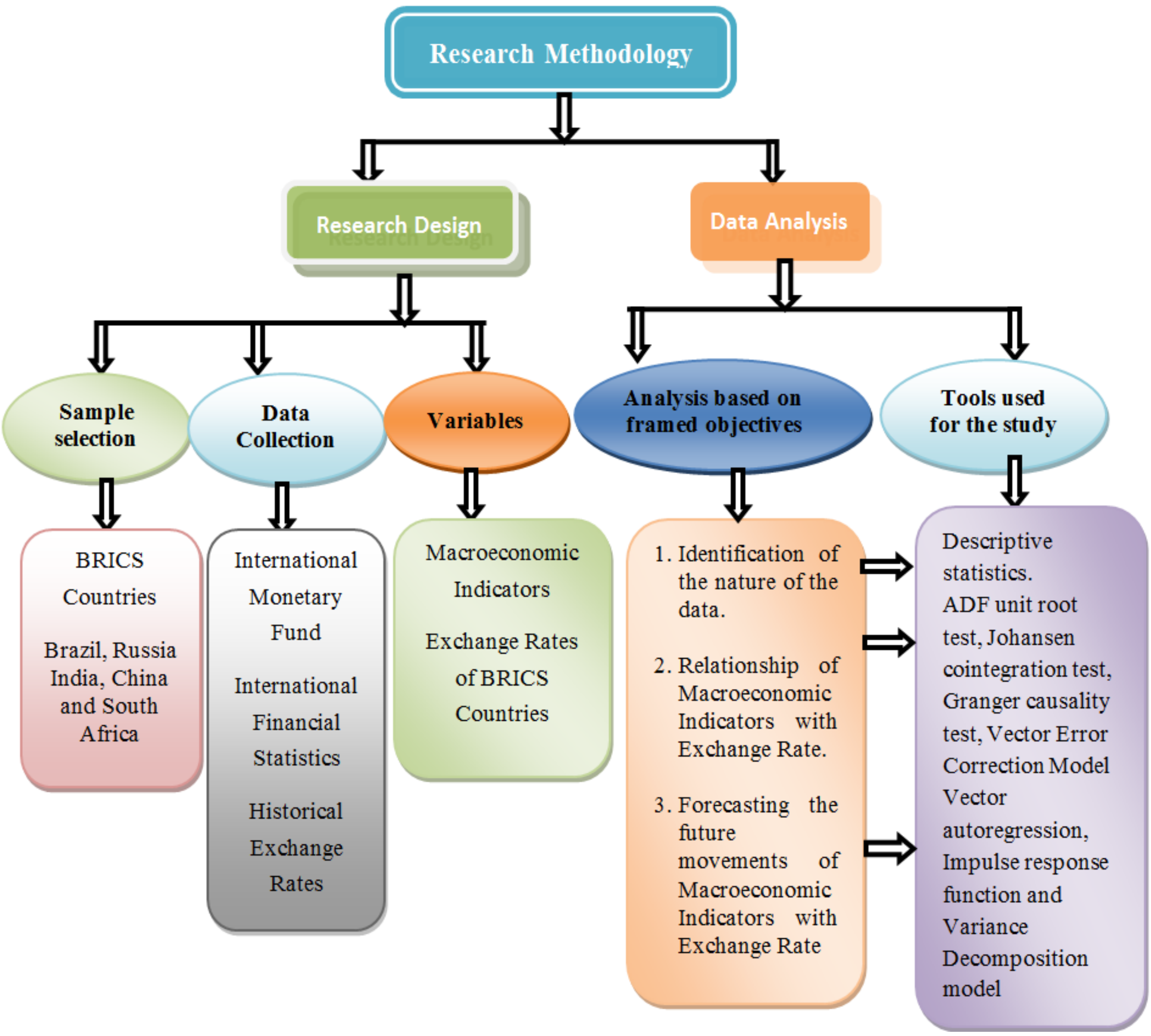
Chapter – 3
Research methodology

Research methodology is a scientific and structured search to investigate a specific problem encountered and that needs a solution. It is a systematic process, in-depth study of any particular subject area of investigation and used to collect information and data for the purpose of making prudent business decisions. Research methodology includes concepts such as paradigm, theoretical model, phases and quantitative or qualitative techniques. It is termed as organized, systematic, data-based, critical, objective, and scientific investigation into a specific problem, undertaken with the purpose of finding solutions to the problem**.** The methodology adopted in the current study is depicted in the chart below.

Chart 3.1

Research Framework



3.1 Research design

In order to analyze the research problem undertaken for the study, descriptive and analytical research using secondary data is considered appropriate.

Descriptive research involves gathering data that describe events and then organizes, tabulates, depicts and describes the data collection (Glass & Hopkins, 1984) The analytical research usually concerns itself with cause-effect relationships. The methods of collecting data for descriptive research can be employed singly or in various combinations, depending on the research questions.

3.2 Sources of the research instrument

For the purpose of studying the objectives and testing the hypothesis, the data are collected from secondary sources such as the International Monetary Fund, International Financial Statistics and Historical Exchange Rates. The Select Macroeconomic Indicators includes Prices, Production, and Labour, Effective Exchange rate based on SDR and CPI, Balance of payments, GDP, Government Finance, Interest Rates, International Liquidity, and Foreign Trade. The reason for selecting the above mentioned eight parameters is that it is only made available in the IMF data portal. Government Finance of China was omitted due to lack of data in the portal. In order to render equal importance to all the indicators, all the parameters were taken into consideration for the conduct of the study. The below chart depicts the sources of research instrument and the list of Select Macroeconomic Indicators.

Chart 3.2

Sources of the research instrument

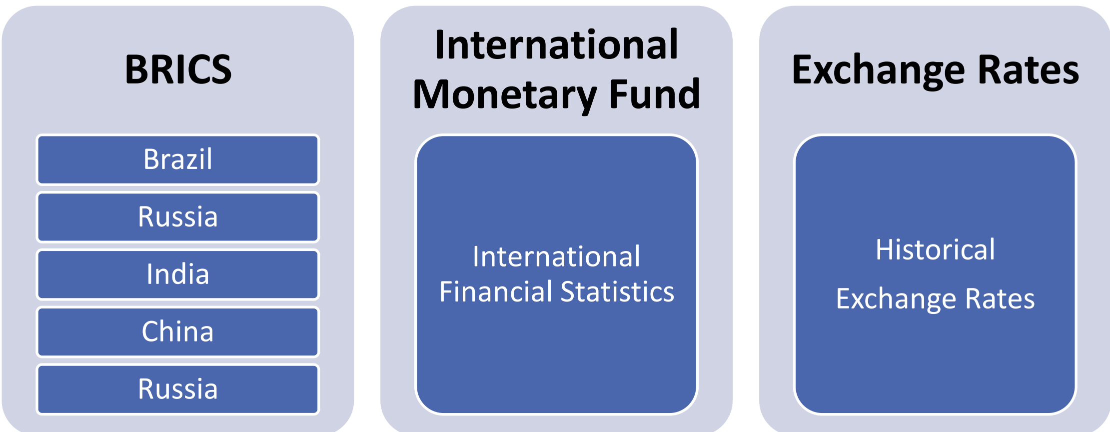


Chart 3.3

List of Select Macroeconomic Indicators

Prices, Production and Labour

- Producer price, Consumer price,Industrial production, Labour Markets,Wage rates,Number of employed and Number of unemployed

Effective Exchange rate based on SDR and CPI

- National Currency as per SDR, Exchange rate based on CPI

Balance of payments

Gross Domestic Product

- National accounts, Current prices, Gross Domestic product and Government consumption Expenditure

Government Finance

- Operations statement, Cash flow statement, currency deposits and Loans

Interest Rates

- Savings rate,Deposit rate, Lending rate, Government bonds, Central banking policy rate, Discount rate and refinancing rate

International Liquidity

- International Reserves, Total reserves, official reserves including and excluding SDR and USD

Foreign trade

- Goods value of Imports and Exports

3.3 Period of study

In this study monthly Exchange Rate of BRICS Countries data for fifteen years from 1st January 2002 to 31st December 2017 and the Macroeconomic indicators have been taken to confine the dynamics. The data was extracted from the International Monetary Fund, International Financial Statistics, and Historical Exchange Rates.

A number of econometric methods have been employed to test the linkages of Exchange Rate of BRICS countries with the macroeconomic indicators. Firstly an attempt is made to understand the properties of the data from an econometric perspective with the help of various cointegration to establish the equilibrium relationship between Exchange Rate of BRICS countries with the Macroeconomic indicators.

3.4 Tools used for analysis

The following are the tools used for the study

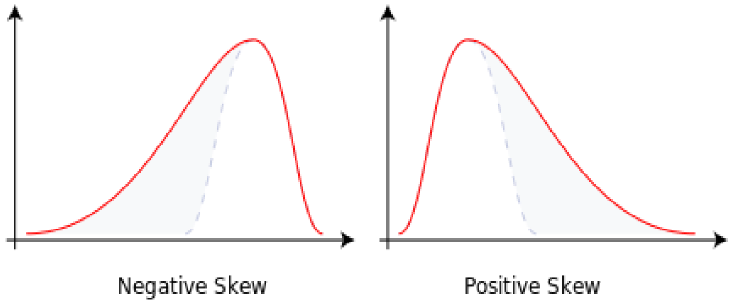
- Descriptive statistics are used to identify the nature of data in the study.
- Augmented Dickey-Fuller (ADF) unit root test is employed to check stationarity for the variables
- Johansen cointegration test the existence of a long-run equilibrium relationship between the variables
- Granger causality test is used to determine the direction of causality between the variables.
- Vector Error Correction Model is used to determine the effect of the long-run relationship between the variables
- Vector autoregression is used to examine the dynamic effects of the variables.
- The impulse response function is used to forecast the future movement of variables
- Variance Decomposition model is used to examine the exogenous shock between the variables.

3.5 Descriptive statistics Descriptive Statistics are used to present the nature of data. Descriptive statistics help to simplify large amounts of data in a sensible way.

3.5.1 Mean and Median are used to test the reliability of Exchange Rates and Macroeconomic indicators

3.5.2 Standard Deviation is a more accurate and detailed estimate of dispersion. The Standard Deviation shows the relation of set of scores to the mean of the sample of Macroeconomic indicators and Exchange rates.

3.5.3 Skewness. Skewness is used to characterize the location and variability of Macroeconomic Indicators and Exchange Rates. The distribution is said to be of two types positive skew and negative skew.



3.5.4 kurtosis is a measure of the combined sizes of the two tails. It is a measure of the "tailedness" of the probability distribution of a real-valued random variable. Hence it is used to predict the future fluctuations of Macroeconomic Indicators and Exchange Rates

3.6 Augmented Dickey-Fuller (ADF) (1979 and 1981) unit root test is a test for stationarity of the time series sample. It is the augmented version of the Dickey-Fuller test for a large and more complicated set of time series models. The following is the model that is used in this study.

$$\Delta y_t = \alpha + \pi + \delta y_{t-1} + \sum_{i=1}^{m} \beta i \Delta y_{t-1} + \varepsilon_t$$

Where, $\Delta = 1 - L; y_t$ indicates Macroeconomic indicator such as Prices, production and labor, Exchange rates as per CPI and SDR, Balance of payments, Gross Domestic Product, Government Finance, Interest rates, International liquidity, and Foreign Trade; t is a trend variable; and ε_t is a white noise term. The null hypothesis of ADF unit root test that $\delta = 1$ means the series has a unit root; it is tested against the alternative hypothesis that $\delta < 0$, and that the series is stationary. If the calculated ADF statistic is smaller than the test critical value, then the null hypothesis is rejected. If the variable is non-stationary at the level, the ADF test will be run at the first difference of the variable.

3.7 Johansen cointegration test (Johansen and Juselius, 1990) has been applied to check the long-run equilibrium relationship exists between select Macroeconomic indicators and Exchange Rates. This test is performed by calculating the trace test statistic and the maximum eigenvalue test statistic. The trace test examines the null hypothesis that the number of distinct cointegrating vectors is less than or equal to the number of cointegrating vectors (r) against a general alternative. The trace test statistic is calculated by using the maximum likelihood ratio as per the following formula:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} 1n\,(1 - \lambda_i)$$

The next step is to calculate the maximum eigenvalue test statistic. The maximum eigenvalue test is based on the method of finding the characteristic root. This statistic tests the null that the number of cointegrating vectors is r, against the alternative of $r + 1$. The formula for calculating this statistic is as follows:

$$\lambda_{max}(r, r + 1) = -T1n(1 - \lambda_{r+1})$$

Where, λ_i represents the estimated values of the characteristic roots obtained from the estimated π and the number of observations is denoted by T.

3.8 Granger causality test was developed in 1960 by Prof. Clive W.J. Granger. It is applied to find out the direction of causality between select Macroeconomic indicators and Exchange Rates. This direction guides in forecasting the future values of the series. To test for Granger causality, following bivariate regression model can be used.If all the coefficients of regression equations are significant, then the null hypothesis stating no causality exists between select Macroeconomic indicators and Exchange Rates are rejected

3.9 Diagnostic tests is enforced to evaluate model residuals, it also serves as tests of model adequacy. These test has been adapted to check whether the residuals are normally distributed, free from heteroskedasticity and serially correlated. Breusch-Godfrey serial correlation Lagrange Multiplier (LM) test, Histogram normal distribution, and ARCH test was used to find out the stability condition of Macroeconomic indicators and Exchange Rates.

3.10 Vector Error correction model An error correction model belongs to the category of multiple time series models most commonly used for data where the underlying variables have a long-run stochastic trend, also known as cointegration. Error correction models are theoretically driven approach useful for estimating both short-term and long-term effects of someone-times on another. The term error correction relates to the fact that last periods deviation from a long-run equilibrium, the error, influences its short-run dynamics. Thus ECM directly estimates the speed at which a dependent (Macroeconomic variables) variable returns to equilibrium after a change in other variables (Exchange Rates).

3.11 Vector autoregression (VAR) was introduced by Sims (1980) as a technique that could be used by macroeconomists to characterize the joint dynamic behavior of a collection of variables without requiring strong restrictions of the kind needed to identify underlying structural parameters. It has become a prevalent method of time-series modeling.

Although estimating the equations of a VAR does not require strong identification assumptions, some of the most useful applications of the estimates, such as calculating impulse response functions (IRFs) or variance decompositions do require identifying restrictions. A typical restriction takes the form of an assumption about the dynamic relationship between a pair of variables, for example, that x affects y only with a lag, or that x does not affect y in the long run.

A VAR system contains a set of m variables, each of which is expressed as a linear function of p lags of itself and of all of the other m – 1 variable, plus an error term. (It is possible to include exogenous variables such as seasonal dummies or time trends in a VAR, but we shall focus on the simple case.) With two variables, x, and y, an order-p VAR would be the two equations. OLS can produce asymptotically desirable estimators.

The error terms in represent the parts of i_t and x_t that are not related to past values of the two variables: the unpredictable "innovation" in each variable. These innovations will, in general, be correlated with one another because there will usually be some tendency for movements in i_t and x_t to be correlated, perhaps because of a contemporaneous causal relationship (or because of the common influence of other variables). A key distinction in understanding and applying VARs is between the innovation terms v in the VAR and underlying exogenous, orthogonal shocks to each variable. Exogenous shocks can be identified from the estimates of the VAR coefficients and residuals.

3.12 Variance Decomposition and Impulse Response Functions

Two variables that have a dynamic relationship in a VAR system are also likely to have some degree of contemporaneous association. This will be reflected in correlation in the innovation terms v in because there is no other place in the equations for this association to be manifested. It is natural to think of the VAR system as the reduced form of a structural model in which contemporaneous effects among the variables have been "solved out." Identification of the underlying structural shocks is necessary to estimate the effects of an exogenous shock to a single variable on the dynamic paths of all of the variables of the system, called as impulse-response functions (IRFs). It is used to identify the structural shocks to each variable in a VAR, two kinds of analysis explain how each shock affects the dynamic path of all of the variables of the system. Impulse-response functions (IRFs) measure the dynamic marginal effects of each shock on all of the variables over time. Variance decompositions examine how important each of the shocks is as a component of the overall (unpredictable) variance of each of the variables over time.

Unlike forecasts and Granger causality tests, both IRFs and variance decompositions can only be calculated based on a set of identifying assumptions and that a different set of identification assumptions may lead to different conclusions. IRFs are usually presented graphically with the time lag s running from zero up to some user-set limit S on the horizontal axis and the impact at the s-order lag on the vertical. They can also be expressed in tabular form if the numbers themselves are important. One common format for the entire collection of IRFs corresponding to a VAR is as an $n \times n$ matrix of graphs, with the "impulse variable" (the shock) on one dimension and the "response variable" on the other.

Like IRFs, variance decompositions can be sensitive to the identification assumptions. Computations of IRFs and variance decompositions for alternative orderings will give similar results, from the results it can be found that our conclusions are not sensitive to the (perhaps arbitrary) assumptions we make about contemporaneous causality. If alternative assumptions lead to different conclusions, we must be more careful about drawing conclusions**.**

Impulse response functions show the effects of shocks on the adjustment path of the variables. Forecast error variance decompositions measure the contribution of each type of shock to the forecast error variance. Both computations are useful in assessing how shocks to economic variables reverberate through a system. Impulse response functions (IRFs) and forecast error variance decompositions (FEVD) can be produced after using the var basic command.