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Econometric Forecasting of Money Mobilization Through Public Issues in Indian Primary Capital Market using Box-Jenkins ARIMA Model

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Abstract
Corporate finance is raised from the primary capital market through public offers, rights issues and private placement, etc. Public offer is the largest sources of funds from the primary capital market to the company. Basically, an invitation is made by a company to the public to subscribe to its securities offered through prospectus is called as public offers, which can be adopted either under fixed price, book- building method or pure auction method. Public issues are of two types, namely Initial Public Offer (IPO) and Further Public Offer (FPO). The study analyses the trend and forecasting of money mobilization through public issues in Indian primary capital market during 2000-2001 to 2020-2021 based on data during 2000-2001 to 2018-2019 using ARIMA Modeling. The study finds that the ARMA (6, 5) model has become the best model to depict the behaviour of the first differences of the capital raised through public issues over the study period. The study also explores that the forecast values of capital raised through public issues in India for 2018-2019, 2019-2020 and 2020-2021, may be 95100.58, 119465.6, and 107820.3 (crore in rupees), respectively.
Keywords: Indian Primary Capital Market, Resource Mobilization, Public Issues, ARIMA Model.

1. Introduction

Corporate finance is raised from the primary capital market through public offers, rights issues and private placement, etc. Public offer is the largest sources of funds from the primary capital market to the company. Basically, an invitation is made by a company to the public to subscribe to its securities offered through prospectus is called public offers, which can be adopted either under fixed price method, or book- building method or pure auction method (Saha, 2015). Capital is generated in the Indian primary capital market through capital issue management process performed by SEBI registered merchant bankers called book runner lead managers (BRLMs).When a company makes a fresh issue to new investors and/or offer of securities is made to new investors for becoming part of shareholders' family of the issuer, it is called public issues. There are two types of public issues: Initial Public Offer (IPO) and Further Public Offer (FPO). IPO, basically, is applicable to those companies which are not listed to the stock exchanges. When a fresh issue of securities of an unlisted company or its existing securities are offered for sale for the first time to the public, called IPO. IPOs are subsequently listed to the stock exchanges and traded in accordance with the SEBI guidelines. On the other hand, FPO or follow on offer is applicable to those companies which are already listed to the stock exchanges. When a listed company makes either a fresh issue of securities to the public or an offer for sale to the public, it is called a FPO. In case of public issues (either IPOs or FPOs), company makes only (a) fresh issue of securities to the public through offer document/red herring prospectus or (b) makes fresh issue of securities to the public along with offer for sale through offer document/red herring prospectus. This offer for sale is made by the existing shareholder(s) of a company (i.e. promoters or other shareholders of the company) (Saha, 2018).

Efficient and stable financial markets are keys to developing a broader and deeper economy. Financial markets ensures the optimal use of capital, and at the same time transfer, pool, mitigate and reduce the existing and potential risks through capital agglomeration, allocation and monitoring. In global context, financial globalization and capital mobility derived and developed from financial markets. Capital formation for economic growth has always been a strategic concern in Indian economy. Capital market is the driver of capital formation and an indicator of economic development. Corporate enterprises and Government raise long terms funds from this market and use it for productive purposes. The segment of the market where resources are mobilised and fresh funds are channelled is known as primary capital market. Behavior of capital generation in this market indicates savings habit of people and influence economic growth of the country (Ahuja, 2012). However, in the post independence era, conservative financial policies by the Government, credit based financial system and financial repression slackened the growth of this market. Economic reform took place in India in 1991and Liberalization policies led to economic growth. Real savings was augmented and channelized into the primary market which helped the market to prosper. Scientific allocation of this fund reduced cost of capital and increased efficiency of investment. Deregulation, an urge for attaining global benchmark, scope of accessing global market and increased inflow of foreign capital also acted as a positive catalyst to the development of this market. With the introduction of several new concepts (e.g. book building method, IPO grading, green shoe option etc.) resource mobilization in this market has become a simple affair. Abolition of Capital Issues Control Act, 1947 and establishment of Securities Exchange Board of India (SEBI) in 1988 as a statutory body to control operation of stock exchanges and other market intermediaries, promote development of this market and protect interest of corporate stakeholders also appealed to a huge section of middle class Indian population who once viewed this market with acute skepticism (Saha, 2013). All these factors led to a steady growth of resource mobilization in this market. Data on total capital generated through public issues in a year from 2000-2001 to 2017-2018 has been collected from SEBI Bulletin. Based on secondary data on overall capital generated in primary capital market through public issues in post-reforms period, the study seeks to analyze the econometric forecasting of money mobilization through public issues in Indian primary capital market during 2018-2019 to 2020-2021 considering data during 2000-2001 to 2018-2019 using Autoregressive Integrated moving Average (ARIMA) Model.

2. Past Studies

Indian primary capital market has become a significant subject of research for authors and researchers across the world. Saha (2016) in his book has elaborated issue of securities under different route in Indian primary capital market. Pricing of public issues, allotment process, green shoe option operation are also discussed as per SEBI (ICDR) Regulations. 2009. Burch & Foester (2004) in their book has made special emphasis on United States (US) Initial Public Offer (IPO) market. Chakraborti & De (2010) have taken an analytical approach to assess operational efficiency of Indian primary market. In Indian environment, impact of regulatory interventions and reforms in post liberation era on this market always received special attention of the researchers (Ahuja, 2012; Nagraj, 1996; Nayak, 2010). Nayak (2010) in their study also discussed common grievances in the new issue market and regulatory measures to address the same. Ahuja (2012) in his research has compared Indian primary capital market with primary market of other developing countries of the world. Juman & Irshad (2015) in their paper have reviewed the process of growth of capital markets, their evolving structure and their functioning through stock exchanges in India. They have examined existing technical analysis for investment decision making and suggested modifications with special emphasize on recent development after the implementation of New Economic Policy. Rubani (2017) in his paper has analyzed the structure of financial market in India and discussed the functions of Indian capital market. Jenica (2017) in her paper has studied role of Indian primary market in resource mobilization during 2014-2016 covering the method of resource mobilization like offer for sale, private placement, qualified institution investor, right issues and so on. Agu, Nwankwo, & Onwuka (2017) in their paper have appraised the impact of capital market in mobilizing domestic resources for economic development in Nigeria from 2000 to 2015. The long-run effect which was determined using co-integration approach indicating the Nigerian capital market has a negative and significant effect on the development of the Nigerian economy.

2.1. Research Gap

Studies reviewed so far, analyze different aspect of capital markets in India and abroad. However, role of Indian primary market in resource mobilization has also been studied analytically. None of the studies consulted, so far, took an attempt to examining the forecasting of money mobilization through public issues in Indian primary capital market during 2018-2019 to 2020-2021 based on data during 2000-2001 to 2018-2019 using ARIMA Model.

3. Objectives

The objective of this study is to forecast the volume of public issues for 3 years (2018-2019 to 2020-2021) beyond the end of sample period (2000-2001 to 2017-2018). This study employs Box-Jenkins methodology of building ARIMA model to achieve the aim of the study.

4. Data and Methodology

The study is an attempt to build a time series model to forecast the volume of Public Issues in Indian primary capital market over the coming period. Annual time series secondary data for the volume of Public Issues in India over the period of 2000-2001 to 2017-2018 obtained from SEBI Bulletin have been utilized. The study has employed Box-Jenkins methodology to build ARIMA model. Accuracy and the selected models have been tested by performing different diagnostics tests to ensure the accuracy of the results obtained. There have been enormous forecasting models ranging from simple models to sophisticated ones. Box – Jenkins model has been preferred in this study not only due to its simplicity but also for its appropriateness with respect to sample dataset of the study. The computer program -Eviews-8 has been used for data analysis and forecasting.

The study is based on Augmented Dickey Fuller test for stationary test, forecasting the volume of Public Issues has been made using ARIMA Model and the selected models are tested considering different diagnostic tools to ensure the accuracy of the results obtained.

4.1. Testing for Stationarity

Stationarity implies that mean, variance and covariance of the return distribution are time independent. In any time series analysis, the test for stationarity is important because, in the presence of non-stationary series, the standard estimation procedures are not applicable. There are two principal methods of detecting non-stationarity: (a) Graphical inspection of correlogram; (b) Formal statistical tests for Unit Root using Augmented Dickey – Fuller Tests (ADF) or other tests.

4.2. Graphical Inspection of Correlogram: Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF)

For the time series Y_t, the autocorrelation of order k is known as ACF of order k.
The ACF at lag k is defined as:

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{Cov(y_t, y_{t-k})}{Var(y_t)} \qquad \text{..........(1)}$$

A graphical plot of ρ_k against k is called correlogram. The correlogram helps to understand whether the series is stationary. If the value of ρ_k at various lags around zero, the series is stationary, otherwise, it is non-stationary. The autocorrelation function (ACF) and partial autocorrelation function (PACF) of time series are plotted in order to identify the appropriate model.

4.3 Test of Autocorrelation: Box-pierce Q Test

The Q-statistic can be used to test whether a group of autocorrelation is significantly different from zero or not. Box-Pierce (1970) used the sample autocorrelations to form the Q-statistic as,

$$Q_{BP} = T\sum_{k=1}^{m} \rho_k \qquad \text{..........(2)}$$

Where, T = number of observations and m = maximum lag length and ρ_k be the k-th order sample autocorrelation coefficient. Under the null hypothesis that all values of $\rho = 0$, Q is asymptotically Chi-square (χ^2) distribution with k degrees of freedom. If the calculated value of Q exceeds the appropriate critical value in a chi-square table ($\chi^2_{obs} > \chi^2_{Tab}$), we reject the null hypothesis and the series is non-stationary.

4.4 Formal statistical tests for Unit Root using Augmented Dickey – Fuller Tests (ADF)

If the data is non-stationary, the regression results using such data would be spurious, and the usual 't' test would not be applicable to test the significance of coefficients. To investigate whether the data and its first difference are stationary, the Augmented Dickey-Fuller (ADF) test can be applied for the time series. The unit root test for stationarity can be represented as Augmented Dickey Fuller (1979, 1981) Regression is as follows:

The ADF test is more general form of Dickey-Fuller test. Since simple DF can be applied only to the AR (1) process, we employ ADF in order to capture the higher lags (p lags). So, the lag length selection is also important for ADF. Dickey and Fuller (1979) actually consider three different regression equations that can be used to test for the present the unit root. The first is a pure random walk model, the second model adds an intercept term or drift term and the third include both a drift and a linear time trend. The models are

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + e_t$$

$$\Delta y_t = \alpha + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + e_t$$

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + e_t \qquad \text{..........(3)}$$

Where $\gamma = (\rho - 1)$, α is a constant (drift), β is the coefficient on a time trend and *p* is the lag order of the autoregressive process and e_t is a white noise error term.

Unit root test is realized under the null hypothesis that the series has unit root, and the alternative is the series has no unit root; i.e.,

$$H_0 : \gamma = 0 \ i.e. \ \rho = 1 \ and \ H_1 : \gamma < 0 \ i.e. \ \rho < 1 \quad \text{.............................(3.1)}$$

The test statistic is $DF_\tau = \dfrac{\hat{\gamma}}{SE(\hat{\gamma})}$ ....(3.2)

If the ADF test-statistic (τ - stat.) is greater than (in the absolute value) than Mackinnon critical t-value, the null hypothesis of a unit root can be rejected for the time series and hence, it can be said that the series is stationary at their levels. Otherwise, the null hypothesis of unit root can be accepted and it can be said that the series has unit root, and hence, the series is non-stationary at level.

4.5 Econometric Forecasting: Box-Jenkins (BJ) Methodology

Forecasting is the process of making predictions of the future based on past and present data in analyzing trends. In this section, an attempt has been made to discuss one of the most popular approaches towards econometric forecasting which is known as Autoregressive Integrated moving Average (ARIMA) forecasting method. Box and Jenkins (1976) introduced first the ARIMA model and hence this method is known as the Box-Jenkins methodology. ARIMA is a combination of AR (*Autoregressive*)**,** I (*Integrated*)**,** and MA (*Moving Average*) process. A convenient notation for ARIMA model is ARIMA (p, d, q). Here, p, d, and q are the levels for each of the AR, I, and MA process. Thus, given the values of p, d, and q, it can be said that what process is being modelled. Each of these three processes is an effort to make the final residuals displaying a white noise pattern (or no pattern at all). Before proceeding the ARIMA model, it is necessary to check that the underlying time series are stationary or they can be made stationary with appropriate transformations (Bhaumik, 2015).

Box and Jenkins put forward a new generation forecasting tool, popularly known as the Box–Jenkins (BJ) methodology, technically known as the ARIMA methodology. The BJ-type time series models allow Y_t to be explained by past, or lagged, values of *Y* itself and stochastic error terms. The BJ methodology is based on the assumption that the time series under the study is stationary. If a time series is stationary, we can model it in a variety of ways. Y_t is an autoregressive model of order *p* or AR (*p*) process in following difference equation or model,

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + ... + \rho_p y_{t-p} + e_t \quad \text{..(4)}$$

On the other hand, Y_t is expressed as weighted or moving average of the current and past white noise error terms, it is known as Moving Average of order *q* or MA (*q*) model. It is written as follows.

$$y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-1} + ... + \theta_q e_{t-q} \quad \text{..(5)}$$

By combining AR and MA models, one can get the ARMA *(p, q)* model, with *p* autoregressive terms and *q* moving average terms. It is shown as below:

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + ... + \rho_p y_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + ... + \theta_q e_{t-q} \quad \text{..................(6)}$$

If a time series is integrated of order *d* and ARMA (*p, q*) model is applied to it, it can be said that the original time series is generally known as Auto Regressive Integrated Moving Average or ARIMA (*p, d, q*) model, where d denotes the number of times a time series has to be differenced to make it stationary. If stationary at level only, therefore they can be termed as I(0) and there is an absence of *d.*

However, the BJ forecasting method consists of following steps:

Step 1: Identification of best fit ARIMA model
- (a) Plot time series data
- (b) Difference data to make stationary on mean (remove trend)
- (c) Log transform data to make data stationary on variance
- (d) Difference log transform data to make data stationary on both mean and variance
- (e) Plot ACF and PACF to identify potential AR and MA model

Step 2: Estimation of the best fitted model

Step 3: Diagnostics checking, i.e., finding out whether estimated residuals are white noise. If yes, go to the next step. If no, return to steps 1.

Step 4: Forecasting using the best fit ARIMA model

Step 5: Forecast Evaluation

Step 1: Identification of the model

(i) The correlogram of the original series can be obtained to study the auto correlation function (ACF) and partial auto correlation function (PACF). This can be followed by ADF test to confirm presence/

absence of unit root of the series. If the series is found to be stationary, step (iii) can be followed, if not, step (ii) can be followed.

(ii) Taking the first difference of the original series, the ACF and PACF of it can be studied and the ADF test can be applied to confirm presence/ absence of unit root of the series.

(iii) Models can be identified on the basis of the ACF and PACF and resulting correlograms, which are simply the plots of ACFs and PACFs against the lag length.

Step 2: Estimation of the chosen model

Estimation of the chosen model is related with estimation of the parameters of the autoregressive and moving average terms included in the model. This is basically done using least square or any other technique such as maximum likelihood method.

Step 3: Diagnostic checking

Diagnostic checking is essential to know as to whether the estimated model is good enough for the purpose of forecasting. It involves: (a) examining ACF and PACF of the residual series corresponding to the estimated model followed by ADF test for knowing stationarity of the residual series; (b) usual t test or z tests can be used for examining statistical significance of the parameters; (c) larger p and q indicates the model is fit. However, the value of AIC (Akaike Information Criterion) and SBC (Schwertz Bayseain Information Criterion) together with the adjusted-R^2 of alternative estimated models can be checked to find out the parsimonious model (i.e., minimizes AIC and SBC and has highest value of adjusted-R^2) (Bhaumik,2015).

Step 4: Econometric Forecasting

Once estimated model has been found adequate, it can be used for forecasting.

Step 5: Forecast Evaluation (goodness of fit)

Evaluation of the quality of a forecast requires comparing the forecast values to actual values of the target variable over a forecast period. After estimating the model, evaluating the model with forecast evaluation statistics (goodness of fit) is required to measure the performance of forecast or forecast accuracy. Some of the statistical measures of forecast accuracy are RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and the Theil inequality Coefficient as follows:

(i) Mean Absolute Error (MAE):

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |y_t - \overline{y_t}|$$

(ii) Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{T}\sum_{t=1}^{T} |y_t - \overline{y_t}|$$

(iii) Mean Square Error (MSE):

$$MSE = \frac{1}{T}\sum_{t=1}^{T} (y_t - \overline{y_t})^2$$

(iv) Root Mean Square Error (RMSE):

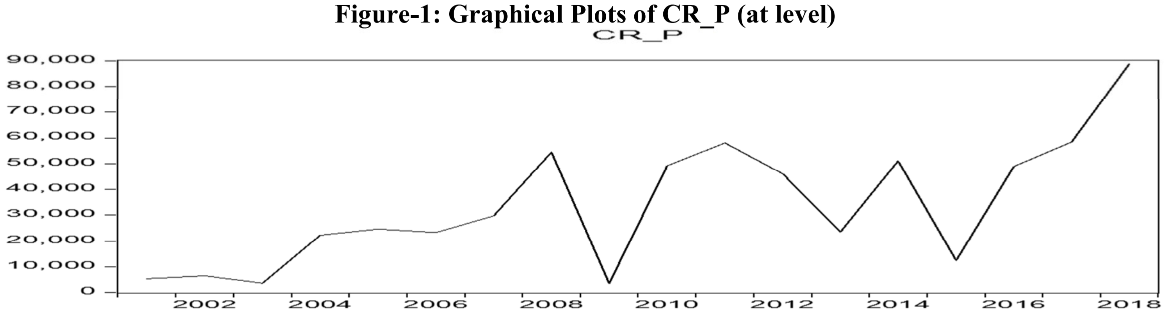
$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (y_t - \overline{y_t})^2}$$

6. Empirical Results and Analysis

6.1 Plotting Time Series Data

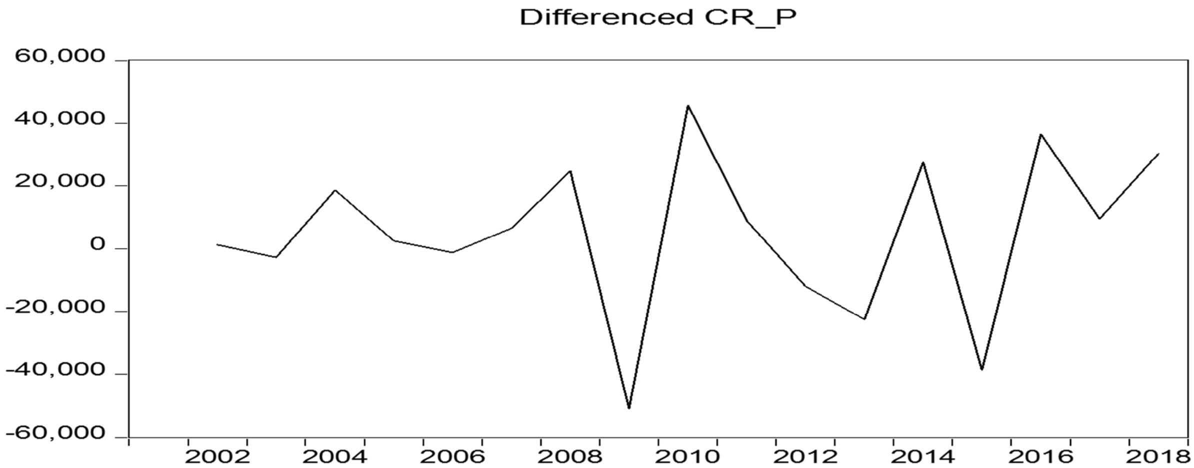
As part of the diagnostics, we begin with a visual inspection of the time plot of capital raised through public issues (CR_P) and its first difference (D(CR_P)) for the period (2000-01 to 2017-18) under review and these are presented in Figure –1 and Figure –2 respectably. A time plot shows the data against the time.

Figure-1: Graphical Plots of CR_P (at level)



(Source: Author's calculation based on data from SEBI)

Figure-2: Graphical plots of CR_P (at 1st difference)



(Source: Author's calculation based on data from SEBI)

From the above plot (Figure –1), a time series data with a linearly upward trend is displayed. Plot (Figure –2) is the 1st order differenced plot for the same data showing the difference data (residual) does not display any trend.

6.2 Descriptive Statistics

Various descriptive statistics are calculated and reported in Table-1 in order to specify the distributional properties of the data (CR_P) during the period under study. It is seen that the CR_P during the study period varies from 3582 to 88740. Therefore, a wide range of fluctuation in data series can be observed. The mean during the study period is 33898.89. The skewness statistics for data is 0.446. Thus, it is lies between -0.5 and 0.5, the distribution is approximately symmetric. Furthermore, the kurtosis is 2.475, suggests that the underlying distribution was platykurtic distribution. It is also observed that the JB statistics is insignificant at 5% level of significance. It means that the null hypothesis of normality accepts the normality assumption.

Table–1. Descriptive Statistic of CR_P (at level)

Descriptive Statistic	CR_P
Mean	33898.89
Median	27218.00
Minimum	3582.00
Maximum	88740.00
Range	85158.00
Standard Deviation	24061.34
Skewness	0.446
Kurtosis	2.475
Jarque-Bera	0.803
Probability	0.669
Sum	610180.00
Sum sq. Dev.	9.84E+09
Observation	18

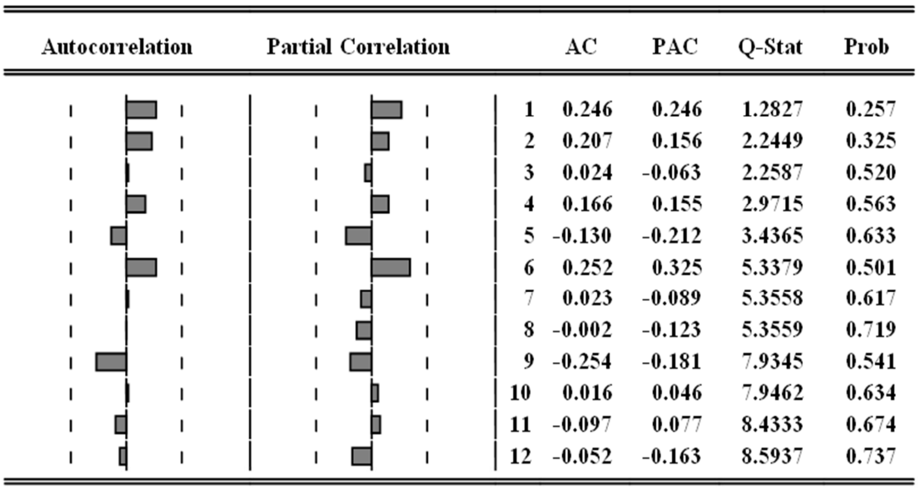
(Source: Author's calculation based on data from SEBI)

6.3 Stationarity Test: Unit Root Test Analysis

6.3.1 Stationarity Test using Correlogram

In this segment, an attempt has been made to test stationarity using correlogram, which is followed by application of ADF test to examine the presence of unit root (non-stationary) in the CR_P series. The correlogram of the series CR_P is shown in Figure – 3.

Figure–3: Correlogram of CR_P



Sample: 2001 -2018
Included observations: 18

	AC	PAC	Q-Stat	Prob
1	0.246	0.246	1.2827	0.257
2	0.207	0.156	2.2449	0.325
3	0.024	-0.063	2.2587	0.520
4	0.166	0.155	2.9715	0.563
5	-0.130	-0.212	3.4365	0.633
6	0.252	0.325	5.3379	0.501
7	0.023	-0.089	5.3558	0.617
8	-0.002	-0.123	5.3559	0.719
9	-0.254	-0.181	7.9345	0.541
10	0.016	0.046	7.9462	0.634
11	-0.097	0.077	8.4333	0.674
12	-0.052	-0.163	8.5937	0.737

(Source: Author's calculation using Eviews-8 based on data from SEBI)

(Source: Author's calculation using Eviews-8 based on data from SEBI)

The first two columns of the correlogram graphically display autocorrelations (AC) and partial autocorrelations (PAC) of the CR_P series at various lags, which is provided in third column. The corresponding numerical values of AC and PAC are reported in the fourth and fifth column respectably. As a rule of thumb, the computed value of AC and PAC are statistically significant if it outside $0 \pm 1.96/\sqrt{T}$ band (shown by dotted line), where T is the number of observation. The last two columns gives the values of Ljug-Box Q-statistic and P-value associated with computed LB-statistic. It is observed that the ACF of the series exhibits a dying-out pattern of the spikes (insignificant ACF values) and there is no significant spike for PACF. These observations indicate that our data set (CR_P) is non-stationary. Now, let us check the unit root test by applying ADF test.

6.3.2 Stationarity Test using ADF Test

Unit root test is very significant test to check the stationarity of a time series variable. The stationarity of the data set can be checked in order to avoid the spurious regression. In this study, Augmented Dickey-Fuller (ADF) test has been used to check the existence of unit root or not. Table – 2 depicts the ADF test statistic at level with three variations as without trend and intercept, Intercept, and trend & intercept.

Table – 2: Unit root test of CR_P (at level)

Model	**t-stat.**	**Prob.**	**C.V (1%)**	**Null hypothesis (H_0): CR_P has unit root (Decision Rule: if the absolute value of $\lvert\tau_{Obs}\rvert > \lvert\tau_{Tab}\rvert$, H_0 is rejected)**	**Remarks (non-stationary series =I(1)/ stationary series =I(0))**
No Intercept & No Trend/ None	0.613	0.838	-2.717	**H_0 accepted**	I(1)
Intercept	-2.195	0.215	-3.886	**H_0 accepted**	I(1)
Intercept & Trend	-3.988	0.031	-4.616	**H_0 accepted**	I(1)

(Source: Author's calculation using Eviews-8 based on data from SEBI)

It is observed (Table – 2) that the null hypothesis of unit root in all three variations is accepted at 1% significant level. Hence, our data set (CR_P) has unit root at level indicating non-stationary. In order to make it stationary, we need to take first difference of the variable and again check the stationary at first difference. The results of this test are as follows:

Table – 3: Unit root test of CR_P (at first difference)

Model	t-stat.	Prob.	C.V (1%)	Null hypothesis (H_0): CR_P has unit root (Decision Rule: if the absolute value of $\lvert\tau_{Obs}\rvert > \lvert\tau_{Tab}\rvert$, H_0 is rejected)	Remarks (non-stationary series =I(1)/ stationary series =I(0))
No Intercept & No Trend	-6.572	0.000	-2.717	**H_0 rejected**	I(0)
Intercept	-6.773	0.000	-3.920	**H_0 rejected**	I(0)
Intercept & Trend	-6.593	0.000	-4.667	**H_0 rejected**	I(0)

It is evident (Table – 3) that the null hypothesis of unit root in all three variations is rejected at 1% significant level. Hence, our data set (CR_P) has no unit root at the first difference indicating stationary series. Now, let us move to forecasting with the help of ARIMA Model.

6.4 Econometric Forecasting of CR_P: BJ-ARIMA Model

It is observed that the capital raised through public issues (CR_P) is non-stationary at level, while the first difference of that [d(CR_P)] is stationary. Since the BJ methodology is based on stationary time series, let's work with d(CR_P) instead of CR_P to model this time series, where d(CR_P) stands for the first difference of CR_P. With a view to exploring which ARMA model fits d(CR_P), the following BJ methodology can be followed.

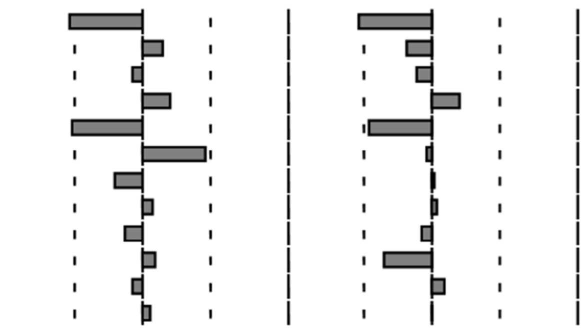
6.4.1 Identification of the Model

Since CR_P series is non-stationary, it is appropriate to obtain the correlogram of first differenced series for CR_P [d(CR_P)]. Such correlogram is presented here (Figure-4).

Figure–4. Correlogram of D(CR_P)

Date: 07/16/18 Time: 14:53
Sample: 2001 -2018
Included observations: 17

Autocorrelation **Partial Correlation**



	AC	PAC	Q-Stat	Prob
1	-0.529	-0.529	5.6591	0.017
2	0.149	-0.182	6.1383	0.046
3	-0.066	-0.099	6.2376	0.101
4	0.192	0.195	7.1575	0.128
5	-0.501	-0.444	13.913	0.016
6	0.445	-0.030	19.734	0.003
7	-0.201	0.018	21.044	0.004
8	0.080	0.032	21.272	0.006
9	-0.125	-0.075	21.899	0.009
10	0.095	-0.342	22.319	0.014
11	-0.069	0.086	22.579	0.020
12	0.049	0.008	22.731	0.030

(Source: Author's calculation using Eviews-8 based on data from SEBI)

(Source: Author's calculation using Eviews-8 based on data from SEBI)

As we know that the ACFs and PACFs of AR (p) and MA (q) have opposite patterns. In the AR (p) case, the ACF declines exponentially or with damped sine wave pattern or both but PACF cuts off after p lags. The opposite happens to an MA (q) process. A mixed process is required when neither the ACF nor PACF show a definite cut-off. Though identification of an appropriate model becomes difficult in this situation, it is not impossible.

Here, it is found that both ACFs and PACFs alternate between negative and positive values and do not follow any pattern. It shows that ACF of the d(CR_P) series has a significant spike at lag 1, 5 and 6. On the other hand, PACF contains significant spikes at lag 1 and 5. On the basis of these patterns of ACF and PACF, it can be said that d(CR_P) series is stationary. This is again confirmed by the ADF test the results which are presented in Table–3. As we know that the 95% confidence interval for the true correlation coefficient is about $0 \pm 1.96/\sqrt{T}$. The correlation coefficients lying outside these bounds are statistically significant at the 5% level. Based on this, it can be stated that the ACF and PACF correlation at lag (1, 5 & 6) and lag (1 & 5) are statistically significant respectively. We now identify the ARIMA structure of the d(CR_P) series. Inspection of

ACF and PACF for d(CR_P) series suggests that it might be modeled as an ARIMA{(1,5,6), 1, (1,5)} structure.

6.4.2 Estimation and Selection of the ARIMA Model

In this stage, we estimate the parameters of the autoregressive and moving average terms included in the model. This can be done using least square technique. Before estimating such a model, the sample range is to be resized and forecasting can be made for next three year (2018-2019 to 2020-2021). Now we estimate an ARIMA{(1,5,6), 1, (1,5)} model in EViwes. However, four ARIMA model have been estimated such as ARMA (1, 5), ARMA (5, 1), ARMA (5, 5), and ARMA (6, 5) for forecasting of the series CR_P over the study period (2000-2001 to 2017-2018).

The total estimated ARIMA models are reported in Table–4. It can be summed up that the ARMA (6, 5) model is probably an appropriate model to depict the behaviour of the first differences of the CR_P over the study period. The estimated coefficients of both AR (6) and MA (5) terms are statistically significant at 1% level.

Table – 4 : Estimated ARIMA Model

Dependent Variable: D(CR_P), Method: Least Squares						
Sample (adjusted): 2003 2018, Included observations: 16 after adjustments						
Convergence achieved after 27 iterations						
ARMA(1,5)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**		
C	4013.001	3078.699	1.303473	0.2150		
AR(1)	-0.493474	0.249968	-1.974144	0.0700		
MA(5)	-0.850354	0.093040	-9.139698	0.0000		
Akaike info criterion	22.56453	Hannan-Quinn criter.	22.57195			
Schwarz criterion	22.70939	Durbin-Watson stat	2.094152			
Inverted AR Roots	-.49					
Inverted MA Roots	.97	.30-.92i	.30+.92i	-.78+.57i	.97	
ARMA(5,1)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**		
C	3032.222	814.3833	3.723336	0.0047		
AR(5)	-0.887832	0.362304	-2.450518	0.0367		
MA(1)	-0.937240	0.109047	-8.594808	0.0000		
Akaike info criterion	22.76622	Hannan-Quinn criter.	22.72134			
Schwarz criterion	22.88745	Durbin-Watson stat	1.928270			
Inverted AR Roots	.79-.57i	.79+.57i	-.30+.93i	-.30-.93i	.79-.57i	
Inverted MA Roots	.94					
ARMA(5,5)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**		
C	1625.558	2978.703	0.545727	0.5985		
AR(5)	-0.740658	0.218190	-3.394556	0.0079		
MA(5)	-0.913449	0.053729	-17.00110	0.0000		
Akaike info criterion	22.00561	Hannan-Quinn criter.	21.96073			
Schwarz criterion	22.12684	Durbin-Watson stat	2.286852			
Inverted AR Roots	.76-.55i	.76+.55i	-.29+.90i	-.29-.90i	.76-.55i	
Inverted MA Roots	.98	.30-.93i	.30+.93i	-.79+.58i	.98	
ARMA(6,5)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**		
C	30491.23	26953.52	1.131	0.290		
AR(6)	0.739	0.179	4.109	**0.003**		
MA(5)	-0.972	0.066	-14.779	**0.000**		
Akaike info criterion	**21.797**	**Hannan-Quinn criter.**	**21.728**			
Schwarz criterion	**21.906**	**Durbin-Watson stat**	**2.018**			
Inverted AR Roots	.95	.48-.82i	.48+.82i	-.48+.82i	.95	.48-.82i
Inverted MA Roots	.99	.31+.95i	.31-.95i	-.80-.58i	.99	

(Source: Author's calculation using Eviews-8 based on data from SEBI)

Table-4 shows that all the information criteria – AIC, SBC and HQ of the ARMA (6, 5) model are minimum as compared to other three models. The criterion is that it has to be lowest all possible ARIMA models that might be estimated with the CR_P series. On the basis of information criterion, the best ARIMA model is ARMA (6, 5). All inverted AR and MA roots are lies within the unit circle which implies that the chosen ARIMA structure is stationary and the model has been correctly specified.

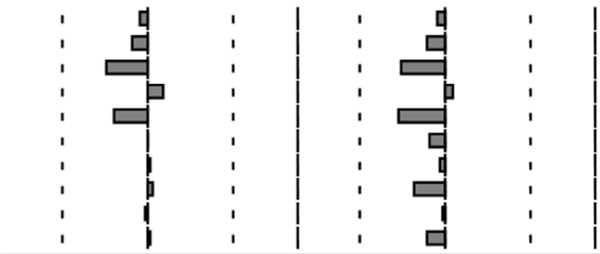
6.4.3 Diagnostic Checking

(i) Stationarity Test using Correlogram

In this step, it is checked that which estimated model is good enough for the purpose of forecasting. Residual Correlogram of the estimated ARMA (6, 5) Model is presented here (Figure-5).

Figure–5: Residual Correlogram of the estimated ARMA (6, 5) Model

Date: 08/02/18 Time: 13:29
Sample: 2001-2021
Included observations: 11
Q-statistic probabilities adjusted for 2 ARMA terms



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.051	-0.051	0.0373	
		2	-0.112	-0.115	0.2370	
		3	-0.279	-0.296	1.6273	0.202
		4	0.111	0.062	1.8775	0.391
		5	-0.244	-0.335	3.2945	0.348
		6	0.005	-0.112	3.2953	0.510
		7	0.023	-0.036	3.3148	0.652
		8	0.038	-0.205	3.3821	0.760
		9	-0.011	-0.019	3.3909	0.847
		10	0.020	-0.115	3.4500	0.903

(Source: Author's calculation using Eviews-8 based on data from SEBI)

Now, the ACF and PACF of the residual series corresponding to the estimated ARMA (6, 5) Model are examined. ACF and PACF of residuals (Figure–5) show that CR_P series has no problem with residuals and there are no significant spikes which indicate a good sign for using this model for forecasting. Apart from that, DW statistic for the estimated ARMA (6, 5) Model is 2.01, i.e., very close to 2 (Table-4). So, there is no autocorrelation in the residual of the model and we use ARMA (6, 5) model for forecasting.

(ii) Stationarity Test using ADF Test

Unit root test results of Residual of the estimated ARMA (6, 5) Model is presented in table-5 in order to know stationarity of the residual series.

Table – 5: Unit root test results of Residual of the estimated ARMA (6, 5) Model

Model	t-stat.	Prob.	C.V (1%)	Null hypothesis (H_0): CR_P has unit root (Decision Rule: if the absolute value of $\lvert\tau_{Obs}\rvert > \lvert\tau_{Tab}\rvert$, H_0 is rejected)	Remarks (non-stationary series =I(1)/ stationary series =I(0))
Intercept	-3.038	0.064	-4.297	**H_0 rejected**	I(0)
Intercept & Trend	-2.809	0.228	-5.295	**H_0 rejected**	I(0)

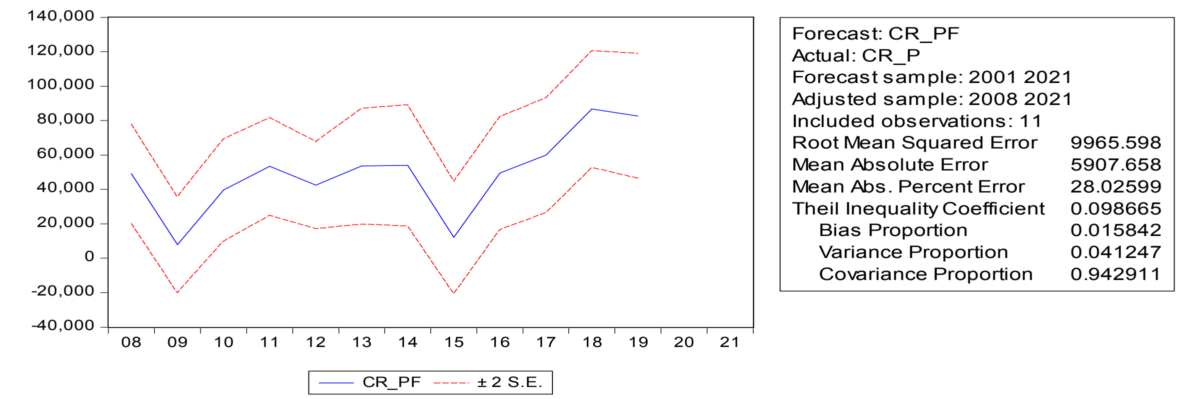
(Source: Author's calculation using Eviews-8 based on data from SEBI)

It is observed (Table-5) that the null hypothesis of unit root is rejected. So, the residual of the estimated ARMA (6, 5) model has stationary or white noise. Hence, ARMA (6, 5) model can be used for forecasting.

6.4.4 Forecasting with ARIMA

Once a particular ARMA model is fitted, that fitted model can be used for forecasting. There are two types of forecast: static and dynamic forecast. The static forecast uses the actual current and lagged values of the forecast variable, where as in dynamic forecasts, after the first period forecast, we use previously forecast value of the forecast variable. Using the ARMA (6, 5) model, the static forecast is shown in Figure–6. This figure gives the forecast values of CR_P as well as the confidence interval of forecast.

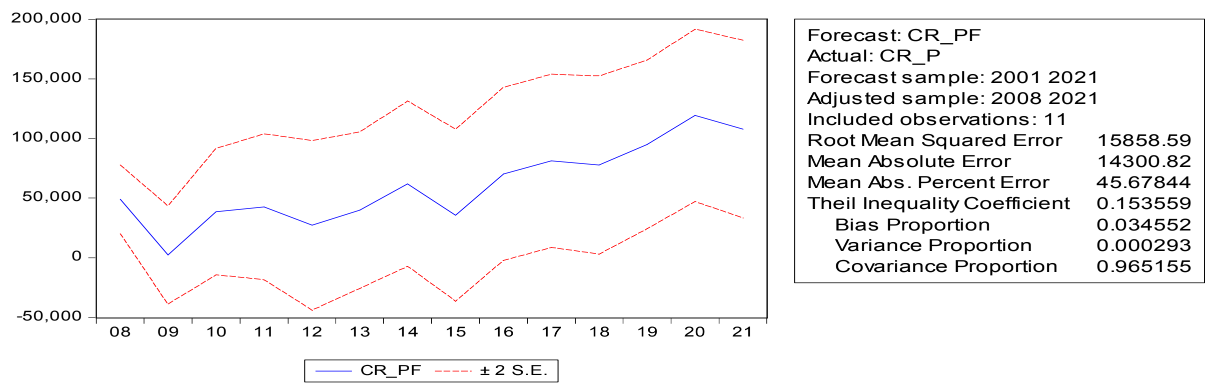
Figure–6: Graphical Display of Static Forecast of CR_P



(Source: Author's calculation using Eviews-8 based on data from SEBI)

The picture of the dynamic forecast is given in Figure–7. This figure gives the forecast values of CR_P as well as the confidence interval of forecast.

Figure–7: Graphical Display of Dynamic Forecast of CR_P



(Source: Author's calculation using Eviews-8 based on data from SEBI)

The actual values of capital raised through public issues (CR_P) during 2000-2001 to 2017-2018 and forecast values of CR_P during 2000-2001 to 2020-2021 are given in Table–6 under Dynamic Forecast. The table shows the forecast values of CR_P in India for 2018-19, 2019-20 and 2020-21, which are 95100.58, 119465.6, and 107820.3 (crore in rupees), respectively.

Table –6. Actual and Forecast Level of Capital Raised through Public Issues (CR_P)

Year	Actual amount of public issues (Rs. in Crore)	Forecasted amount of public issues (Rs. in Crore)
2001	5378.000	NA
2002	6502.000	NA
2003	3639.000	NA
2004	22265.00	NA
2005	24640.00	NA
2006	23294.00	NA
2007	29796.00	NA
2008	54511.00	49079.41
2009	3582.000	2481.815
2010	49236.00	38632.47
2011	58105.00	42742.30
2012	46093.00	27167.62
2013	23510.00	39923.08
2014	51075.00	62128.12
2015	12453.00	35625.87
2016	48928.00	70301.24
2017	58433.00	81288.11
2018	88740.00	77721.80
2019	NA	95100.58
2020	NA	119465.6
2021	NA	107820.3

(Source: Author's calculation using Eviews-8 based on data from SEBI)

6.4.5 Evaluation of Forecasts

The accompany table of forecast graph gives the measures of the quality of the forecast, such as root mean square, mean absolute error, mean absolute percentage error and the Theil Inequality coefficient. Truly speaking, the criterion is that all those value has to be lowest in all possible ARIMA models that might be estimated with the series. The value of Root mean Square Error for the estimated ARIMA (6, 5) model is 9965.598 (Figure–6) under static forecast, which seems to be low as compared to other three models. On the other hand, The value of Root mean Square Error for the estimated ARIMA (6, 5) model is 15858.59 (Figure–7) under the dynamic forecast, which seems to be low in comparison with other three models. However, it is observed that the value of Root mean Square Error for the estimated ARIMA (6, 5) model under static forecast is lower than the value of Root mean Square Error for the estimated ARIMA (6, 5) model under the dynamic forecast. Hence, the static forecast may give better result than dynamic forecast. Moreover, the static forecast shows Theil coefficient 0.098 as compared to dynamic forecast showing Theil coefficient 0.153. On the basis of the Theil coefficient, it can be stated that static forecast may give better result than dynamic forecast as static forecast gives lowest results of Theil coefficient. The values of 'bias proportion', 'variance proportion' and 'covariance proportion' are 0.015, 0.041, and 0.942, respectively (Figure–6) under static forecast. Since the values of bias and variance proportions are low and that of covariance proportion is high; the forecast may be considered satisfactory.

7. Conclusions

The present study has adopted ARIMA Model to analyze the econometric forecasting of money mobilization through public issues in Indian primary capital market during 2018-2019 to 2020-2021 considering data during 2000-2001 to 2018-2019. There is a very limited existing empirical research on this issue. On the basis of through analysis of date relating to money mobilization through public issues in Indian primary capital, the paper has estimated four ARIMA model such as ARMA (1, 5), ARMA (5, 1), ARMA (5, 5), and ARMA (6, 5) for forecasting of the series CR_P over the study period (2000-2001 to 2017-2018). It can be stated that the ARMA (6, 5) model has become the best model to depict the behaviour of the first differences of the CR_P over the study period. Moreover, the residual of the estimated ARMA (6, 5) model has stationary or white noise and ARMA (6, 5) model has been used for forecasting of the series CR_P for the year 2018-19, 2019-20 and 2020-21. The forecast values of capital raised through public issues in India for 2018-2019, 2019-2020 and 2020-2021, may be 95100.58, 119465.6, and 107820.3 (crore in rupees), respectively showing upward trend till 2019-2020, while there may be a possibility of declining trend in the year 2020-2021. However, the actual result may advocate the forecast values of capital raised through public issues in India for 2018-2019, 2019-2020 and 2020-2021.

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