order '1' and denoted by I(1). Similarly, if we are required to take the first difference of the first difference from the original series i.e. second difference in order to get stationarity of data, the original series is said to be integrated of order '2' denoted by I(2). Hence in general, if the time series is required to be differenced '*d*' times to achieve stationarity, then the original series will be called integrated of order '*d*' denoted by I(d). By convention, in a stationary time series it will be integrated of order '0' denoted by I(0) and $d = 0$. Therefore, the terms 'a stationary process' and 'a I(0) process' are generally used synonymously.

Then in order to verify the result we can use the Philips and Peron (PP) Test to detect the unit roots in the given time series. Phillips–Perron test is also a unit root test. It is used in time series analysis to test the null hypothesis that a time series is integrated of order 1. It builds on the Dickey–Fuller test of the null hypothesis $\delta = 0$ in Δ, where $\Delta Y_t = \delta Y_{t-1} + U_t$ is the first difference operator. Phillips–Perron test addresses the issue that the process generating data for Y_t might have a higher order of autocorrelation than is admitted in the test equation - making Y_{t-1} endogenous and thus invalidating the Dickey–Fuller t-test. Whilst the augmented Dickey–Fuller test addresses this issue by introducing lags of ΔY_t as regressor in the test equation, the Phillips–Perron test makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroskedasticity in the disturbance process of the test equation.

$$\text{Modified } t_s = t_s \left(\frac{\gamma_0}{f_0}\right)^{1/2} - \frac{T(f_0 - \gamma_0)(se(\delta))}{2 f_0^{1/2} s}$$

δ = coefficient of $y\ t - 1$

t_s = t-ratio of δ,

$se\ (\delta)$ = coefficient's standard error,

s = standard error of the test regression,

γ = consistent estimate of the error variance

f_0 = an estimator of residual spectrum at frequency zero

n = No. of observations.

The asymptotic distribution of the PP test is like that of the ADF test statistics if the absolute value of the tau statistic (τ) exceeds the DF tau statistics critical tau value, the null hypothesis that series is non-stationary will be rejected under PP test and the alternative that time series is stationary will be accepted. On the other hand, if the computed (τ) does not exceed the critical tau value, the null hypothesis will not be rejected, in which case the time series is non-stationary.

ARMA Test

Auto Regressive Integrated Moving Average (ARIMA) model is used as a new generation forecasting tools developed by Box and Jenkins (1976) and is known as Box-Jenkins methodology. The emphasis of this method is to analyze the probabilistic or stochastic properties of the time series data on their own under the philosophy "let the data speak for themselves". The ARIMA model allows y_t to be explained by its past or lagged values of y_t itself and its stochastic error term. Financial time series data are integrated in nature and therefore, are non-stationary in nature which means the time series have unit roots. If a time series is integrated of order one [i.e. it is I(1)], its first difference is stationary i.e. I(0). Similarly, if a time series is integrated of order two i.e. I(2) its second difference will make the series stationary i.e. I(0) that is stationary. In general if a time series is I(*d*) after differencing it d times, then I(0) series or stationary series is obtained. I(1) and I(2) series can wander a long way from their mean value and cross the mean value, while I(0) series should cross the mean frequently. Hence a time series is to be differenced '*d*' times (where d may be 1, 2, 3 etc.) times to make it stationary. After obtaining stationary time series by means of differencing the time series original data for *d* times, the next step is to get the AR terms as well as MA terms in the differenced series.

Auto-Regressive (AR) Model

An autoregressive model is one where the current value of a variable 'y_t' depends on its previous value at different lags. An autoregressive model of order 'P' denoted as AR (*p*) can be stated as:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + u_t$$

(Chris Brooks, Introductory Econometrics for Finance, 2nd, p-215)

where, α_0 = constant term

$\alpha_1, \alpha_2, ..., \alpha_p$ = AR coefficients of the lagged values of y_t respectively for $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ (*i* varies from 1, 2, …, *p*)

y_t = daily log return series of time series under study

$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ = lagged log return series upto period '*p*'

u_t = residual

The above model states that the current value series y_t is dependent on its previous lagged values of order '*p*' provided the autocorrelation coefficients i.e. α_i are statistically significant.

Moving Average (MA) Model

The concept of MA model is developed when the current value of a time series depends on the current and previous values of residuals obtained from the above AR model.

$$y_t = \alpha_0 + \sum_{j=1}^{q} \beta_i u_{t-j} + u_t$$

(Chris Brooks, Introductory Econometrics for Finance, 2nd, p-211)

where, α_0 = constant term

$\alpha_1, \alpha_2, ..., \alpha_p$ = AR coefficients of the lagged values of y_t respectively for $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ (i varies from 1, 2, …, p)

$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ = lagged log return series upto period 'p'

$\beta_1, \beta_2, ..., \beta$ = MA coefficients of the lagged values of y_t respectively for $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ (i varies from 1, 2, …, p)

y_t = daily log return series of time series under study

u_t = current value of residuals

u_{t-j} = previous value of residuals upto lag q

Autoregressive Moving Average (ARMA) Model

Auto-Regressive Moving Average (ARMA) model is obtained by combing the AR(p) and MA(q) models. ARMA (p, q) model states that the current values of time series data y_t depends linearly on its own previous values plus a combination of current and previous values of residuals. An ARMA (p, q) model follows the following linear approach.

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_i u_{t-j} + u_t$$

The above equation states that the current value of the series depends linearly on its own previous values up to lags p plus a combination of current and previous values of residual (u_t) up to lag q.

where, α_0 = constant term

$\beta_1, \beta_2, ..., \beta$ = MA coefficients of the lagged values of y_t respectively for $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ (i varies from 1, 2, …, p)

y_t = daily log return series of time series under study

$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ = lagged log return series up to period 'p'

u_t = current value of residuals

u_{t-j} = previous value of residuals u_t

Box-Jenkins (BJ) Methodology

Box-Jenkins (1976) methodology is to be employed to study whether the return series of the indices follows a purely AR process or a purely MA process or ARMA process or ARIMA process. The lag lengths of p, *d* and *q* as applicable for respective model are obtained by using BJ methodology. It primarily consists of three following steps:

1. *Identification* of tentative AR/MA/ ARMA and ARIMA order by visual inspection of Autocorrelation (AC) and Partial Autocorrelation (PAC) of the return series of Indices through Correlogram. Graphically plotting the values of AC and PAC against different lags is known as Correlogram.
2. *Estimation* involves the followings steps:
   (a) Estimation of the statistical significance of the values of the parameters (co-efficient) of the tentative AR/MA/ARMA and ARIMA model.
   (b) Estimation of Akaike's Information Criteria (AIC) and Schwarz's Bayesian Information Criteria (SBIC).
   (c) Estimation of stationarity and Invertibility of AR and MA terms.
3. *Diagnostic Checking* involves the following steps:
   (a) Diagnostic Checking of no autocorrelation in the ordinary residual, obtained from Ordinary Least Square (OLS) regression by specifying appropriate order of AR/MA/ ARMA.
   (b) Diagnostic Checking of autocorrelation in the in the squared residual, obtained from Ordinary Least Square (OLS) regression by specifying appropriate order of AR/MA/ARMA Methodology suggested by Box-Jenkins follows a repeated process.

The above stated steps will be repeated till an appropriate (parsimonious) model is selected. A parsimonious model describes all the features of the data using as few parameters as possible.

But before we go for ARMA modeling, the data set needs to be stationary. And for this purpose traditionally the natural logarithm is applied to a time series of the type we are exposed to in the present study. It is done with the following formula:

$$Y_t = \ln\left[C_t / C_{t-1}\right] \times 100$$

where, Y_t = Daily Continuous Compound Rate of Return

l_n = Natural Logarithm with base *e*

C_t = Closing Value of the Index for the Current Day '*t*'

C_{t-1} = Closing Value of the Index for the Previous Day '$t - 1$'

Once the research tools have been selected, next to it the data collection exercise is needed to be performed. For this purpose, the leading emerging financial markets of the world were taken into consideration and the data on their top indices were taken from www.yahoo.finance.com. The following is a description of the countries selected in the present study and the names of their indices from which the daily returns data have been taken.

Table 3.1
Name of the Selected Emerging Financial Markets and their Stock Indices

S.No.	*Name of the Country*	*Index*	*Period*	*No. of Observations*
1	Brazil	Bovespa	01/07/1997 to 31/12/2016	4848
2	China	Shanghai Composite	01/07/1997 to 31/12/2016	4933
3	Greece	Athex Composite	01/07/1997 to 31/12/2016	4854
4	India	BSE 30	01/07/1997 to 31/12/2016	4811
5	Indonesia	Jakarta Composite	01/07/1997 to 31/12/2016	4837
6	Malaysia	KLSE Composite	01/07/1997 to 31/12/2016	4451
7	Mexico	IPC	01/07/1997 to 31/12/2016	4906
8	South Korea	KOSPI Composite	01/07/1997 to 31/12/2016	4820
9	Taiwan	Taiwan Weighted	01/07/1997 to 31/12/2016	4813

Note: Name of the countries arranged alphabetically.
Source: Researchers' Distillation.

4. RESULTS AND DISCUSSIONS

The first and foremost objective of the present study is to profile the selected financial markets and for this purpose we have taken three important variables under consideration: (1) Stock of FDI at home, (2) Stock of FDI abroad and (3) Exchange Rate. As per the definition given by Central Intelligence Agency, "stock of direct foreign investment – at home compares the cumulative US dollar value of all investments in the home country made directly by residents - primarily companies - of other countries as of the end of the time period indicated. Direct investment excludes investment through purchase of shares". And "Stock of direct foreign investment - abroad compares the cumulative US dollar value of all investments in foreign countries made directly by residents - primarily companies - of the home country, as of the end of the time period indicated. Direct investment excludes investment through purchase of shares". Exchange rate provides the average annual price of a country's monetary unit for the time period specified, expressed in units of local currency per US dollar, as determined by international market forces or by official fiat. These three parameters can clearly represent the state of a particular financial market. Table 4.1 shows the state of the selected financial markets basis the discussed variables.

Table 4.1
Profile of the Selected Financial Markets

S.No.	*Name of the Country*	*Stock of FDI at Home*	*Stock of FDI Abroad*	*Exchange Rate*
1	Brazil	$ 673 Billion	$ 295.3 Billion	$ 1 = 3.483 Reals,
2	China	$ 1.458 Trillion	$ 1.285 Trillion	$ 1 = 6.626 Yuan
3	Greece	$ 22.15 Billion	$ 29.67 Billion	$ 1 = 0.9214 Euros
4	India	$ 351.8 Billion	$ 149 Billion	$ 1 = 68.3 Rupees
5	Indonesia	$ 292.8 Billion	$ 42.82 Billion	$ 1 = 13, 483 Rupiah
6	Malaysia	$ 154.7 Billion	$ 155.6 Billion	$ 1 = 4.079 Ringgits
7	Mexico	$ 384.3 Billion	$ 153.3 Billion	$ 1 = 18.34 Pesos
8	South Korea	$ 179.6 Billion	$ 318 Billion	$ 1 = 1, 167.6 Won
9	Taiwan	$ 74.64 Billion	$ 346.9 Billion	$ 1 = 32.85 Taiwan Dollar

Note: All figures are basis year 2016 estimates.
Source: Central Intelligence Agency, USA; www.cia.gov.in

From the above table it can be easily seen that China is having highest direct investments at home as well as abroad. The rest of the economies in the list are almost similar in terms of the selected variables. Table 4.2 presents the descriptive statistics obtained from the level data that includes Mean, Median, Standard Deviation, Skewness, Kurtosis, Jarque Bera and Probability of the nine variables: Bovespa, Shanghai Composite, Athex Composite, BSE 30, Jakarta Composite, KLSE Composite, IPC, KOSPI Composite and Taiwan Weighted. The average daily closing level price and standard deviation for the stock market indices are almost different for the period under study. The skewness statistics of daily data whether found to be positive or negative, but are less than 1 for all the indices except Shanghai Composite indicating that the level data distribution is almost symmetric. In case of Shanghai Composite, the distribution is asymmetric. Kurtosis is less than three for all the indices again except Shanghai Composite during the period suggests that the underlying data is platykurtic i.e. squat with short tails about the mean, which indicates that the data is not normally distributed. Shanghai Composite kurtosis value is more than three i.e. 4.8 which indicates that the distribution is having high kurtosis. Additionally the application of Jarque-Bera (JB) statistics calculated to test the null hypothesis of normality in the data rejects the normality assumption at 5% level of significance. The results confirm the well known fact that daily level data of the indices under consideration are not at all normally distributed and so they are skewed.

Table 4.2
Descriptive Statistics & Distribution Test Results of Level Data

Index Name	*Mean*	*Median*	*SD*	*Skew.*	*Kurt.*	*JB*	*Prob.*
Bovespa	37391.4	40309.0	20850.6	0.0	1.4	489.9	0.00
Shanghai Composite	2193.1	2041.3	923.6	1.3	4.8	1981.2	0.00
Athex Composite	2417.5	2204.9	1326.0	0.6	2.5	358.3	0.00
BSE 30	12524.1	12019.7	8251.3	0.4	1.8	390.4	0.00
Jakarta Composite	2212.4	1563.2	1745.9	0.5	1.7	534.2	0.00
KLSE Composite	1095.2	933.3	417.5	0.4	1.9	344.5	0.00
IPC	23016.1	21994.0	15226.9	0.1	1.4	521.3	0.00
KOSPI Composite	1325.5	1374.3	580.2	-0.1	1.5	490.3	0.00
Taiwan Weighted	7283.5	7570.3	1482.9	-0.4	2.2	235.1	0.00

Note: Null Hypothesis: Level data series follow normal distribution. Alternative Hypothesis: Level data series do not follow normal distribution.
Source: Compiled from E-Views Output

The graphical presentations of the variables seem of having a trend, implying that the data are non-stationary in nature. However, the results of ADF Test and PP Test are given in Table 4.3. In case of Dickey Fuller (DF) Test, there may create a problem of autocorrelation. To tackle autocorrelation problem, Dickey Fuller have developed a test that has three shapes which has been already discussed in the previous section i.e. research design. From the application of ADF Test, we come to a conclusion that the level data of selected stock indices are nonstationary and in order to verify the results the PP Test has also been performed which gave similar results. But, when the ADF and PP Tests are again applied to the first differences of the selected indices, they became stationary (See Table 4.4). Hence, it implies that since all the selected indices are nonstationary in their level form and are becoming stationary in their first difference, we may call them integrated of order '1' i.e. I(1)

Table 4.3
ADF & PP Test Results of Level Data

Name of the Index	*ADF Test Results*			*PP Test Results*		
	Computed Value	*Critical Value at 5% Level*	*P Value*	*Computed Value*	*Critical Value at 5% Level*	*P Value*
Bovespa	–2.26	–3.41	0.45	–2.10	–3.41	0.53
Shanghai Composite	–2.34	–3.41	0.40	–2.28	–3.41	0.44
Athex Composite	–2.17	–3.41	0.50	–2.11	–3.41	0.53
BSE 30	–2.97	–3.41	0.13	–2.83	–3.41	0.18
Jakarta Composite	–2.68	–3.41	0.24	–2.65	–3.41	0.25
KLSE Composite	–3.06	–3.41	0.07	–3.07	–3.41	0.06
IPC	–3.10	–3.41	0.10	–2.76	–3.41	0.20
KOSPI Composite	–3.17	–3.41	0.09	–3.20	–3.41	0.08
Taiwan Weighted	–3.09	–3.41	0.10	–3.08	–3.41	0.10

Note: Null Hypothesis: There is unit root. Alternative Hypothesis: There is no unit root
Source: Compiled from E Views Output

Table 4.4
ADF & PP Test Results of First Difference in Level Data

Name of the Index	*ADF Test Results*			*PP Test Results*		
	Computed Value	*Critical Value at 5% Level*	*P Value*	*Computed Value*	*Critical Value at 5% Level*	*P Value*
Bovespa	–70.81	–3.41	0.00	–71.03	–3.41	0.00
Shanghai Composite	–31.70	–3.41	0.00	–68.05	–3.41	0.00
Athex Composite	–61.43	–3.41	0.00	–61.11	–3.41	0.00
BSE 30	–64.28	–3.41	0.00	–64.29	–3.41	0.00
Jakarta Composite	–42.44	–3.41	0.00	–64.23	–3.41	0.00
KLSE Composite	–66.68	–3.41	0.00	–66.69	–3.41	0.00
IPC	–65.41	–3.41	0.00	–65.57	–3.41	0.00
KOSPI Composite	–67.22	–3.41	0.00	–67.19	–3.41	0.00
Taiwan Weighted	–66.26	–3.41	0.00	–66.28	–3.41	0.00

Note: Null Hypothesis: There is unit root. Alternative Hypothesis: There is no unit root
Source: Compiled from E Views Output

Now, we may proceed for ARMA modeling of these time series data sets. For ARMA or any other type of modeling of data, the precondition is that the data set should be stationary. Since the selected series of data are nonstationary in the level and stationary in the first differences, it is known to be integrated of order '1'. So, if we are required to take stationary data sets we can take the level data at its first difference instead of the level data itself. Though the level data in the form of first difference comes solely from the level data only, making regression estimation by taking first or higher order difference would severely put adverse effects on valuable long term relationship between the variables under consideration. Since here the variables under consideration are positions of stock indices (dependent variable) and time (independent variable), we may say that this kind of operation will harm the predicted positions of stock indices explained by time. Hence, traditionally in such cases the natural logarithms are used. After applying natural logarithms in the time series, when the unit root tests were again employed through ADF Test and PP Test, the data became stationary which can be seen from Table 4.5.

Table 4.5
ADF & PP Test Results of Return Series

Name of the Index	*ADF Test Results*			*PP Test Results*		
	Computed Value	*Critical Value at 5% Level*	*P Value*	*Computed Value*	*Critical Value at 5% Level*	*P Value*
Bovespa	–68.33	–3.41	0.00	–68.44	–3.41	0.00
Shanghai Composite	–32.94	–3.41	0.00	–69.16	–3.41	0.00
Athex Composite	–64.12	–3.41	0.00	–64.07	–3.41	0.00
BSE 30	–64.63	–3.41	0.00	–64.53	–3.41	0.00
Jakarta Composite	–59.96	–3.41	0.00	–60.04	–3.41	0.00
KLSE Composite	–29.65	–3.41	0.00	–66.07	–3.41	0.00
IPC	–64.35	–3.41	0.00	–64.13	–3.41	0.00
KOSPI Composite	–49.73	–3.41	0.00	–65.11	–3.41	0.00
Taiwan Weighted	–66.07	–3.41	0.00	–66.05	–3.41	0.00

Note: Null Hypothesis: There is unit root. Alternative Hypothesis: There is no unit root
Source: Compiled from E Views Output

Now, once the time series data under consideration has become stationary by application of natural logarithms, we can move forward for ARMA modeling. The procedure of ARMA modeling has already been narrated in the previous section. Following the prescribed procedures the following ARMA models are selected for the different indices under consideration as the best fit models.

Table 4.6
Arma Test Results

Index Name	*Bovespa*	*Shanghai Composite*	*Athex Composite*	*BSE 30*	*Jakarta Composite*	*KLSE Composite*	*IPC*	*KOSPI Composite*	*Taiwan Weighted*
C	0.06*	0.02	0.00	0.06*	0.04*	0.01	0.04	0.05*	0.02
AR(1)		0.98*	0.39*	0.08*		0.11*	0.08*		1.01*
AR(2)	–0.03*				0.15*			–0.12*	–0.03
AR(6)					–0.03*			–0.03*	
AR(8)					0.04*				
AR(17)								0.03*	
MA(1)		–0.97*	–0.31*						–0.97*
MA(2)					–0.16*			0.12*	
MA(3)			0.03*				–0.03*		
MA(5)							0.03*		
MA(8)			0.03*						
Best ARMA Model =	ARMA (2,0)	ARMA (1,1)	AR(1) MA(1,3,8)	ARMA (1,0)	AR(2,6,8) MA(2)	ARMA (1,0)	AR(1) MA(3,5)	AR(2,6,17) MA(2)	AR(1,2) MA(1)
Outliers =	10.99%	24.93%	10.49%	5.85%	29.84%	12.05%	4.73%	8.98%	5.61%

Note: '*': Significant at 5% Level.
Source: Compiled from E Views Output

The above table shows the best fit ARMA models for the selected financial markets and the proportion of outliers which were present in the series. Here, the financial market with less proportion of outlier would obviously shall be considered as the most stable. In this sense the financial markets in order of stability are: Mexico, Taiwan, India, South Korea, Greece, Brazil, Malaysia, China and Indonesia. Then on the basis of AR and MA terms, an efficient market should not have these terms at all. But, in order to assess the degree of efficiency we may say that: the less the number of AR and MA terms, the more the efficient the financial market is. In this sense; Brazil, India and Malaysia have the least number of AR and MA terms. So these three financial markets are comparatively more efficient than the rest of the markets. China comes next to these three markets on the basis of AR and MA terms. And Greece, Indonesia, Mexico, South Korea and Taiwan come after China in efficiency basis AR and MA terms.

5. CONCLUDING REMARKS

Since in our study, we are taking some selected stock indices of the world it is noteworthy here that there is a famous saying by the believers of Efficient Market Hypothesis (EMH): “If one could predict tomorrow’s price on the basis of today’s price, we would all be millionaires”. This statement simply indicates that stock prices are essentially random and it does not leave scope to make profitable speculations. An efficient market must follow this principle which indicates that the behavior of stock indices in efficient financial markets should be random walks. But, since in all the time series data sets we are able to detect AR and MA terms, it means that current prices of the selected indices are able to reflect historical information and they are not random walks. In other words, all the nine selected emerging financial markets in the present study are not weak form efficient. However, if we would attempt to make comparison among the selected financial markets it can be classified on the basis of their degree of inefficiency. Here, financial markets of Brazil, India and Malaysia may come in the first category since they have the least number of AR and MA terms detected. These three markets may become efficient if proper policy measures will be undertaken. It is also an interesting fact which has been detected here that these three financial markets have also remained quite stable over the period of study. Then comes the Chinese financial market which may be put in the second category since it has comparatively low number of AR and MA terms. But it should also be noted here that the Chinese financial market has been highly unstable over the period of study. The rest of the financial markets which includes Greece, Indonesia, Mexico, South Korea and Taiwan may be considered in third category on the basis of AR and MA terms. Hence, from the empirical evidences we can conclude that the financial markets of Brazil, India and Malaysia are comparatively more promising for investors out of the selected emerging financial markets of the study.

The above is an attempt to measure the efficiency of a few selected financial markets by use of Distribution test, Unit root test and ARMA test. There are many other tests which are prescribed by econometricians to detect efficiency level of a financial market. In this context the Runs test and GARCH test are very popular which we were not able to implement. Hence, this may be considered a limitation of the present study and left for further researches.

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