# Time Series Approach for Modelling the Merger and Acquisition Series: An Application to Indian Banking System 

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In time series, present observation not only depend upon own past observation(s) but also involve other explanatory or exogenous variables. These variables are not continuously influence or impact for long run and may be removed or discontinued or merger and acquisition (M\&A) because its effect may be reduced due to less significant correlation. The M\&A theory is developed when one or more variables are not meet out the required circumstance to survive in the system. To analyze the performance of M\&A concept, this study proposes a merged autoregressive ( $M-A R$ ) model for examining the impact of merger into the parameters as well as acquired series. Bayesian approach is considered for parameter estimation under different loss functions and compared with least square estimator. To test the presence/association of merger series in the acquire series, Bayes factor, full Bayesian significance test and posterior probability based on credible interval are derived. A simulation study and an empirical application of banking indicators for Indian Banks are carried out to evaluate the performance of the proposed model. The study concludes that proposed time series models solved the problems of discontinuity in the series and also able to manage model statistically.

Keywords: autoregressive model, Bayesian inference, merger and acquisition series, Indian bank

## 1. Introduction

Time series models are preferred to analyze and establish the functional relationship, considering it is an own dependence (Box and Jenkins 1970, Newbold 1983) as well as dependence with some explanatory variables/ covariate(s) which alike parallel influence the series. However, these covariates may not survive in
the long run because of merged with observed series. Such type of functional relationship is not explored by researchers yet, but there are so many linear or non-linear models proposed in time series to analyse in distinct circumstances. Haggan and Ozaki (1981) developed a non-linear exponential autoregressive model for modelling and forecasting the periodic behaviour of the series. A new volatility model named autoregressive conditional heteroscedasticity (ARCH) model was introduced by Engle (1982) for analysing the serially uncorrelated processes with non-constant variances in a wage-price equation for the United Kingdom. Chan and Tong (1986) proposed a least square estimation method for the smooth threshold autoregressive model in the presence of structural break. Chon and Cohen (1997) investigated the equivalence of the artificial neural network to the linear and nonlinear ARMA models using computer simulated data and application on lung volume and heart rate data. Based on efficiency and accuracy, the preferred time-dependent model is chosen for further analysis and then does the forecasting.

In daily real-life situations, time series is recorded for every business and organization, and this plays a very important role in analyzing the economic development of the organization as well as the nation. In the present competitive market, all financial institutions feed upon the growth of their business by utilizing the available information and follow some basic business principles. Last few decades, the rate of consolidations has been increasing tremendously to achieve the goal of higher profitability and widen the business horizon. For this, higher capability institutions have a significant impact directly on weaker institutions. With the change on market strategies, some financial institutions are continuously working as well as growing well, but there are few firms which are not efficiently operating as per public/state/ owner's need and may be acquired by other strong company or possibly consolidated voluntarily or forcedly. Thus, a merger is a long-run process to combine two or more than two companies freely which are having a better understanding under certain conditions. Sometimes strong company secures small companies due to not getting high-quality performance in the market and also covers their financial losses. Then, these companies are voluntarily merged into a well-established company to meet economic and financial conditions with inferior risk.

In the last few decades, researchers are doing research and making inference in the field of merger concept (Epstein 2005, Ismail et al. 2011 and Huh 2015) for the development of business and analyze the impact or performance after the merger. Lubatkin (1983) addressed the issues of merger and showed the benefits related to the acquiring firm from merging based on technical, pecuniary, and diversification synergies. Healy et al. (1992) examined post-acquisition performance for the 50 largest United Sates mergers and showed significant improvements in asset productivity relative to their industries, leading to higher operating cash flow returns. This performance improvement is particularly strong
for firms with highly overlapping businesses. Berger et al. (1999) provided a comprehensive review of studies for evaluating mergers and acquisitions (M\&As) in the banking industry and suggested some improvements in profit efficiency and diversification of risks. Maditinos et al. (2009) investigated the short as well as long merger effects of two banks and performance was recorded from the balance sheet that shows the merger positive and negative aspects in relation to the bank itself and to the rest of the banking industry.

Golbe and White (1988) discussed a time-dependent series of M\&As and used ordinary least square (OLS) and two stage least square (2SLS) estimates to see the expected changes in the future and concluded that the merger series strongly follows an autoregressive pattern. They also employed a time series regression model to observe the simultaneous relationship between merger and acquired variables. Choi and Jeon (2011) applied time series econometric tools to investigate the dynamic impact of aggregated merger activity in the United States economy and found that macroeconomic variables and various alternative measures have a long-run equilibrium relationship at the merger point. Real GDP, stock market performance and monetary policy were the most important macroeconomic variables for affecting merger activity in the United States. Rao et al. (2016) studied M\&As in emerging markets by investigating the post-M\&A performance of ASEAN companies. They found out that a decrease in performance is particularly significant for M\&As and has high cash reserves. Pandya (2017) measured the trend in mergers and acquisitions activity in the manufacturing and non-manufacturing sectors of India with the help of time series analysis and recorded the impact of a merger by changes with government policies and political factors.

The above literatures discuss an economical and financial point of view whereas merged series can be explored to know the dependence on time as well as own past observations. So, the merger concept may be analyzed to model the series because the merger of firms or companies is very specific due to the failure of a firm or company. However, this is almost untouched for forecasting purposes as time series models are the most useful for forecasting. Both theoretical and empirical findings in existing literature argued that the merger is effective for the economy both positively and negatively as per limitations under reference (Rao et al. 2016). Therefore, a time series model is developed to analyse the merger process and show the appropriateness and effectiveness of the methodology in the present study. We study an autoregressive model to construct a new model that accommodates the merger/acquisition of series. The inferences of the merger model identify using Bayesian methodology. The performance of the constructed model is demonstrated for a recorded series of the mobile banking transaction of State Bank of India and its associate banks. The study reveals that M\&A concept is a key point factor for knowing the profitability and financial performance of a firm based on market scenario.

## 2. Merger Autoregressive (M-AR) Model

Let us consider $\left\{y_{t}: \mathrm{t}=1,2, \ldots, \mathrm{~T}\right\}$ as a time series from $\operatorname{AR}\left(p_{1}\right)$ model associated with k time dependent explanatory variables/covariates up to a certain time point called merger time $T_{m}$. After a considerable period, associated variables are merged in the observed series as AR model with different order $p_{2}$. Then, the form of time series merger model is
$y_{t}= \begin{cases}\theta_{1}+\sum_{i=1}^{p_{1}} \varphi_{1 i} y_{t-i}+\sum_{m=1}^{k} \sum_{j=1}^{r_{m}} \delta_{m j} z_{m, t-j}+\varepsilon_{t} & t \leq T_{m} \\ \theta_{2}+\sum_{i=1}^{p_{2}} \varphi_{2 i} y_{t-i}+\varepsilon_{t} & t>T_{m}\end{cases}$
where $\delta_{m}$ is merging coefficient of $m^{\text {th }}$ series/variable and $\varepsilon_{t}$ assumed to be i.i.d. normal random variable. Model discussed in equation (1) is a particular case of AR model with explanatory variables when the associated variables are not merged at any time point. In this case, explanatory variables only depend on the AR series and continuously influence the series at every time point (Dufour and Kiviet 1998, Zhao and Wang 2011, Yang and Wang 2017). This model is also discussed by Chaturvedi et al. (2017) before the merger time point when lagged dependence among own past observations are also existed in explanatory variables, called as covariates. Without loss of generality, we assume that the number of merging series $k$, their merger time $T_{m}$ and orders $\left(p_{i:} i=1,2\right)$ of the AR process are to be know in advance. Model (1) can be casted in matrix notation before and after the merger as follows

$$
\begin{align*}
& Y_{T_{m}}=\theta_{1} l_{T_{m}}+\beta_{1} X_{T_{m}}+\delta Z_{T_{m}}+\varepsilon_{T_{m}}  \tag{2}\\
& Y_{T-T_{m}}=\theta_{2} l_{T-T_{m}}+\beta_{2} X_{T-T_{m}}+\varepsilon_{T-T_{m}} \tag{3}
\end{align*}
$$

Combined equation (2) and equation (3) in vector form, produce the following equation

$$
\begin{equation*}
\mathrm{Y}=l \theta+X \beta+Z \delta+\varepsilon \tag{4}
\end{equation*}
$$

where
$Y_{T_{m}}=\left(\begin{array}{llll}y_{1} & y_{2} & \cdots & y_{T_{m}}\end{array}\right)^{\prime} ; \quad Y_{T-T_{m}}=\left(\begin{array}{llll}y_{T_{m}+1} & y_{T_{n}+2} & \cdots & y_{T}\end{array}\right)^{\prime} ; \quad Y=\binom{Y_{T_{m}}}{Y_{T-T_{m}}} ;$
$l=\left(\begin{array}{cc}l_{T_{m}} & 0 \\ 0 & l_{T-T_{m}}\end{array}\right) ; \quad \theta=\binom{\theta_{1}}{\theta_{2}} ; \quad \beta_{1}=\left(\begin{array}{llll}\varphi_{11} & \varphi_{12} & \cdots & \varphi_{1 p_{1}}\end{array}\right)^{\prime} ; \quad \beta_{2}=\left(\begin{array}{llll}\varphi_{21} & \varphi_{22} & \cdots & \varphi_{2 p_{2}}\end{array}\right)^{\prime}$
$\beta=\binom{\beta_{1}}{\beta_{2}} ; \quad \delta_{m}=\left(\begin{array}{llll}\delta_{m 1} & \delta_{m 2} & \cdots & \delta_{m r_{m}}\end{array}\right)^{\prime} ; \quad \delta=\left(\begin{array}{llll}\delta_{1} & \delta_{2} & \cdots & \delta_{k}\end{array}\right)^{\prime} ;$

$$
\begin{aligned}
& X_{T_{m}}=\left(\begin{array}{cccc}
y_{0} & y_{-1} & \cdots & y_{1-p_{1}} \\
y_{1} & y_{0} & \cdots & y_{2-p_{1}} \\
\vdots & \vdots & \ddots & \vdots \\
y_{T_{m}-1} & y_{T_{m}-2} & \cdots & y_{T_{m}-p_{1}}
\end{array}\right) ; \quad X_{T-T_{m}}=\left(\begin{array}{cccc}
y_{T_{m}} & y_{T_{m}-1} & \cdots & y_{T_{m}+1-p_{2}} \\
y_{T_{m}+1} & y_{T_{m}} & \cdots & y_{T_{m}+2-p_{2}} \\
\vdots & \vdots & \ddots & \vdots \\
y_{T-1} & y_{T-2} & \cdots & y_{T-p_{2}}
\end{array}\right) ; \quad X=\left(\begin{array}{cc}
X_{T_{m}} & 0 \\
0 & X_{T-T_{m}}
\end{array}\right) ; \\
& Z_{T_{m}}^{m}=\left(\begin{array}{ccccc}
Z_{m, 0} & Z_{m,-1} & \cdots & Z_{m, 1-r_{m}} \\
Z_{m, 1} & Z_{m, 0} & \cdots & Z_{m, 2-r_{m}} \\
\vdots & \vdots & \ddots & \vdots \\
Z_{m, T_{m}-1} & Z_{m, T_{m}-2} & \cdots & Z_{m, T_{m}-r_{m}}
\end{array}\right) ; \quad Z_{T_{m}}=\left(\begin{array}{llll}
Z_{T_{m}}^{1} & Z_{T_{m}}^{2} & \cdots & Z_{T_{m}}^{k}
\end{array}\right) ; \quad Z=\binom{Z_{T_{m}}}{0} ; \\
& \varepsilon_{T_{m}}=\left(\begin{array}{lllll}
\varepsilon_{1} & \varepsilon_{2} & \cdots & \varepsilon_{T_{m}}
\end{array}\right)^{\prime} ; \quad \varepsilon_{T-T_{m}}=\left(\begin{array}{llll}
\varepsilon_{T_{m}+1} & \varepsilon_{T_{m}+2} & \cdots & \varepsilon_{T}
\end{array}\right)^{\prime} ; \quad \varepsilon=\binom{\varepsilon_{T_{m}}}{\varepsilon_{T-T_{m}}}
\end{aligned}
$$

Model (4) is termed as merged autoregressive (M-AR ( $\left.p_{1}, m, p_{2}\right)$ ) model. The purpose behind M-AR model is to make an impress about merger series with acquisition series. This model may be useful to examine the company performance after acquiring the other company in the business. This can be analysis by providing the inferences of the merger model, for that estimation and testing is carried out in the coming section.

## 3. Inference for the Problem

The fundamental inference of any research is to utilize the given information in a way that can easily understand and describe problem under study. In time series, one may be interested to draw inference about the structure of model through estimation as well as conclude the model by testing of hypothesis. Thus, objective of present study is to establish the estimation and testing procedure for which model can handle certain particular situation.

### 3.1 Estimation under classical framework

Present section considers well known regression-based method namely, ordinary least square estimator (OLS). For M-AR model, parameters of interest are $\theta, \beta$ and $\delta$. To make the model more compact, one can write model (4) in further matrix form as

$$
Y=\left(\begin{array}{lll}
l & X & Z
\end{array}\right)\left(\begin{array}{l}
\theta  \tag{5}\\
\beta \\
\delta
\end{array}\right)+\varepsilon=W \Theta+\varepsilon
$$

For a given time series, estimating parameter(s) by least square and its corresponding sum of square residual (SSR) is given as

$$
\hat{\Theta}=\left(\begin{array}{l}
\hat{\theta}  \tag{6}\\
\hat{\beta} \\
\hat{\delta}
\end{array}\right)=\left(W^{\prime} W\right)^{-1} W^{\prime} Y
$$

and

$$
S S R=(Y-W \hat{\Theta})^{\prime}(Y-W \hat{\Theta})=\left(Y-W\left(W^{\prime} W\right)^{-1} W^{\prime} Y\right)^{\prime}\left(Y-W\left(W^{\prime} W\right)^{-1} W^{\prime} Y\right)
$$

### 3.2 Estimation under Bayesian Framework

Prior function provides available information about unknown parameters. Let us consider an informative conjugate prior distribution for all parameters of the model. For intercept, autoregressive and merger coefficient, adopt multivariate normal distribution having different mean but common variance depending upon the length of vector and error variance, assume inverted gamma prior $\sigma^{2} \sim I G$ $(a, b)$. Utilizing these priors, we may obtain the joint prior distribution
$\Pi(\Theta)=\frac{b^{a}\left(\sigma^{2}\right)^{-\left(\frac{\sum_{m=1}^{k} r_{1 m}+p_{1}+p_{2}}{2}\right.}+a+2}{\sum_{\sum_{n=1}^{k} r_{n+1}+p_{1}+p_{2}+2}^{2}} \Gamma(a) \quad \exp \left[-\frac{1}{2 \sigma^{2}}\left\{\begin{array}{l}(\theta-\mu)^{\prime} I_{2}^{-1}(\theta-\mu)+(\beta-\gamma)^{\prime} I_{p_{1}+p_{2}}^{-1}(\beta-\gamma) \\ +(\delta-\alpha)^{\prime} I_{R}^{-1}(\delta-\alpha)+2 b\end{array}\right\}\right]$ (7)
Under the given error assumption, likelihood function for observed series is

$$
\begin{equation*}
L(\Theta \mid y)=\frac{\left(\sigma^{2}\right)^{-\frac{T}{2}}}{(2 \pi)^{\frac{T}{2}}} \exp \left[-\frac{1}{2 \sigma^{2}}\left\{(Y-l \theta-X \beta-Z \delta)^{\prime}(Y-l \theta-X \beta-Z \delta)\right\}\right] \tag{8}
\end{equation*}
$$

$$
\begin{align*}
\Pi(\Theta \mid y)= & \frac{\left.b^{a}\left(\sigma^{2}\right)^{-\left(\frac{T+R+p_{1}+p_{2}}{2}+a+2\right.}\right)}{(2 \pi)^{\frac{T+R+p_{1}+p_{2}}{2}+1} \Gamma(a)} \exp \left[-\frac{1}{2 \sigma^{2}}\left\{(Y-l \theta-X \beta-Z \delta)^{\prime}(Y-l \theta-X \beta-Z \delta)\right.\right. \\
& \left.\left.+(\theta-\mu)^{\prime} I_{2}^{-1}(\theta-\mu)+(\beta-\gamma)^{\prime} I_{p_{1}+p_{2}}^{-1}(\beta-\gamma)+(\delta-\alpha)^{\prime} I_{R}^{-1}(\delta-\alpha)+2 b\right\}\right] \tag{9}
\end{align*}
$$

Under Bayesian approach, posterior distribution can be obtained from the joint prior distribution with combined information of observed series. For the proposed model, posterior distribution having the form

Here, we are interested to estimate the parameters of the model under Bayesian framework. For that a loss function must be specified and is used in
decision theory to represent a penalty associated with each possible estimate and select an optimal estimator. Since, there is no specific analytical procedure that allows us to identify the appropriate loss function. Usually, researchers reviewed various loss functions for better understanding. Therefore, we have considered following loss function (1) Squared Error Loss Function (SELF), (2) LINEX Loss function (LLF), and (3) Absolute Loss Function (ALF) (Ali et al. 2013). Under these loss functions, we do not get closed form expressions of Bayes estimators due to multiple integrations. Hence, Gibbs sampling, an iterative procedure is used to get the approximate values of the estimators using conditional posterior distribution. The credible interval is also computed using Markov chain Monte Carlo (MCMC) method proposed by Chen and Shao (1999). The conditional posterior distributions of the parameters are

$$
\begin{align*}
& \theta \mid \beta, \delta, \sigma^{2}, y \sim M V N\left(\left((Y-X \beta-Z \delta)^{\prime} l+\mu^{\prime} I_{2}^{-1}\right)\left(l^{\prime} l+I_{2}^{-1}\right)^{-1},\left(l^{\prime} l+I_{2}^{-1}\right)^{-1} \sigma^{2}\right)  \tag{10}\\
& \beta \mid \theta, \delta, \sigma^{2}, y \sim M V N\left(\left((Y-l \theta-Z \delta)^{\prime} X+\gamma^{\prime} I_{p_{1}+p_{2}}^{-1}\right)\left(X^{\prime} X+I_{p_{1}+p_{2}}^{-1}\right)^{-1},\left(X^{\prime} X+I_{p_{1}+p_{2}}^{-1}\right)^{-1} \sigma^{2}\right)  \tag{11}\\
& \delta \mid \theta, \beta, \sigma^{2}, y \sim M V N\left(\left((Y-l \theta-X \beta)^{\prime} Z+\alpha^{\prime} I_{R}^{-1}\right)\left(Z^{\prime} Z+I_{R}^{-1}\right)^{-1},\left(Z^{\prime} Z+I_{R}^{-1}\right)^{-}\right.  \tag{12}\\
& \sigma^{2} \mid \theta, \beta, \delta, y \sim I G\left(\frac{T+R+p_{1}+p_{2}}{2}+a+1, S\right) \tag{13}
\end{align*}
$$

where

$$
\begin{aligned}
S=\frac{1}{2}[ & (Y-l \theta-X \beta-Z \delta)^{\prime}(Y-l \theta-X \beta-Z \delta)+(\theta-\mu)^{\prime} I_{2}^{-1}(\theta-\mu) \\
& \left.+(\beta-\gamma)^{\prime} I_{p_{1}+p_{2}}^{-1}(\beta-\gamma)+(\delta-\alpha)^{\prime} I_{R}^{-1}(\delta-\alpha)+2 b\right]
\end{aligned}
$$

### 3.3 Significance Test for Merger Coefficient

This section provides testing procedure to test the impact of merger series in model and targeting to analysis the impact on model as associate series may be influencing the model. The merger may have a positive or negative impact. Therefore, null hypothesis is assumed that merger coefficients are equal to zero $H_{0}: \delta=0$ against the alternative hypothesis that merger has a significant impact to the observed series $H_{1}: \delta \neq 0$. Under the null and alternative hypothesis, models are as

$$
\begin{equation*}
\text { Under } H_{0}: Y=l \theta+X \beta+\varepsilon \tag{14}
\end{equation*}
$$

$$
\begin{equation*}
\text { Under } H_{1}: Y=l \theta+X \beta+Z \delta+\varepsilon \tag{15}
\end{equation*}
$$

There are several Bayesian methods to handle the problem of testing the hypothesis. The commonly used testing strategies are Bayes factor, full Bayesian significance test and test based on credible interval. Here, one can easily understand the seriousness of appropriate significance test. Bayes factor is the ratio of posterior probability under assumed hypothesis, notation given as:

$$
\begin{equation*}
B F_{10}=\frac{P\left(y \mid H_{1}\right)}{P\left(y \mid H_{0}\right)} \tag{16}
\end{equation*}
$$

The Bayes factor is obtained by using of posterior probability under null hypothesis is

$$
\begin{equation*}
P\left(y \mid H_{0}\right)=\frac{b^{a}\left|A_{1}\right|^{-\frac{1}{2}}\left|A_{2}\right|^{-\frac{1}{2}} \Gamma\left(\frac{T}{2}+a\right)}{(2 \pi)^{\frac{T}{2}} \Gamma(a)\left(\frac{S_{0}}{2}\right)^{\frac{T}{2}+a}} \tag{17}
\end{equation*}
$$

and posterior probability under alternative hypothesis is

$$
\begin{equation*}
P\left(y \mid H_{1}\right)=\frac{b^{a}\left|A_{1}\right|^{-\frac{1}{2}}\left|A_{2}\right|^{-\frac{1}{2}}\left|A_{3}\right|^{-\frac{1}{2}} \Gamma\left(\frac{T}{2}+a\right)}{(2 \pi)^{\frac{T}{2}} \Gamma(a)\left(\frac{S_{1}}{2}\right)^{\frac{T}{2}+a}} \tag{18}
\end{equation*}
$$

where
$A_{1}=\left(l^{\prime} l+I_{2}^{-1}\right)$
$A_{2}=X^{\prime} X+I_{p_{1}+p_{2}}^{-1}-X^{\prime} l A_{1}^{-1} l^{\prime} X$
$A_{3}=Z^{\prime} Z+I_{R}^{-1}-Z^{\prime} l A_{1}^{-1} l^{\prime} Z-\left(Z^{\prime} X-Z^{\prime} l A_{1}^{-1} l^{\prime} X\right)^{\prime} A_{2}^{-1}\left(Z^{\prime} X-Z^{\prime} l A_{1}^{-1} l^{\prime} X\right)$
$B_{21}^{\prime}=Y^{\prime} X+\gamma^{\prime} I_{p_{1}+p_{2}}^{-1}-\left(Y^{\prime} l+\mu^{\prime} I_{2}^{-1}\right)^{\prime} A_{1}^{-1} l^{\prime} X$
$B_{3}=Y^{\prime} Z+\alpha^{\prime} I_{R}^{-1}-\left(Y^{\prime} l+\mu^{\prime} I_{2}^{-1}\right)^{\prime} A_{1}^{-1} l^{\prime} Z-B_{21}^{\prime} A_{2}^{-1}\left(Z^{\prime} X-Z^{\prime} l A_{1}^{-1} l^{\prime} X\right)$
$C_{1}=(Y-X \beta)^{\prime} l+\mu^{\prime} I_{2}^{-1}$
$S_{0}=Y^{\prime} Y+\gamma^{\prime} I_{p_{1}+p_{2}}^{-1} \gamma+\mu^{\prime} I_{2}^{-1} \mu+2 b-\left(Y^{\prime} l+\mu^{\prime} I_{2}^{-1}\right)^{\prime} A_{1}^{-1}\left(Y^{\prime} l+\mu^{\prime} I_{2}^{-1}\right)-B_{21}^{\prime} A_{2}^{-1} B_{21}$
$S_{1}=S_{0}+\alpha^{\prime} I_{R}^{-1} \alpha-B_{3}^{\prime} A_{3}^{-1} B_{3}$

Using the Bayes factor, one can easily make a decision regarding the acceptance or rejection of hypothesis. For higher values of $B F_{10}$, leads to rejection the null hypothesis. With the help of $B F_{I O}$, posterior probability of $H_{1}$ is obtained for the given data which is

$$
\begin{equation*}
P P=P\left(H_{1} \mid y\right)=\left[1+B F_{10}^{-1}\right]^{-1} \tag{19}
\end{equation*}
$$

Sometimes, researchers may find the credible interval for a specified value in which rejection of null hypothesis depends upon the fact that how many estimated coefficients fall outside the interval. The credible intervals are highest posterior density which can be obtained from posterior density of the critical values and most of the time, posterior density expressions are not obtainable in closed form. Therefore, an alternative procedure is used to find out the credible region and so decision can be taken easily. Given $\alpha \in(0,1)$, highest posterior density (HPD) region with a posterior probability $\alpha$, is defined as

$$
\begin{equation*}
\mathrm{HPD}=\{\delta \in R ; P(\delta \mid y \geq \alpha\} \text { s.t. } P(H P D \mid y)=\alpha \tag{20}
\end{equation*}
$$

Recently, a new Bayesian measure of evidence is used by researchers for choice of model or hypothesis testing named full Bayesian significance test (FBST). According to Bragança Pereira and Stern (1999), who developed FBST test to measure the evidence in favour of a null hypothesis $H_{0}$ whenever it is large. For testing the presence of merger series in AR model, we also use FBST and evidence measure is defined as $E v=1-\gamma$ under the assumption that

$$
\begin{equation*}
\gamma=P\left(\delta: \pi(\delta \mid \mathrm{y})>\pi\left(\delta_{0} \mid y\right)\right) \tag{21}
\end{equation*}
$$

## 4. Simulation Study

A simulation study is illustrated to demonstrate the performance of the M\&A concept and a comparative study on the parameter estimations is carried out based on the proposed model. We have generated series form M-AR model for different sizes of the series $\mathrm{T}=(100,200,300)$ with different merger time $\mathrm{T}_{\mathrm{M}}=(\mathrm{T} / 5,2 \mathrm{~T} / 5$, $3 T / 5,4 \mathrm{~T} / 5)$. The true value of the model parameters is assumed in the Equation (22) and data are generated based on model (22)
$y_{t}= \begin{cases}0.2+0.5 y_{t-1}+0.05 z_{1, t-1}+0.1 z_{2, t-1}+0.15 z_{3, t-1}+\varepsilon_{t} & t \leq T_{M} \\ 0.3+0.3 y_{t-1}+0.5 y_{t-2}+\varepsilon_{t} & t>T_{M}\end{cases}$
with an error term $N(0,2)$. For simplicity, all merger series $\left(z_{i}, i=1,2,3\right)$ follows $\operatorname{AR}(1)$ process with intercept term is 0.05 and $\operatorname{AR}(1)$ coefficient 0.5 . The initial value of $y_{0}=5$ and $z_{0}=\{1.9,2.7,1.5\}$ are assumed to initiate the process. For recording the results of the posterior density of each model parameter, an analytical and numerical technique is applied. As the conditional posterior distribution expression is in standard distribution form, so Gibbs sampling algorithm with 10,000 replications is used to approximate the value of conditional posterior density for parameter estimation and posterior probability to test the hypothesis associated therein. To get a more generalized idea of the M-AR model, compared different methods of estimation under the classical and Bayesian approach and reported in terms of mean squared error (MSE) and absolute bias (AB) by Figures 1-9.

From Figures 1-9, it records that as the size of series increases, MSE and AB are decreased for different time points of the merger. It is also observed that the performance of the OLS estimator is not better as compare to Bayesian estimator. But when we make a comparison between the loss function, both symmetric SELF and ALF show better results in comparison to OLS as well as asymmetric loss function except error variance. Bayes estimator under SELF is equally applicable as ALF in estimating the parameters since both the estimators show similar magnitudes for their MSE. Hence, the choice of the loss function is concerned with the nature of parameters, and sometimes it shows the same results approximately.

From the figures, it is also recorded that with the increase in the size of the merger series, MSE and AB decreases before the merger time, whereas increases MSE and AB of estimator after the merger times. Further, the confidence interval based on different sample series and different values of merger points is also computed. The highest posterior interval is calculated based on 10,000 replications to obtain the upper and lower bound of the parameter at $5 \%$ level of significance which is reported in Tables 1-4.


Figure 1. AB and MSE of the Estimator $\boldsymbol{\theta}_{l}$, with Varying $T$ and $T_{M}$


Figure 2. AB and MSE of the Estimator $\boldsymbol{\theta}_{2}$, with Varying $T$ and $T_{M}$


Figure 3. AB and MSE of the Estimator $\phi_{I I}$, with Varying $T$ and $T_{M}$


Figure 4. AB and MSE of the Estimator $\phi_{2 l}$, with varying $T$ and $T_{M}$


Figure 5. AB and MSE of the Estimator $\phi_{22}$, with Varying $T$ and $T_{M}$


Figure 6. AB and MSE of the Estimator $\boldsymbol{\delta}_{I I}$, with varying $T$ and $T_{M}$


Figure 7. AB and MSE of the Estimator $\boldsymbol{\delta}_{2 l}$, with varying $T$ and $T_{M}$


Figure 8. AB and MSE of the Estimator $\boldsymbol{\delta}_{3 l}$, with Varying $T$ and $T_{M}$


Figure 9. AB and MSE of the Estimator $\boldsymbol{\sigma}^{2}$, with Varying $T$ and $T_{M}$

From Tables 1-4, one can observe that the minimum average width is achieved from the LLF estimator as compared to other estimators. To compute the Bayes factor, we assume that each prior probability is equally likely associated with the null and alternative hypotheses. A 5\% level is taken to calculate the FBST and credible interval test, i.e., coverage probability (CP) in Table 5.

From Table 5, it is noticed that if a merger occurs in the first quartile, the impact is not much, but it is significant to reject the null hypothesis, whereas, in the third quartile, a strong correlation is examining in merger and acquire series using Bayes factor. The coverage probability is high with the increase of the size of the series, but it is inversely proportional to the point of merger series which see in the results. Similarly, using the FBST evidence measure, there is a rejection of the null hypothesis for a small value of merger points, but as a merger point occurs near the size of the series (T), substantial evidence is recorded against the null hypothesis.
Table 1. Credible and Confidence Interval of Intercept Parameters with Varying $T$ and $T_{M}$

|  |  | $\theta_{1}$ |  |  |  | $\theta_{2}$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| T | $\mathrm{T}_{\mathrm{M}}$ | SELF | LLF | ALF | OLS | SELF | LLF | ALF | OLS |
| 100 | 20 | (-0.47-0.93) | (-0.58-0.80) | (-0.48-0.93) | (-0.51-1.37) | (-0.06-0.76) | (-0.07-0.71) | (-0.06-0.75) | (-0.07-0.93) |
|  | 40 | (-0.24-0.70) | (-0.25-0.67) | (-0.23-0.70) | (-0.25-0.83) | (-0.12-0.93) | (-0.14-0.86) | (-0.12-0.94) | (-0.12-1.19) |
|  | 60 | (-0.15-0.61) | (-0.17-0.59) | (-0.15-0.62) | (-0.16-0.68) | (-0.24-1.10) | (-0.25-1.04) | (-0.24-1.17) | (-0.19-1.53) |
|  | 80 | (-0.10-0.57) | (-0.12-0.55) | (-0.13-0.54) | (-0.14-0.57) | (-0.89-1.69) | (-1.12-1.55) | (-1.02-1.86) | (-0.80-2.27) |
| 200 | 40 | (-0.27-0.67) | (-0.29-0.63) | (-0.27-0.66) | (-0.28-0.79) | (0.07-0.63) | (0.07-0.61) | (0.08-0.63) | (0.07-0.70) |
|  | 80 | (-0.11-0.53) | (-0.12-0.51) | (-0.11-0.53) | (-0.12-0.56) | (0.04-0.68) | (0.03-0.66) | (0.04-0.67) | (0.01-0.75) |
|  | 120 | (-0.04-0.50) | (-0.05-0.49) | (-0.04-0.50) | (-0.05-0.51) | (-0.05-0.82) | (-0.03-0.80) | (-0.05-0.81) | (-0.08-0.97) |
|  | 160 | (-0.01-0.48) | (-0.02-0.48) | (-0.01-0.48) | (-0.02-0.49) | (-0.31-1.05) | (-0.34-0.96) | (-0.31-1.05) | (-0.29-1.43) |
| 300 | 60 | (-0.14-0.64) | (-0.16-0.61) | (-0.15-0.63) | (-0.15-0.71) | (0.11-0.58) | (0.10-0.57) | (0.11-0.58) | (0.11-0.60) |
|  | 120 | (-0.01-0.51) | (-0.02-0.50) | (-0.03-0.50) | (-0.03-0.51) | (-0.03-0.80) | (-0.05-0.75) | (-0.03-0.80) | (-0.05-0.98) |
|  | 180 | (0.01-0.44) | (0.00-0.43) | (0.01-0.44) | (0.01-0.44) | (0.00-0.69) | (-0.01-0.66) | (0.00-0.69) | (0.03-0.87) |
|  | 240 | (0.04-0.41) | (0.03-0.41) | (0.04-0.42) | (0.04-0.42) | (-0.11-0.94) | (-0.13-0.88) | (-0.20-0.87) | (-0.15-1.18) |

Table 2. Credible and Confidence Interval of AR Parameters with Varying T and $\mathrm{T}_{\mathrm{M}}$

|  |  | $\phi_{11}$ |  |  |  | $\phi_{21}$ |  |  |  | $\phi_{22}$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| T | $\mathrm{T}_{\mathrm{M}}$ | SELF | LLF | ALF | OLS | SELF | LLF | ALF | OLS | SELF | LLF | ALF | OLS |
| $\bigcirc$ | 20 | (0.13-0.77) | (0.11-0.76) | (0.14-0.78) | (0.06-0.79) | (0.09-0.48) | (0.09-0.48) | (0.10-0.49) | (0.08-0.48) | (0.26-0.63) | (0.26-0.63) | (0.26-0.63) | (0.26-0.64) |
|  | 40 | (0.22-0.71) | (0.21-0.70) | (0.22-0.71) | (0.20-0.71) | (0.03-0.51) | (0.02-0.50) | (0.03-0.51) | (0.02-0.51) | (0.22-0.67) | (0.22-0.66) | (0.22-0.67) | (0.20-0.66) |
|  | 60 | (0.27-0.67) | (0.27-0.66) | (0.27-0.67) | (0.26-0.67) | (-0.03-0.56) | (-0.04-0.55) | (-0.02-0.57) | (-0.08-0.54) | (0.12-0.67) | (0.11-0.66) | (0.12-0.67) | (0.10-0.66) |
|  | 80 | (0.30-0.64) | (0.29-0.64) | (0.29-0.64) | (0.29-0.64) | (-0.29-0.65) | (-0.33-0.61) | (-0.29-0.65) | (-0.32-0.66) | (0.06-0.72) | (0.10-0.70) | (0.08-0.71) | (0.13-0.70) |
| $\stackrel{8}{1}$ | 40 | (0.25-0.71) | (0.24-0.71) | (0.25-0.71) | (0.24-0.72) | (0.16-0.43) | (0.16-0.43) | (0.16-0.43) | (0.16-0.43) | (0.34-0.61) | (0.34-0.61) | (0.34-0.61) | (0.34-0.61) |
|  | 80 | (0.31-0.67) | (0.30-0.66) | (0.31-0.67) | (0.30-0.66) | (0.13-0.46) | (0.13-0.46) | (0.13-0.46) | (0.13-0.46) | (0.31-0.61) | (0.30-0.61) | (0.31-0.62) | (0.30-0.61) |
|  | 120 | (0.33-0.63) | (0.33-0.63) | (0.33-0.63) | (0.33-0.63) | (0.07-0.47) | (0.07-0.48) | (0.07-0.48) | (0.07-0.48) | (0.25-0.63) | (0.24-0.63) | (0.25-0.63) | (0.25-0.64) |
|  | 160 | (0.37-0.63) | (0.36-0.63) | (0.37-0.63) | (0.36-0.63) | (-0.05-0.56) | (-0.07-0.54) | (-0.04-0.57) | (-0.09-0.56) | (0.12-0.67) | (0.11-0.67) | (0.12-0.67) | (0.09-0.66) |
| \% | 60 | (0.28-0.67) | (0.27-0.67) | (0.28-0.67) | (0.27-0.67) | (0.18-0.40) | (0.18-0.40) | (0.18-0.40) | (0.18-0.40) | (0.37-0.60) | (0.37-0.60) | (0.37-0.60) | (0.36-0.59) |
|  | 120 | (0.35-0.64) | (0.35-0.64) | (0.35-0.65) | (0.35-0.65) | (0.06-0.47) | (0.05-0.46) | (0.06-0.47) | (0.05-0.48) | (0.24-0.63) | (0.24-0.63) | (0.25-0.63) | (0.24-0.64) |
|  | 180 | (0.36-0.61) | (0.35-0.60) | (0.36-0.60) | (0.36-0.61) | (0.13-0.44) | (0.13-0.44) | (0.13-0.44) | (0.12-0.44) | (0.32-0.62) | (0.32-0.62) | (0.32-0.62) | (0.32-0.62) |
|  | 240 | (0.39-0.61) | (0.39-0.61) | (0.39-0.61) | (0.39-0.61) | (0.04-0.50) | (0.03-0.49) | (0.03-0.50) | (0.03-0.51) | (0.22-0.67) | (0.20-0.67) | (0.21-0.67) | (0.19-0.66) |

Table 3. Credible and Confidence interval of merger coefficients with varying T and $\mathrm{T}_{\mathrm{M}}$

|  |  | $\delta_{1}$ |  |  |  | $\delta_{2}$ |  |  |  | $\delta_{3}$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| T | $\mathrm{T}_{\mathrm{M}}$ | SELF | LLF | ALF | OLS | SELF | LLF | ALF | OLS | SELF | LLF | ALF | OLS |
| \% | 20 | (-0.75-0.68) | (-0.82-0.63) | (-0.75-0.68) | (-0.83-0.79) | (-0.64-0.69) | (-0.71-0.64) | (-0.65-0.69) | (-0.78-0.74) | (-0.64-0.69) | (-0.71-0.64) | (-0.64-0.69) | (-0.78-0.74) |
|  | 40 | (-0.50-0.42) | (-0.52-0.40) | (-0.50-0.42) | (-0.50-0.46) | (-0.44-0.48) | (-0.47-0.45) | (-0.45-0.47) | (-0.48-0.48) | (-0.44-0.48) | (-0.47-0.45) | (-0.44-0.48) | (-0.48-0.48) |
|  | 60 | (-0.37-0.38) | (-0.39-0.37) | (-0.37-0.38) | (-0.39-0.38) | (-0.37-0.38) | (-0.39-0.36) | (-0.36-0.39) | (-0.38-0.39) | (-0.37-0.38) | (-0.39-0.36) | (-0.37-0.38) | (-0.38-0.39) |
|  | 80 | (-0.30-0.33) | (-0.32-0.31) | (-0.31-0.33) | (-0.31-0.33) | (-0.31-0.32) | (-0.31-0.33) | (-0.31-0.32) | (-0.32-0.33) | (-0.31-0.32) | (-0.31-0.33) | (-0.31-0.32) | (-0.32-0.33) |
| $\bigcirc$ | 40 | (-0.49-0.47) | (-0.53-0.44) | (-0.49-0.47) | (-0.51-0.50) | (-0.45-0.45) | (-0.47-0.42) | (-0.44-0.45) | (-0.47-0.47) | (-0.45-0.45) | (-0.47-0.42) | (-0.45-0.45) | (-0.47-0.47) |
|  | 80 | (-0.32-0.32) | (-0.36-0.29) | (-0.34-0.31) | (-0.33-0.33) | (-0.33-0.30) | (-0.34-0.29) | (-0.33-0.30) | (-0.32-0.32) | (-0.33-0.30) | (-0.34-0.29) | (-0.33-0.30) | (-0.32-0.32) |
|  | 120 | (-0.27-0.25) | (-0.28-0.24) | (-0.27-0.25) | (-0.27-0.25) | (-0.26-0.28) | (-0.26-0.27) | (-0.26-0.28) | (-0.26-0.28) | (-0.26-0.28) | (-0.26-0.27) | (-0.26-0.28) | (-0.26-0.28) |
|  | 160 | (-0.23-0.21) | (-0.24-0.21) | (-0.23-0.21) | (-0.24-0.21) | (-0.21-0.23) | (-0.22-0.23) | (-0.21-0.23) | (-0.21-0.23) | (-0.21-0.23) | (-0.22-0.23) | (-0.21-0.23) | (-0.21-0.23) |
| \% | 60 | (-0.36-0.34) | (-0.38-0.33) | (-0.36-0.35) | (-0.37-0.35) | (-0.38-0.36) | (-0.40-0.34) | (-0.35-0.39) | (-0.37-0.39) | (-0.38-0.36) | (-0.40-0.34) | (-0.38-0.36) | (-0.37-0.39) |
|  | 120 | (-0.23-0.27) | (-0.26-0.25) | (-0.23-0.27) | (-0.25-0.27) | (-0.23-0.28) | (-0.23-0.27) | (-0.22-0.28) | (-0.23-0.28) | (-0.23-0.28) | (-0.23-0.27) | (-0.23-0.28) | (-0.23-0.28) |
|  | 180 | (-0.22-0.19) | (-0.23-0.19) | (-0.21-0.20) | (-0.21-0.20) | (-0.20-0.23) | (-0.21-0.22) | (-0.20-0.23) | (-0.21-0.22) | (-0.20-0.23) | (-0.21-0.22) | (-0.20-0.23) | (-0.21-0.22) |
|  | 240 | (-0.19-0.18) | (-0.19-0.18) | (-0.18-0.18) | (-0.18-0.19) | (-0.17-0.18) | (-0.18-0.18) | (-0.17-0.18) | (-0.17-0.18) | (-0.17-0.18) | (-0.18-0.18) | (-0.17-0.18) | (-0.17-0.18) |

Table 4. Credible and Confidence Interval of Error Variance with Varying $T$ and $T_{M}$

| T | $\mathrm{T}_{M}$ | SELF | LLF | ALF | OLS |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 100 | 20 | $(1.20-2.05)$ | $(1.19-2.01)$ | $(1.19-2.03)$ | $(1.50-2.61)$ |
|  | 40 | $(1.17-2.04)$ | $(1.16-2.00)$ | $(1.14-2.00)$ | $(1.50-2.62)$ |
|  | 60 | $(1.17-2.07)$ | $(1.15-2.03)$ | $(1.16-2.05)$ | $(1.43-2.60)$ |
|  | 80 | $(1.17-2.08)$ | $(1.16-2.05)$ | $(1.16-2.06)$ | $(1.44-2.61)$ |
|  | 40 | $(1.45-2.12)$ | $(1.44-2.10)$ | $(1.44-2.11)$ | $(1.62-2.40)$ |
|  | 80 | $(1.43-2.11)$ | $(1.45-2.12)$ | $(1.45-2.12)$ | $(1.62-2.39)$ |
|  | 120 | $(1.45-2.16)$ | $(1.43-2.12)$ | $(1.44-2.14)$ | $(1.63-2.44)$ |
| 300 | 160 | $(1.42-2.17)$ | $(1.41-2.15)$ | $(1.40-2.15)$ | $(1.64-2.49)$ |
|  | 60 | $(1.58-2.17)$ | $(1.57-2.15)$ | $(1.56-2.15)$ | $(1.71-2.36)$ |
|  | 120 | $(1.45-2.15)$ | $(1.45-2.14)$ | $(1.45-2.15)$ | $(1.63-2.43)$ |
|  | 180 | $(1.58-2.20)$ | $(1.57-2.18)$ | $(1.53-2.14)$ | $(1.70-2.38)$ |
|  | 240 | $(1.56-2.16)$ | $(1.56-2.15)$ | $(1.56-2.15)$ | $(1.68-2.33)$ |

Table 5. Evidence Measures for Testing Null Hypotheses with Varying $T$ and $T_{M}$

| T | $\mathrm{T}_{\mathrm{M}}$ | BF | PP | CP | FBST |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 100 | 20 | $2.27 \mathrm{E}+19$ | 0.9459 | 0.9208 | 0.0004 |
|  | 40 | $1.67 \mathrm{E}+43$ | 0.9295 | 0.9093 | 0.0042 |
|  | 60 | $8.35 \mathrm{E}+187$ | 0.8459 | 0.8897 | 0.0212 |
|  | 80 | $1.58 \mathrm{E}+299$ | 0.5824 | 0.8900 | 0.1222 |
|  | 40 | $1.11 \mathrm{E}+03$ | 0.9597 | 0.9292 | 0.0000 |
|  | 80 | $7.65 \mathrm{E}+34$ | 0.9605 | 0.9228 | 0.0004 |
|  | 120 | $7.01 \mathrm{E}+150$ | 0.8611 | 0.9200 | 0.0128 |
|  | 160 | $5.67 \mathrm{E}+176$ | 0.5977 | 0.9132 | 0.0818 |
| 300 | 60 | $4.97 \mathrm{E}+01$ | 0.9668 | 0.9348 | 0.0000 |
|  | 120 | $2.52 \mathrm{E}+04$ | 0.9581 | 0.9303 | 0.0000 |
|  | 180 | $1.09 \mathrm{E}+26$ | 0.8791 | 0.9270 | 0.0004 |
|  | 240 | $2.58 \mathrm{E}+134$ | 0.6876 | 0.9222 | 0.0180 |

## 5. Merger in Indian Banking Industry: An Application

It is well defined that the banking sector has a strong contribution to any economy. It is adopting various approaches for smooth working in the global front. Merger and acquisition are some of the finest approaches to consolidation that offers potential growth in Indian banking. State bank of India (SBI) is the largest bank in India. Recently SBI has merged with five of its associate banks namely, State Bank of Bikaner \& Jaipur (SBBJ), State Bank of Hyderabad (SBH),

State Bank of Mysore (SBM), State Bank of Patiala (SBP) and State Bank of Travancore (SBT) to becoming the largest lender in the list of top 50 banks in the world. The combined base of SBI is expected to increase productivity, reduce geographical risk and enhance operating efficiency. In India, there are various channels to transfer the payment on-line. Mobile banking is one of the important channels to transfer money using mobile devices which is introduced since 2002 and become popular after demonetization as a fast and effective mode of banking.

For analysis of the proposed model, we have taken monthly data series of mobile banking of SBI as acquire series over the period from November, 2009 to November, 2019 whereas it's associate banks as merged variables take the data from November, 2009 to March, 2017. So, the merger time took place in April, 2017. Here, after the merger time point, the SBI series is denoted as M-SBI which is shorter than the before SBI series. Data series gives information about the total number of transactions with its total payment in a specific month for a fixed bank. For analysis purposes, we have converted data into payment per transactions for the merger banks. The objective of the proposed study is to observe the impact of the merger series. First, we fit an autoregressive model to mobile banking series to find out the most preferred order (lag) of SBI and its associate merger banks and then study the inference. Table 6 shows descriptive statistics and lag of the AR model with estimated coefficients for each series.

Table 6. Descriptive Statistics and Order of the Mobile Banking Series

| Series | Mean | SD | Skewness | Kurtosis | Order | $\phi_{1}$ | $\phi_{2}$ | $\phi_{3}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SBI | 4.4983 | 8.3656 | 2.1974 | 3.5764 | 1 | 0.9297 | - | - |
| SBBJ | 0.7745 | 0.6569 | 2.4332 | 5.3273 | 2 | 1.0845 | -0.2113 | - |
| SBH | 0.7125 | 0.8462 | 2.7081 | 6.6017 | 2 | 1.044 | -0.1683 | - |
| SBM | 0.9295 | 0.8768 | 2.1176 | 4.0361 | 1 | 0.8934 | - | - |
| SBP | 0.985 | 1.1079 | 2.215 | 3.7352 | 3 | 0.7663 | 0.2626 | -0.1646 |
| SBT | 0.8781 | 0.7335 | 2.432 | 5.5085 | 1 | 0.8909 | - | - |
| M-SBI | 10.2032 | 4.6229 | 0.4149 | -1.8709 | 1 | 0.5768 | - | - |

From Table 6, we observe that SBI series follow AR(1) process before and after the merger whereas associated banks namely SBBJ, SBH, SBM, SBP, and SBT contain $\operatorname{AR}(2), \operatorname{AR}(2), \operatorname{AR}(1), \operatorname{AR}(3)$ and $\operatorname{AR}(1)$ process, respectively. Once getting the lag (order) of each associate series, we apply the M-AR model to estimate the model parameters using OLS and Bayesian approach which are recorded in Table 7 and observed that there might be a change in estimated value when considering merger in the series.

Table 7. OLS and Bayesian Estimates for Mobile Banking Series

| Parameter | OLS | SELF | LLF | ALF |
| :---: | :---: | :---: | :---: | :---: |
| $\theta_{1}$ | -0.2840 | -0.1170 | -0.1326 | -0.1120 |
| $\theta_{2}$ | 4.6410 | 5.2540 | 5.1345 | 5.1070 |
| $\phi_{11}$ | 0.9590 | 0.9630 | 0.9630 | 0.9590 |
| $\phi_{21}$ | 0.3180 | 0.3344 | 0.3341 | 0.3390 |
| $\delta_{11}$ | -5.0600 | -2.7872 | -3.7244 | -2.0700 |
| $\delta_{12}$ | 4.6140 | 2.0816 | 1.3773 | 1.6700 |
| $\delta_{21}$ | 1.7640 | 0.9102 | 0.4315 | 1.4500 |
| $\delta_{22}$ | -3.9340 | -2.2504 | -2.7448 | -2.0230 |
| $\delta_{31}$ | 1.4570 | 1.0344 | 0.9453 | 1.0180 |
| $\delta_{41}$ | -0.9260 | -0.7404 | -0.7770 | -0.8750 |
| $\delta_{42}$ | 0.0030 | -0.1806 | -0.2423 | -0.2230 |
| $\delta_{43}$ | 2.0160 | 1.8968 | 1.8704 | 1.8920 |
| $\delta_{51}$ | 0.3870 | 0.3318 | 0.2763 | 0.1770 |
| $\sigma^{2}$ | 2.3110 | 2.9672 | 2.8947 | 3.1220 |

Table 8. Testing the Hypothesis Based on Mobile Banking Series

| Testing Procedure | BF | PP | FBST |
| :---: | :---: | :---: | :---: |
|  | $1.53 \mathrm{E}+76$ | 0.7467 | 0.0404 |

From Tables 6-7, conclude that there is a negative change happens due to SBBJ and SBP series because the sign of coefficient value is transformed, whereas other remaining series have positive impacts that not much affect the SBI series. To know the impact of associate banks series, testing the presence of merged series and reported in Table 8. Table 8 explained the connection between associate banks with SBI and observed that banks merger has a significant impact on SBI series and after the merger point, there is a decrease in mobile banking transactions. All assumed tests are correctly identifying the effect of the merger.

## 6. Conclusion

Time series model is to establish/know the dependency with own past observation(s) as well as other associated observed series(s), which are partially or fully influencing the current observation. After the merger, few series do not record due to discontinuation of series because of many reasons like inadequate performance, new technology changes, increasing market operation, etc. This M\&A concept is dealt with by various econometricians and policymakers. They termed this as a merger and acquisition of series. For a few decades, it's becoming very popular to handle the problem of a weaker organization to improve its functioning and acquire it which helps the employees as well as continue the
ongoing business. Therefore, a model is proposed in the time series to classify the merger and acquisition scenario for modelling purposes. Bayesian inference is obtained for point and interval estimations and compared with the OLS estimator. Various testing methods are used to observe the presence of merger series in the acquired series. A simulation study has verified the use and purpose of the M-AR model. Recently, SBI associated banks are merged in SBI to strengthen the Indian banking system. Thus, mobile banking data of these banks are used to analyze the empirical presentation of the model and recorded that the merger has a significant effect on the SBI series in terms of reducing the transactions.

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