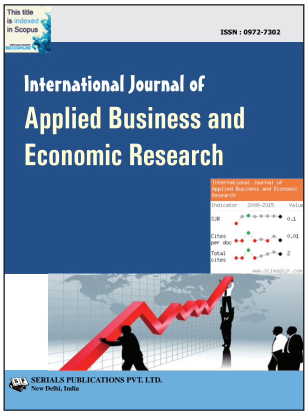



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# An Empirical Investigation on Weak Form Financial Market Efficiency by Application of Box – Jenkins Method: The Case of India in Comparison with Selected Developed Economies


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**ABSTRACT**

Most of the literatures available on measurement of efficiency of financial markets are by nature descriptive and not conclusive. The present study is an attempt to fulfill this research gap by initiating an empirical investigation implementing Distribution Test, Unit Root Test and ARMA Test based on Box Jenkins approach to estimate weak form efficiency of financial market of India along with thirteen financial markets of the developed economies including Australia, Austria, Belgium, Canada, France, Germany, Hong Kong, Israel, Japan, Singapore, Switzerland, UK and USA. The results reveal that none of the selected financial markets are weak form efficient.



***JEL Codes:*** G11, G12, G14, G15.

***Keywords:*** Efficient Market Hypothesis (EMH), Box Jenkins Methodology, ARMA Test, Unit Root Test.


## 1. INTRODUCTION

In the year 1970, Eugene Fama first of all advocated on the concept of Efficient Market Hypothesis (EMH) for which he got the prestigious Nobel Prize in Economics for the year 2013. Measuring efficiency of a financial market before investing is a preliminary step to every successful investor and there is a famous saying by the believers of 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. Hence the most efficient financial market is that in which there is least scope for making predictions of stock prices and therefore the financial markets can be classified on the basis of their degrees of efficiency. One of the most trusted and reputed organization popularly known as Morgan Stanley classifies different financial markets of the world as: Developed Markets, Emerging Markets and Frontier Markets (MSCI, 2015). Emerging markets are those which seek the emergence of a market economy so that it can attain the status of a matured market (Das, 2004). Though very few of financial economists may be remembering the past state of different financial markets, UK, USA and Japan were emerging at one point in time; but today they are coming in the list for developed markets. Similarly, Hong Kong and Singapore shifted from the status of emerging markets to developed markets in the beginning of present decade only. EMH especially in the literature of financial economics is closely associated with the idea of 'random walk' which stands for a series of prices representing random departures from their previous positions (Malkeil, 2003). Consequently, the price changes become unpredictable that ensures almost equal returns to uninformed investors as well as to the experts. There are some obvious arguments laid down against EMH, but still measurement of efficiency in any financial market is considered the first step before investing even today. There are various sophisticated econometric tools like Distribution Test, Unit Root Test and Box-Jenkins Methodology etc. available in finance literature to estimate the efficiency of financial markets and the present study is an attempt to make an empirical investigation on weak form financial market efficiency of India in comparison to financial markets of some selected developed economies.

## 2. A THEORETICAL ANALYSIS THROUGH THE REVIEW OF LITERATURE

The Box Jenkins (B/J) method is used when the series of data exhibits complicated patterns like combination of a trend, seasonal factor, cyclical and random fluctuations (Hoshmand, 2010). The major advantages of B/J method are: (1) a myriad of data patterns can be captured by this method, (2) the 'best fit' model can be identified by this method, (3) it has got relatively well specified rules, (4) through statistical measurement, the reliability of the forecasts can be tested in this method, (5) this method does not make assumptions about the number of terms used for modeling or the relative weight assigned to them. Since, B/J models are classified as the autoregressive models (AR), the moving average models (MA), or a combination of the two, they are popularly also known as Auto Regressive Moving Average (ARMA) Models or Auto Regressive Integrated Moving Average (ARIMA) Models. The B/J technique has been used by Pavlov and Yang (2010) in their Master's thesis to test the efficiency of stock markets in Ukraine, China, Russia and USA. They have used the Distribution test, Unit Root test, Runs test, ARMA test and GARCH test for measuring the efficiency of these stock markets. The results of these tests unveiled the fact that none of the selected stock markets are weak-form efficient. Out of the tests suggested by the authors' duo, ARMA test which is just another name of B/J technique and the GARCH test are most popular for testing efficiency of financial markets by investors. Similarly Green (2011) applied ARIMA model for classifying time series data sets based on their pattern of behavior in her Master's thesis. She found that the application of ARIMA models based on B/J approach is the most appropriate for classification of time series data sets. In this context, Peter and Silvia (2012) conducted a study to compare ARIMA models with ARIMAX models. They took a popular macroeconomic variable in their study i.e. GDP per capita and modeled the time series data sets using ARIMA as well as ARIMAX models. They found that ARIMA models are slightly more accurate than ARIMAX models while forecasting. Similarly, Mondal et. al., (2014) also took stocks from various sectors of Indian economy and implemented ARIMA models for their forecasting. They found that the forecasting ability in terms of accuracy of ARIMA models is significantly higher. They added that the model is preferred because of its simplicity and wide acceptability. There are many other researchers who have implemented ARIMA models on stock indices of different counties that include: Paul et. al., (2013) implemented ARIMA models in stock indices of Bangladesh, Isenah and Olubusoye (2014) used ARIMA models in Nigerian Stock Market and Junior et. al., (2014) employed ARIMA models in Bovespa Stock Index of Brazil. And all of them have concluded that ARIMA is the most robust econometric technique for modeling time series data on stock indices. Apart from financial time series, there are also many other fields where ARIMA could provide fruitful results are: demand forecasting (Da Viega et. al., 2014), engineering (Williams and Hoel, 2003) and agriculture (Babazadeh and Shamsnia, 2014). 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. The present study has been undertaken to measure the weak form efficiency of some selected financial markets by use of ARMA models based on Box-Jenkins approach.

## 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 India started liberalizing only in 1991 and financial liberalization in a true sense in the economy came during the second generation of financial sector reforms started in 1997. 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;

$$\text{JB Statistic JB} = n\left[\frac{s^2}{6} + \frac{(k-3)^2}{24}\right] \quad (1)$$

This test statistic follows a chi–square ($\chi^2$) 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 $\bar{Y} = \sum_{t=1}^{n} \frac{Y_t}{n-1}$ : $1^{st}$ moment (2)

(ii) Standard Deviation $(\delta) = \left[\sum_{t=1}^{n} \frac{Y_t - \bar{Y}}{n-1}\right]^{1/2}$ : $2^{nd}$ moment (3)

(iii) Skewness $(S) = \dfrac{\sum_{t=1}^{n} \frac{(Y_t - \bar{Y})^3}{n} - 1}{\delta^2}$ : $3^{rd}$ moment (4)

(iv) Kurtosis ($k$) = $$\frac{\sum_{t=1}^{n} \frac{(Y_t - \bar{Y})^4}{n} - 1}{\left[\sum_{t=1}^{n} \frac{(Y_t - \bar{Y})}{n-1}\right]^2} \text{ : } 4^{th} \text{ moment} \quad (5)$$

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

$$Y_t = Y_{t-1} + u_t \quad (6)$$

where, $u_t$ is the stochastic error term that follows the classical assumptions; namely, it has zero mean, constant variance $\delta^2$, 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,

$$Y_t = \rho Y_{t-1} + u_t \quad (7)$$

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 $\tau$ (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:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + u_t \quad (8)$$

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:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + \varepsilon_t \quad (9)$$

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 $\Delta$, 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 $\Delta Y_t$ 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.

$$\text{Modified } t_s = t_s\left(\frac{\gamma_0}{f_0}\right)^{1/2} - \frac{T(f_0 - \gamma_0)\,(se(\delta))}{2 f_0^{1/2} s} \tag{10}$$

where, $\delta$ = coefficient of $y_{t-1}$

$t_s$ = *t*-ratio of $\delta$,

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

$s$ = standard error of the test regression,

$\gamma$ = 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 ($\tau$) 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 ($\tau$) 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:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + u_t \tag{11}$$

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

where, $\alpha_0$ = 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. $\alpha_i$ 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.

$$y_t = \alpha_0 + \sum_{j=1}^{q} \beta_i u_{t-j} + u_t \tag{12}$$

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

where, $\alpha_0$ = 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.

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_i u_{t-j} + u_t \tag{13}$$

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, $\alpha_0$ = 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:

$$Y_t = ln\left[{C_t}/{C_{t-1}}\right] \times 100 \tag{14}$$

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 developed 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 1**
**Name of the Selected Developed Financial Markets and their Stock Indices**

| *S.No.* | *Name of the Country* | *Index* | *Period* | *No. of Observations* |
|---|---|---|---|---|
| 1 | Australia | ASX | 01/07/1997 to 31/12/2016 | 4818 |
| 2 | Austria | ATX | 01/07/1997 to 31/12/2016 | 4837 |
| 3 | Belgium | BEL 20 | 01/07/1997 to 31/12/2016 | 4976 |
| 4 | Canada | S&P TSX Composite | 01/07/1997 to 31/12/2016 | 4985 |
| 5 | France | CAC 40 | 01/07/1997 to 31/12/2016 | 4978 |
| 6 | Germany | DAX | 01/07/1997 to 31/12/2016 | 4962 |
| 7 | Hong Kong | Hang Seng | 01/07/1997 to 31/12/2016 | 4858 |
| 8 | India* | BSE 30 | 01/07/1997 to 31/12/2016 | 4811 |
| 9 | Israel | TA 100 | 01/07/1997 to 31/12/2016 | 4746 |
| 10 | Japan | Nikkei 225 | 01/07/1997 to 31/12/2016 | 4801 |
| 11 | Singapore | Straits Times | 01/07/1997 to 31/12/2016 | 4547 |
| 12 | Switzerland | Swiss Market | 01/07/1997 to 31/12/2016 | 4940 |
| 13 | UK | FTSE 100 | 01/07/1997 to 31/12/2016 | 4684 |
| 14 | USA | S&P 500 | 01/07/1997 to 31/12/2016 | 4909 |

'*' = Emerging Market.
*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 2 shows the state of the selected financial markets basis the discussed variables.

**Table 2**
**Profile of the Selected Financial Markets**

| *S.No.* | *Name of the Country* | *Stock of FDI at Home* | *Stock of FDI Abroad* | *Exchange Rate* |
|---|---|---|---|---|
| 1 | Australia | $ 614.5 Billion | $ 441.9 Billion | $ 1 = 1.352 Australian Dollars |
| 2 | Austria | $ 304.7 Billion | $ 363.3 Billion | $ 1 = 0.9214 Euros |
| 3 | Belgium | $ 1.045 Trillion | $ 1.01 Trillion | $ 1 = 0.9214 Euros |
| 4 | Canada | $ 1.099 Trillion | $ 1.334 Trillion | $ 1 = 1.331 Canadian Dollar |
| 5 | France | $ 796.8 Billion | $ 1.339 Trillion | $ 1 = 0.9214 Euros |
| 6 | Germany | $ 1.416 Trillion | $ 2.08 Trillion | $ 1 = 0.9214 Euros |
| 7 | Hong Kong | $ 1.891 Trillion | $ 1.766 Trillion | $ 1 = 7.779 Hong Kong Dollars |
| 8 | India* | $ 351.8 Billion | $ 149 Billion | $ 1 = 68.3 Indian Rupees |
| 9 | Israel | $ 113.2 Billion | $ 95.74 Billion | $ 1 = 3.871 New Israeli Shekels |
| 10 | Japan | $ 204.3 Billion | $ 1.418 Trillion | $ 1 = 107.1 Yen |
| 11 | Singapore | $ 1.041 Trillion | $ 673 Billion | $ 1 = 1.379 Singapore Dollar |
| 12 | Switzerland | $ 1.359 Trillion | $ 1.565 Trillion | $ 1 = 0.9992 Swiss Francs |
| 13 | UK | $ 2.069 Trillion | $ 1.975 Trillion | $ 1 = 0.7391 British Pounds |
| 14 | USA | $ 3.648 Trillion | $ 5.566 Trillion | $ 1 = 1 $, USD |

*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 USA is having highest direct investments at home as well as abroad. After USA, there is UK which comes in this context. The rest of the economies in the list are almost similar in terms of the selected variables. Table 3 presents the descriptive statistics obtained from the level data that includes Mean, Median, Standard Deviation, Skewness, Kurtosis, Jarque Bera and Probability of the fourteen variables: ASX, ATX, BEL 20, S&P TSX Composite, CAC 40, DAX, Hang Seng, BSE 30, TA 100, Nikkei 225, Straits Times, Swiss Market, FTSE 100 and S&P 500. 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 indicating that the level data distribution is almost symmetric. Kurtosis is less than three for all the indices again 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. 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 3**
**Descriptive Statistics & Distribution Test Results of Level Data**

| *Index Name* | *Mean* | *Median* | *SD* | *Skew.* | *Kurt.* | *JB* | *Prob.* |
|---|---|---|---|---|---|---|---|
| ASX | 4173.6 | 4239.8 | 1078.1 | 0.2 | 1.9 | 271.2 | 0.00 |
| ATX | 2240.4 | 982.1 | 986.8 | 0.9 | 3.1 | 587.2 | 0.00 |
| BEL 20 | 2930.0 | 2882.9 | 653.3 | 0.4 | 2.8 | 171.7 | 0.00 |
| S&P TSX Composite | 10685.4 | 11379.2 | 2820.1 | -0.1 | 1.6 | 397.4 | 0.00 |
| CAC 40 | 4233.6 | 4141.3 | 900.1 | 0.6 | 2.8 | 285.3 | 0.00 |
| DAX | 6376.1 | 6039.2 | 2133.5 | 0.6 | 2.7 | 334.1 | 0.00 |
| Hang Seng | 17436.5 | 17569.2 | 5244.3 | 0.0 | 1.9 | 265.5 | 0.00 |
| BSE 30 | 12524.1 | 12019.7 | 8251.3 | 0.4 | 1.8 | 390.4 | 0.00 |
| TA 100 | 764.2 | 764.2 | 344.8 | 0.1 | 1.7 | 374.1 | 0.00 |
| Nikkei 225 | 13431.5 | 13504.5 | 3483.5 | 0.1 | 1.8 | 308.9 | 0.00 |
| Straits Times | 2391.3 | 2324.0 | 710.7 | 0.0 | 1.8 | 296.2 | 0.00 |
| Swiss Market | 6983.3 | 6929.5 | 1248.7 | 0.0 | 2.1 | 157.6 | 0.00 |
| FTSE 100 | 5574.6 | 5719.2 | 835.5 | -0.4 | 2.3 | 249.3 | 0.00 |
| S&P 500 | 1347.3 | 1277.4 | 350.6 | 0.9 | 3.0 | 646.3 | 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. 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 5). 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)

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

**Table 4**
**ADF & PP Test Results of Level Data**

| *Index Name* | *ADF Test Results* | | | *PP Test Results* | | |
|---|---|---|---|---|---|---|
| | *Computed Value* | *Critical Value at 5% Level* | *P Value* | *Computed Value* | *Critical Value at 5% Level* | *P Value* |
| ASX | –2.21 | –3.41 | 0.48 | –2.10 | –3.41 | 0.54 |
| ATX | –1.34 | –3.41 | 0.87 | –1.39 | –3.41 | 0.86 |
| BEL 20 | –1.97 | –3.41 | 0.61 | –1.87 | –3.41 | 0.66 |
| S&P TSX Composite | –2.81 | –3.41 | 0.19 | –2.65 | –3.41 | 0.25 |
| CAC 40 | –2.53 | –3.41 | 0.31 | –2.31 | –3.41 | 0.42 |
| DAX | –1.89 | –3.41 | 0.65 | –1.80 | –3.41 | 0.70 |
| Hang Seng | –3.24 | –3.41 | 0.07 | –3.18 | –3.41 | 0.08 |
| BSE 30 | –2.97 | –3.41 | 0.13 | –2.83 | –3.41 | 0.18 |
| TA 100 | –2.47 | –3.41 | 0.33 | –2.51 | –3.41 | 0.32 |
| Nikkei 225 | –2.05 | –3.41 | 0.56 | –1.99 | –3.41 | 0.60 |
| Straits Times | –2.66 | –3.41 | 0.25 | –2.67 | –3.41 | 0.24 |
| Swiss Market | –2.44 | –3.41 | 0.35 | –2.28 | –3.41 | 0.44 |
| FTSE 100 | –2.33 | –3.41 | 0.41 | –2.38 | –3.41 | 0.38 |
| S&P 500 | –1.45 | –3.41 | 0.84 | –1.23 | –3.41 | 0.90 |

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

**Table 5**
**ADF & PP Test Results of First Difference in Level Data**

| *Index Name* | *ADF Test Results* | | | *PP Test Results* | | |
|---|---|---|---|---|---|---|
| | *Computed Value* | *Critical Value at 5% Level* | *P Value* | *Computed Value* | *Critical Value at 5% Level* | *P Value* |
| ASX | –70.86 | –3.41 | 0.00 | –70.97 | –3.41 | 0.00 |
| ATX | –66.69 | –3.41 | 0.00 | –66.66 | –3.41 | 0.00 |
| BEL 20 | –65.92 | –3.41 | 0.00 | –65.89 | –3.41 | 0.00 |
| S&P TSX Composite | –69.61 | –3.41 | 0.00 | –69.80 | –3.41 | 0.00 |
| CAC 40 | –71.83 | –3.41 | 0.00 | –72.38 | –3.41 | 0.00 |
| DAX | –69.80 | –3.41 | 0.00 | –69.87 | –3.41 | 0.00 |
| Hang Seng | –69.89 | –3.41 | 0.00 | –69.91 | –3.41 | 0.00 |
| BSE 30 | –64.28 | –3.41 | 0.00 | –64.29 | –3.41 | 0.00 |
| TA 100 | –70.68 | –3.41 | 0.00 | –70.67 | –3.41 | 0.00 |
| Nikkei 225 | –73.36 | –3.41 | 0.00 | –73.63 | –3.41 | 0.00 |
| Straits Times | –64.26 | –3.41 | 0.00 | –64.26 | –3.41 | 0.00 |
| Swiss Market | –33.80 | –3.41 | 0.00 | –67.73 | –3.41 | 0.00 |
| FTSE 100 | –43.63 | –3.41 | 0.00 | –70.08 | –3.41 | 0.00 |
| S&P 500 | –74.17 | –3.41 | 0.00 | –75.19 | –3.41 | 0.00 |

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

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 6.

**Table 6**
**ADF & PP Test Results of Return Series**

| *Index Name* | *ADF Test Results* | | | *PP Test Results* | | |
|---|---|---|---|---|---|---|
| | *Computed Value* | *Critical Value at 5% Level* | *P Value* | *Computed Value* | *Critical Value at 5% Level* | *P Value* |
| ASX | –70.47 | –3.41 | 0.00 | –70.56 | –3.41 | 0.00 |
| ATX | –65.16 | –3.41 | 0.00 | –65.03 | –3.41 | 0.00 |
| BEL 20 | –65.29 | –3.41 | 0.00 | –65.30 | –3.41 | 0.00 |
| S&P TSX Composite | –51.80 | –3.41 | 0.00 | –69.93 | –3.41 | 0.00 |
| CAC 40 | –34.81 | –3.41 | 0.00 | –72.42 | –3.41 | 0.00 |
| DAX | –70.38 | –3.41 | 0.00 | –70.50 | –3.41 | 0.00 |
| Hang Seng | –69.87 | –3.41 | 0.00 | –69.87 | –3.41 | 0.00 |
| BSE 30 | –64.63 | –3.41 | 0.00 | –64.53 | –3.41 | 0.00 |
| TA 100 | –69.87 | –3.41 | 0.00 | –69.87 | –3.41 | 0.00 |
| Nikkei 225 | –72.85 | –3.41 | 0.00 | –73.18 | –3.41 | 0.00 |
| Straits Times | –61.83 | –3.41 | 0.00 | –61.87 | –3.41 | 0.00 |
| Swiss Market | –34.10 | –3.41 | 0.00 | –67.58 | –3.41 | 0.00 |
| FTSE 100 | –33.36 | –3.41 | 0.00 | –70.62 | –3.41 | 0.00 |
| S&P 500 | –53.94 | –3.41 | 0.00 | –76.20 | –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.

The above table shows the best fit ARMA models for the selected financial markets and the proportion of outliers those present in the series. Here, the financial market with less proportion of outlier would obviously be considered as the most stable. In this sense the financial markets in order of stability are: Canada, France, Germany, Japan, and Belgium; and then comes India. The financial markets of USA, UK, Hong Kong, Israel and Singapore are among them with high volatility in their positions. 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; Austria, Belgium, Canada, France, Germany, Hong Kong, India, Japan, Singapore, UK and USA have the least number of AR and MA terms. So these eleven financial markets are comparatively more efficient than the rest of the markets. Australia and Switzerland comes next to these eleven markets on the basis of AR and MA terms. And Israel comes after these two in efficiency basis AR and MA terms.

**Table 7**
**ARMA Test Results**

| *Index Name* | *ASX* | *ATX* | *BEL 20* | *S&P TSX Composite* | *CAC 40* | *DAX* | *Hang Seng* |
|---|---|---|---|---|---|---|---|
| C | 0.02* | 0.06* | 0.03* | 0.06* | 0.03* | 0.04* | 0.02 |
| AR(1) | | –0.84* | –0.76* | –0.79* | –0.78* | 0.73* | –0.93* |
| AR(2) | –0.38* | | | | | | |
| AR(6) | | | | | | | |
| AR(8) | | | | | | | |
| AR(17) | | | | | | | |
| MA(1) | | 0.86* | 0.78* | 0.80* | 0.78* | –0.74* | 0.93* |
| MA(2) | 0.40* | | | | | | |
| MA(3) | | | | | | | |
| MA(5) | | | | | | | |
| MA(8) | | | | | | | |
| Best ARMA Model = | ARMA (2,2) | ARMA (1,1) | ARMA (1,1) | ARMA (1,1) | ARMA (1,1) | ARMA (1,1) | ARMA (1,1) |

| *Index Name* | *BSE 30* | *TA 100* | *Nikkei 225* | *Straits Times* | *Swiss Market* | *FTSE 100* | *S&P 500* |
|---|---|---|---|---|---|---|---|
| C | 0.06* | 0.01* | 0.03* | 0.02* | 0.04* | 0.02* | 0.03* |
| AR(1) | 0.08* | | 0.79* | | | 0.81* | 0.51* |
| AR(2) | | –0.07* | | –0.27* | | | |
| AR(5) | | –0.03* | | | –0.98* | | |
| AR(6) | | | | | | | |
| AR(8) | | 0.03* | | | | | |
| AR(17) | | | | | | | |
| MA(1) | | | –0.81* | | | –0.85* | –0.54* |
| MA(2) | | 0.08* | | 0.28* | | | |
| MA(3) | | | | | | | |
| MA(5) | | | | | 0.98* | | |
| MA(8) | | | | | | | |
| Best ARMA Model = | ARMA (1,0) | AR (2,5,8) MA (2) | ARMA (1,1) | ARMA (1,1) | ARMA (5,5) | ARMA (1,1) | ARMA (1,1) |

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

## 5. POLICY IMPLICATIONS AND CONCLUSION

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 fourteen selected 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 Austria, Belgium, Canada, France, Germany, Hong Kong, India, Japan, Singapore, UK and USA may come in the first category since they have the least number of AR and MA terms detected. These eleven markets may become efficient if proper policy measures will be undertaken. It is also an interesting fact which has been detected here that these eleven financial markets have also remained quite stable over the period of study. Then comes the Australian and Swiss financial markets which may be put in the second category since they have comparatively low number of AR and MA terms. But it should also be noted here that the Australian and Swiss financial markets have been highly unstable over the period of study. Among the rest of the financial markets is only Israel which 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 Belgium, Canada, France, Germany, India and Japan are comparatively more promising for investors out of the selected 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 econometrician 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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