"in the name of ALLAH the most beneficent the most merciful"

Analysis of the large scale manufacturing growth of Pakistan

By

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A thesis submitted in partial fulfillment of the requirements for the degree of **Master of Science** in **Statistics**

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2022

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MS THESIS WORK

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I dedicate this thesis to everyone who is trying to survive and helps out someone in need every now and then.

Acknowledgments

After the blessings of **Allah Almighty**, none of this would have been possible for me without the efforts and prayers of my parents and grandparents, and the constant love and support from my siblings and friends. I want to especially thank my supervisors and teachers for the encouragement and help wherever I needed it. Lastly, I thank everyone who has ever helped me in any way, I am indebted to you forever.

Abstract

The L.S.M (large-scale Manufacturing) industry is one of the three major components of economic growth of a country, the other two being Agriculture and Services. Through the course of time, Pakistan's L.S.M industry has seen about its fair share of ups and downs but so far, no concrete study has been performed to study this sector. This thesis intends to investigate the behavior of the L.S.M industry of Pakistan for the time periods 2006-07 to 2020-21 and to put light on this sector's future. The study highlights the factors (or variables) that are more significantly impacting the growth of the L.S.M industry in Pakistan, and secondly which statistical model best describes the relationship between the variables. For this study, time series data (setting the base year 2005-06) was collected from the online archives/repositories of the Pakistan Bureau of Statistics and State Bank of Pakistan. After stationarity checks and lag selection, the data was estimated using the O.L.S (ordinary least squares), A.R.I.M.A (autoregressive integrated moving average), V.E.C (vector error correction), V.A.R (vector autoregression) and S.V.A.R (structural vector autoregression) models. Next, we looked at the I.R.F (impulse response function) for the variables keeping L.S.M/QIM (quantum index of manufacturing)as the response, and lastly, the data was also forecasted for the next 36 months. This study can help policymakers as well as scientists in future planning regarding the allocation of national resources in the right sub-sectors of the economy.

Contents

List of Figures

List of Tables

List Of Abbreviations

O.L.S	Ordinary Least Squares
A.R.I.M.A	Auto-Regressive Moving Average
V.E.C	Vector Error Correction
V.A.R	Vector Auto-Regression
S.V.A.R	Structural Vector Auto-Regression
QIM	Quantum Index Of Manufacturing
ML	Manufacturing Loans
WPI	Wholesale Price Index
BOT	Balance Of Trade
FDI	Foreign Direct Investment
TX	Textile
FBT	Food Beverages And Tobacco
CP	Coke And Petroleum
PHA	Pharmaceuticals
NM	Non-Metallic Minerals
AUT	Automobiles
ISP	Iron And Steel Products

FER	Fertilizer
ER	Exchange Rate

Summary

The inspiration behind this research is to first analyze and understand the behavior of the large-scale manufacturing industry of Pakistan, as it is an essential engine of growth of our country, and Secondly, the fact that in Pakistan very little work has been done to explore this sector. The manufacturing sector can be further classified into two categories namely large-scale manufacturing and small-scale manufacturing. We are focusing on the large-scale manufacturing sector as it is the major contributing component of the manufacturing sector. The goal of this research is to identify the predictors/variables that affect the growth of large-scale manufacturing. In addition to this, this research aims to explore the future possibilities of growth in this sector.

Chapter 1

Introduction

1.1 Manufacturing

A country's economy depends on three key factors "Agriculture", "Services" and "Manufacturing". The process of making final goods for usage from raw material (typically on a large-scale) is termed as manufacturing. Raw material is converted into finished goods and products using different engineering, architectural and industrial techniques. Pakistan is a developing third-world country riddled with corruption and economic derail, this is the biggest reason one could have to study this sector and find out how and what factors are pivotal to industrial and economic growth. Historically we find evidence of manufacturing processes centuries ago where initially it was a craft performed by the skilled ones only and passed on from experts to students. By the end of the eighteenth-century A.D the world witnessed the start of the revolution in the manufacturing industry [1]. Adam Smith in his book "The Wealth of Nations" laid the basis for the modern manufacturing procedure. The main takeaway from his book was the idea of division of the labor force [2]. It talks about how over the course of time, the world has seen significant economic growth owing to the division of labor [3]. According to Adam Smith, this economic growth resulted from the specialization or in other words division of labor [2]. The task that took a long time previously to be completed because there were a limited number of people skilled enough to performed it was now divided into a number of different tasks, each component was a specialization of a different person, this increased the production, while significantly decreasing

the amount of time require to produce a finished product, leading to economic growth unlike any other period of history [3].
Over time, the manufacturing sector of Pakistan has seen about its fair share of ebb and flow, reasons for which are mainly the constant political unrest and more recently the advent of the global pandemic in 2019. Almost all major industries fall under the banner of manufacturing, be it edible goods, daily usage products, travel necessities, construction equipment, electronic gadgets, or home appliances.

1.2 Types Of Manufacturing

Manufacturing can be further classified into sub-parts one being "large-scale" and the other "small scale". The economic growth of Pakistan is greatly dependent on the large-scale manufacturing industry. In Pakistan, all firms that fall under THE FACTORIES ACT, 1934 or qualifying for registration come under the banner of large-scale manufacturing industries, and all manufacturing firms that are not coinciding with the criteria of large-scale manufacturing are known as small scale.

1.3 Large Scale Manufacturing

large-scale manufacturing industries, as the name suggests, have huge, fixed assets, a notably large workforce, and infrastructure. The purpose of manufacturing on a large scale is to generate revenue by making goods at a lower cost and selling them at a relatively higher cost. These large-scale manufacturing industries benefit the economy of the country as they pull in foreign investments and produce more jobs. Technological advancement has played a vital role in the boom of manufacturing efficiency.

1.4 Quantum Index Of Manufacturing (QIM)

To gauge the change and growth in the large-scale manufacturing industry, the Pakistan Bureau of Statistics has devised an index that measures over time (cumulative as well as monthly) the changes that occur in the production of large-scale manufacturing industries. A total of one hundred and twelve commodities/items have been selected to compute this Index by quantifying them on the basis of their importance, production, and weightage. This index is known as the Quantum Index of Manufacturing (QIM).

Factors of QIM: There are numerous factors that one can relate to the production of large-scale manufacturing industry and the quantum index of manufacturing, but the main factors that affect the production and the index are manufacturing loans, wholesale price index (W.P.I), foreign direct investment (F.D.I), the balance of trade, and the exchange rate (Pkr. to Usd.). Besides these, we can also look up the production indices of the products that have a higher weightage in the QIM These include Textile, Food, Beverages and Tobacco, Coke and Petroleum, Iron and Steel products, Non-Metallic Mineral products, Automobiles, Fertilizers, and Pharmaceuticals production.

In this thesis, using all the above-mentioned variables/factors, the percent change in the growth of QIM was studied. We analyzed the percent change by using R-studio and the results were then used to make future predictions and recommendations to the policymakers. Statistical techniques that were to be used are Ordinary Least Squares (O.L.S), Vector Auto Regression (V.A.R), Autoregressive Integrated Moving Average (A.R.I.M.A), Structural Vector Auto Regression (S.V.A.R), and Vector Error Correction Model (V.E.C.M).

Chapter 2

Literature Review

In the past, a few researchers have attempted to study the large-scale manufacturing sector of Pakistan, the latest being in 2009. One prominent name that comes up very often in this area is late Mr. Abdul Razzaq Kemal, who is remembered for his notable contributions. Here is a recap of the work that has been done by researchers in the topic under discussion.

In the long run, external debt, foreign direct investment (F.D.I) and gross domestic product (g. d. p.) have showed a positive significant association, while factor remittances showed a positive insignificant association with industry, this study was conducted in 2019.[4]

In another research in 2017, remittances (personal) and trade indicated positive significant connection with industry value added. But on the other hand, the lag value of industry value added revealed a negative significant relation with the industry value added.[5] A study on the south Asian countries proposed that the factors that affect the industrial growth positively and significantly are government expenditures, trade openness, per capita income, governance, and F.D.Iin 2016[6]. Vinish and Raj (in 2013) concluded that manufacturing is in fact working as an engine of growth in the post nineties in India [7]. Considering the similarities in the consumer and worker behavior in the two countries one can think that same hypothesis would be true in Pakistan as well.

In 2012 evidence of the existence of economies of scale was found as profit prior to taxation, total assets and sales were all positively related. Secondly, high expense was a result of one of the two reasons, investment's slow growth rate or the theory of expense performance behavior. And last that the larger firms tend to benefit from their sizes. [8]

Along with most of the series being non-stationary, there was found a cointegrating relation among public development and consumption expenditures, investment (private) and market size. Macroeconomic uncertainty and non-development expenditures affect the investment (private) negatively [9]

The productivity of the manufacturing sector rose at an avg. rate of 2.4 percent which was mainly driven by the raise in capital, whereas the total factor productivity of the economic sector only increased about 1.1 percent in a year [10]. An improvement in the efficiency of the large-scale manufacturing sector was observed in 2006 [11]. The major issues/problems that industrial growth is facing are ineffective import substitutes, pitiable condition of R&D and science and technology and lastly extensive smuggling of products and goods. [12]

Capital intensity was found to be high in most of the industries but Sen's proposition about the working capital and factor intensity was not verified (in 2001)[13]. The neo classical cost function should not be appreciated, compared to labor the raw material and energy is over utilized as compared to labor, and capital as relative to raw material is also over utilized. Elastic behavior is seen in energy and capital whereas raw material and labor exhibit an inelastic behavior. The most inefficiently utilized factor is energy. [14]

An oligopolistic structure is evident in Pakistan's large-scale manufacturing industry, similar structure is present in other countries but according to the standard international efficient minimum plant sizes, Pakistan's industry plant sizes are ridiculously small [15]. Labor and capital are found to be energy's substitute and complement, respectively. [16]

It is evident from the research (1989) that agglomeration economies (A. E.) are also found in developing countries like Pakistan, not only agglomeration but urbanization economies as well. [17] Authors use the trans log cost function instead of the usual

cost function. Capital and labor, and energy and labor are found to be each other's substitutes respectively on the other hand, energy and capital are solid complements of each other. [18]
From 1955 to 1981 Pakistan's large-scale manufacturing sector's growth has been aided by labor, technological change, and capital input by percentages of 18, 29 and the highest 54 respectively. Also, a constant return to scale has been observed. [19] Between 1949 and 1965 economy of Pakistan observed a maximum structural change when large-scale manufacturing's share increased five times. In terms of capital intensity, medium sized establishments were more promising. [20]
Results show that there is substitution elasticity among labor and capital and a change in these two would trigger an effect on the substitution elasticities. [21] A. R. Kemal laid the basis for a consistent time series data for Pakistan's large-scale manufacturing industry after discussing the problems and issues that one could face. [22]
Comparative advantage trend is observed in the manufacturing growth. Journey of industrialization for Pakistan has been luckier than many other developing countries as it avoided disasters like premature subsidies on import. [23] Capital's replacement costs in the industry are quite greater than the ones reported in the CMIs also the growth rates of sectors similarly calculated on the basis of CMI data are way lower than actual ones. Hence the author advises not to use data from CMI. [24]

2.1 Problem Statement

As it is evident from a brief review of the literature available on the large-scale manufacturing industry of Pakistan, no one has attempted to target the recent data (from 2006-07 to 2020-21) to have a clear image of the QIM at the present and predict its nature for future.
Our problem statement was to perform a statistical analysis of time series data on the large-scale manufacturing industry of Pakistan from 2006-07 to 2020-21 and to understand the reasons behind its lack of growth.

Chapter 3

Methodology

First of all, we started by generating time series objects of our variables, next the data was bound together and selected the appropriate lag value.In time series analysis one can not proceed if the data is not stationary. The stationarity of the time series were checked, and non-stationarity was treated by differencing the time series. Afterwards correlation between variables was checked via correlation plot.
After setting up the data, we applied the ordinary least squares (O.L.S) [25] regression to see the individual relations of QIM with the rest of the variables. This method was only applied to have a general idea of how the variables would behave in linear regression, it should be kept in mind that O.L.S only checks the one-way relationship between variables, meaning that if we apply OLS on X¬Y, this would mean we check whether X is affected by Y but not the other way around. Results from the O.L.S were not used to make any conclusions or recommendations. After O.L.S, the autoregressive integrated moving average (A.R.I.M.A) model is applied and forecasted [26]. A.R.I.M.A is a partial autoregressive model that uses a single variable to run and draw forecasts. A.R.I.M.A produces a number of models that are classified by three factors number of 1: autoregressive terms, 2) differences, and 3) lags. Next, the vector error correction (V.E.C) https://www.r-econometrics.com/timeseries/vecintro/ model is applied, first Johansen cointegration test was applied and then the model and after applying it, serial correlation, heteroscedasticity, normality, and stability tests were performed, then the vector autoregression (V.A.R) [27] model was applied on the

data..
Lastly, we applied structural vector autoregression(S.V.A.R) (only to compare its IRFs with V.E.C and V.A.R) [28] model and found impulse response functions for the estimation and at the end, we forecasted the results for future. (IRF) impulse response functions [29] and forecasts are observed. It must be noted that the data was collected from different sources and processed for use, an explanation for which has been provided in the next chapter.

3.1 The Least Squares Method

The least-squares approach is used to reduce the sum of squared errors.

$$f_i = \tau + \upsilon gi + \epsilon_i$$

Lets arrange the eq. for the error term:

$$\epsilon_i = f_i - \tau - \upsilon gi$$

We shall denote the minimum values for τ, υ, and ε as:

$$\{\hat{\tau}, \hat{\upsilon}, \hat{\epsilon}\}$$

It can be said from here that we need the sum of all squared errors that will minimize the expression:

$$S = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} (f_i - \tau - \upsilon gi)^2$$

It is a known fact from calculus that a function has zero slope at its minimum value. In order to obtain the values of τ, υ that minimize the sum of squared errors, we take first difference of S wrt τ, and υ and equate the resulting expression to zero.

$$\begin{bmatrix} \frac{\partial S}{\partial \upsilon} \\ \frac{\partial S}{\partial \tau} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 2\sum_i gi(f_i - \tau - \upsilon gi) \\ 2\sum_i (f_i - \tau - \upsilon gi) \end{bmatrix}$$

The barred values represent averages.

$$\hat{\tau} = \bar{f} - \upsilon \bar{g}$$

$$\hat{\upsilon} = \frac{\sum(g-\bar{g})f}{\sum(g-\bar{g})^2}$$

https://programmathically.com/ordinary-least-squares-regression/.

3.2 Auto Regressive Integrated Moving Average Models

An auto regressive integrated moving average model can be defined as:

$$F_t = \sum_{i=1}^{s} \Psi_i F_{t-i} + c_t - \sum_{j=1}^{q} \zeta_j c_{t-j}$$

where $\Psi_1, \ldots, \Psi_s$, $\zeta_1, \ldots, \zeta_q$ and, $c_1, \ldots, c_t$ are the auto regressive and moving average parameters, residuals/errors respectively. The model is also known as an ARMA(s,q) model. The Box-Jenkins backshift operator can simplify the model:

$$D^s G_t = G_{t-s},$$

$G_1, \ldots, G_t$ is any time series with $s < t$. Backshift operator yields :

$$\left(1 - \sum_{i=1}^{s} \Psi_i D^i\right) F_t = \left(1 - \sum_{j=1}^{q} \zeta_j D^j\right) c_t,$$

which is often reduced further to

$$\Psi_s(D) F_t = \zeta_q(D) c_t,$$

where $\Psi_s(D) = \left(1 - \sum_{i=1}^{s} \Psi_i D^i\right)$ and $\zeta_q(D) = \left(1 - \sum_{j=1}^{q} \zeta_j D^j\right)$. Differences are used when the series is non stationary:

$$\begin{aligned}
H_t = F_t - F_{t-1} &= (1-D)F_t \\
H_t - H_{t-1} &= F_t - 2F_{t-1} + F_{t-2} \\
&= (1-D)^2 F_t \\
&\vdots \\
H_t - \sum_{m=1}^{d} H_{t-m} &= (1-D)^d F_t,
\end{aligned}$$

d being the order of differencing. If F_t in the ARMA model is replaced with the differences we obtain the A.R.I.M.A(s, d, q) model:

$$\Psi_s(D)(1-D)^d F_t = \zeta_q(D)c_t.$$

If the goal is to model the seasonal time series, it can be done through the Box-Jenkins model:

$$\Psi_s(D)\Psi(P)\left(D^s\right)(1-D)^d\left(1-D^s\right)^D F_t = \zeta_q(D)\zeta_Q\left(D^s\right)c_t,$$

where when accounting for the seasonal shift, s,D,S, and Q are (known) number of seasons per timeframe (years/months), order of the seasonal differencing, auto regressive, and moving average orders, respectively. The operator polynomials $\Psi_s(D)$ and $\zeta_q(D)$ are as defined earlier, while $\Psi_P(D) = \left(1-\sum_{i=1}^{P}\Psi_i D^{s\times i}\right)$ and $\zeta_Q(D) = \left(1-\sum_{j=1}^{Q}\zeta_j D^{s\times j}\right)$. Luckily, the maximum value of s, d, q, S, D, and Q is usually 2, so the resulting expression is relatively simple https://online.stat.psu.edu/stat501/lesson/14/14.5/14.5.1.

3.3 Vector Auto Regressive Models

Basically a Vector auto regressive model has various variables that are endogenous in nature, lets say there are M $\boldsymbol{f}_t = (f_{1t}, \ldots, f_{mt}, \ldots, f_{Mt})$ for $m = 1, \ldots M$. Hence we can define the V. A. R(s)-process as:

$$\boldsymbol{f}_t = C_1\boldsymbol{f}_{t-1} + \ldots + C_s\boldsymbol{f}_{t-s} + \boldsymbol{u}_t$$

here C_i are $(M \times M)$ coefficient matrices for $i = 1, \ldots, s$ and $\boldsymbol{u}_t$ is a M-dim.al process with $\mathrm{E}(\boldsymbol{u}_t) = \mathbf{0}$ and has a covariance matrix which is positive definite as well as time invariant $E\left(\boldsymbol{u}_t\boldsymbol{u}_t^\top\right) = \Sigma_{\boldsymbol{u}}$ (white noise).

V. A. R(s)-process is known for its stability. This means that one can obtain a stationary time series with variance covariance matrix and mean (time invariant), if the process has been provided enough starting values. Following polynomial can verify the given statement:

$$\det\left(I_M - C_1 z - \ldots - C_s z^s\right) \neq 0 \quad \text{for } |z| \leq 1.$$

Upon solving the polynomial above, at least a few variables in the system are first order integrated (I(1)), if it satisfies for $z = 1$.If there is evidence of cointegratoin then it is preferred to use the vector error correction model.

One can analyze the stability from the eigen values and the companion form of an empirical V. A. R(s)-process. A V. A. R(s)-process is represented as a V.A.R(1)-process as follows:

$$\boldsymbol{\xi}_t = C\boldsymbol{\xi}_{t-1} + \boldsymbol{v}_t$$

$$\boldsymbol{\xi}_t = \begin{bmatrix} \boldsymbol{f}_t \\ \vdots \\ \boldsymbol{f}_{t-s+1} \end{bmatrix}, C = \begin{bmatrix} C_1 & C_2 & \cdots & C_{s-1} & C_s \\ I & 0 & \cdots & 0 & 0 \\ 0 & I & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{bmatrix}, \boldsymbol{v}_t = \begin{bmatrix} \boldsymbol{u}_t \\ \boldsymbol{0} \\ \vdots \\ \boldsymbol{0} \end{bmatrix},$$

$(MP \times 1)$ is the dim. of $\boldsymbol{v}_t$ and $\boldsymbol{\xi}_t$ vectors and the dim. of C is $(Ms \times Ms)$. The process is considered to be stable if taken the modulus of the matrix C's eigenvalues is obtained less than one.

If we apply the least squares method individually to all equations obtained from the variables and pre sample values ($\boldsymbol{f}_1, \ldots \boldsymbol{f}_J$ and $\boldsymbol{f}_{-s+1}, \ldots, \boldsymbol{f}_0$), the V. A. R($s$) coefficients can be estimated.

The first goal ie. estimation of a V. A. R(s) model, the work is not just done yet. Next, a number of diagnostic tests are to be performed to rule out the possibility of the presence of evidence for non normal errors/residuals, heteroscedasticity, or autocorrelation. Besides these tests it is important to investigate the forecasts and the behavior of the model via impulse response functions :

$$\boldsymbol{f}_t = \Psi_0 \boldsymbol{u}_t + \Psi_1 \boldsymbol{u}_{t-1} + \Psi_2 \boldsymbol{u}_{t-2} + \ldots,$$

$\Psi_0 = I_M$, where

$$\Psi_s = \sum_{j=1}^{s} \Psi_{s-j} C_j \text{ for } s = 1, 2, \ldots, ,$$

whereby $C_j = 0$ for $j > s$. At the end the forecasts of V. A. R(s)-process are generated recursively for horizons $h \geq 1$:

$$\boldsymbol{f}_{J+h|J} = C_1 \boldsymbol{f}_{J+h-1|J} + \ldots + C_s \boldsymbol{f}_{J+h-s|J},$$

where $\boldsymbol{f}_{J+j|J} = \boldsymbol{f}_{J+j}$ for $j \leq 0$. Below is the forecast error covariance matrix:

$$\text{Cov}\left(\begin{bmatrix} \boldsymbol{f}_{J+1} - \boldsymbol{f}_{J+1|J} \\ \vdots \\ \boldsymbol{f}_{J+h} - \boldsymbol{f}_{J+h|J} \end{bmatrix}\right) = \begin{bmatrix} I & 0 & \cdots & 0 \\ \Psi_1 & I & & 0 \\ \vdots & & \ddots & 0 \\ \Psi_{h-1} & \Psi_{h-2} & \cdots & I \end{bmatrix} (\Sigma_{\boldsymbol{u}} \otimes I_h) \begin{bmatrix} I & 0 & \cdots & 0 \\ \Psi_1 & I & & 0 \\ \vdots & & \ddots & 0 \\ \Psi_{h-1} & \Psi_{h-2} & \cdots & I \end{bmatrix}^\top$$

$\otimes$ is the Kronecker product [30].

3.4 Structural Vector Auto Regressive Models

We can describe the V.A.R(s) model to be a reduced form of the S.V.A.R that is stated as:

$$C\boldsymbol{f}_t = C_1^*\boldsymbol{f}_{t-1} + \ldots + C_s^*\boldsymbol{f}_{t-s} + D\varepsilon_t.$$

The coeff. matrices (C_i^* for $i = 1, \ldots, s$) and the structural errors (ε_t) are considered to be the structural coefficients and white noise respectively. This can be observed in the following equations:

$$\begin{aligned} \boldsymbol{f}_t &= C^{-1}C_1^*\boldsymbol{f}_{t-1} + \ldots + C^{-1}C_s^*\boldsymbol{f}_{t-s} + C^{-1}D\varepsilon_t \\ \boldsymbol{f}_t &= C_1\boldsymbol{f}_{t-1} + \ldots + C_s\boldsymbol{f}_{t-s} + \boldsymbol{u}_t \end{aligned}$$

Minimization of the log likelihood function estimates the parameters.:

$$\begin{aligned} \ln L_c(C, D) = &-\frac{MJ}{2}\ln(2\pi) + \frac{J}{2}\ln|C|^2 - \frac{J}{2}\ln|D|^2 \\ &-\frac{J}{2}\operatorname{tr}\left(C^\top D^{-1}D^{-1}C\tilde{\Sigma}_u\right), \end{aligned}$$

[30].

3.5 Vector Error Correction Models

$$\boldsymbol{f}_t = C_1\boldsymbol{f}_{t-1} + \ldots + C_s\boldsymbol{f}_{t-s} + \boldsymbol{u}_t,$$

The vector error correction specifications can be estimated with johansen cointegration:

$$\Delta\boldsymbol{f}_t = \boldsymbol{\tau}\boldsymbol{v}^\top\boldsymbol{f}_{t-s} + \Lambda_1\Delta\boldsymbol{f}_{t-1} + \ldots + \Lambda_{s-1}\boldsymbol{f}_{t-s+1} + \boldsymbol{u}_t$$

$$\Lambda_i = -\left(I - C_1 - \ldots - C_i\right), \quad i = 1, \ldots, s-1.$$

$$\Pi = \boldsymbol{\tau}\boldsymbol{\upsilon}^\top = -\left(I - C_1 - \ldots - C_s\right) \quad .$$

The cumulative long run effects are shown in the Λ_i matrices, the rest are as follows:

$$\Delta \boldsymbol{f}_t = \boldsymbol{\tau}\boldsymbol{\upsilon}^\top \boldsymbol{f}_{t-1} + \Lambda_1 \Delta \boldsymbol{f}_{t-1} + \ldots + \Lambda_{s-1} \boldsymbol{f}_{t-s+1} + \boldsymbol{u}_t$$

with

$$\Lambda_i = -\left(C_{i+1} + \ldots + C_s\right) \quad i = 1, \ldots, s-1.$$

[30].

Chapter 4

Data Source And Explanation

4.1 Data Source

For this study, monthly time series data from 2006-07 to 2020-21 (Jul-Jun) was collected from archives of the state bank of Pakistan, investing, and Pakistan bureau of statistics which are available online.

4.2 Data Explanation

Following fourteen variables were selected:

- Quantum Index Of Manufacturing (Percent Growth Rate) (QIM)
- Manufacturing Loans (Percent Growth Rate) (ML)
- Wholesale Price Index (Percent Growth Rate) (WPI)
- Foreign Direct Investment (Percent Growth Rate) (FDI)
- Balance Of Trade (Percent Growth Rate) (B.O.T.)
- Exchange Rate (Usd. to Pkr.) (Percent Growth Rate) (ER)
- Textiles Production Index (Percent Growth Rate) (TX)

- Food Beverages And Tobacco Production Index (Percent Growth Rate) (FBT)
- Coke And Petroleum Production Index (Percent Growth Rate) (CP)
- Pharmaceuticals Production Index (Percent Growth Rate) (PHA)
- Non-Metallic Mineral Products Production Index (Percent Growth Rate) (NM)
- Automobiles Production Index (Percent Growth Rate) (AUT)
- Iron And Steel Products Production Index (Percent Growth Rate) (ISP)
- Fertilizers Production Index (Percent Growth Rate) (FER)

The total production index was calculated from the indices in the total production index of the large-scale manufacturing industry. The variables with production indices were selected based on their weight in the overall calculation of QIM We used the scale for selection for the weight of the variable to be greater than or equal to 3. Textile had the highest weight among all variables, which was 20.91 followed by food beverages and tobacco, coke and petroleum, iron and steel products, non-metallic mineral products, automobiles, fertilizers, and pharmaceuticals with respective weights of 12.37, 5.51, 5.39, 5.36, 4.61, 4.44, and 3.62. The variables chemicals, electronics, leather products, paper and board, engineering, rubber, and wood products were discarded as their weight in the QIM was lower than 3.

For the QIM, the latest CMI data was used to calculate weights, using a total of one hundred and twelve items having a total weight of 70.3 percent. From the Ministry of industries and production, Provincial bureaus of statistics and oil companies advisory committee we collected the data related to production. From the State bank of Pakistan's online archives, the data for manufacturing loans, balance of trade and foreign direct investment was extracted and converted as per our need (in percent growth form). And from the Pakistan bureau of statistics website we extracted the time-series data tables for the rest of the variables. WPI has been used as a substitute for GDP as it calculates the average change that occurs in the prices of services and goods sold in the wholesale market.

Textile includes the production of yarn, cloth, jute goods, wool and carpet yarn, woolen and worsted cloth, knitting wool, and woolen blankets. Food Beverages and Tobacco includes the production of sugar, cigarettes, cooking oil, vegetable ghee, wheat and grain milling, soft drinks, liquors, juices, syrups and squashes, starch and its products, and tea blended. Pharmaceuticals include tablets, liquids, syrups, injections, capsules, galenical, and ointments. Non-metallic mineral products include cement, glass plates, and sheets. Automobiles include jeeps, cars, motorcycles, tractors, light commercial vehicles, trucks, and buses. Fertilizers include phosphate and nitrate fertilizers.

The figures 4.1 and The Figures 4.2 show the show mapped values of all variables with distinct colors separately before and after applying stationarity. Likewise, the figures 4.3 and 4.4 show the trend, seasonality, and randomness in our variable of interest i.e QIM before and after applying stationarity.

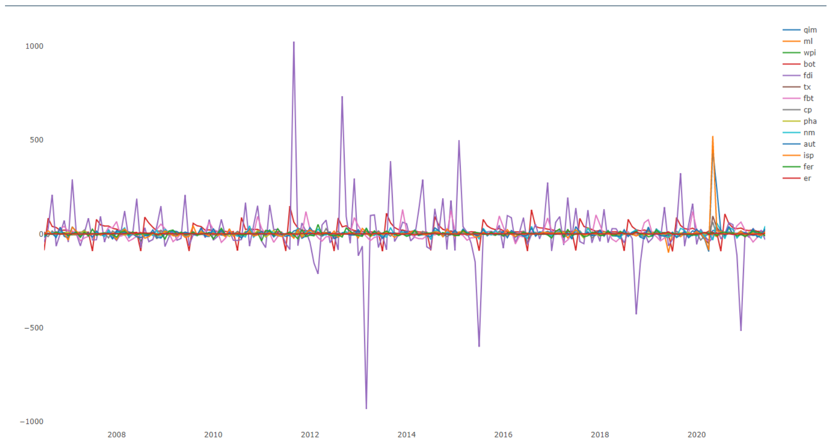


Figure 4.1: This figure represents raw data

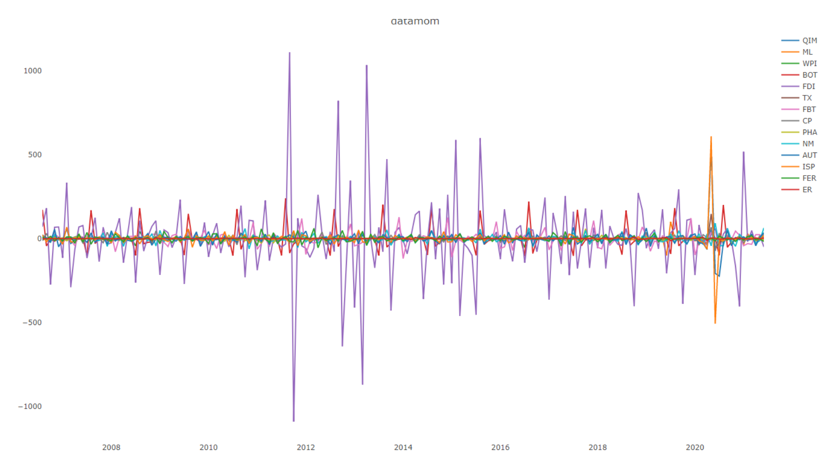


Figure 4.2: This figure represents data after applying stationarity

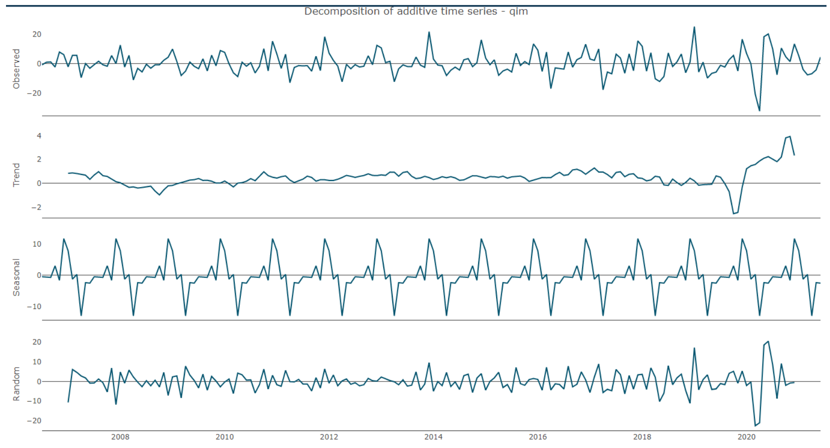


Figure 4.3: Variable of interest "QIM" before stationarity

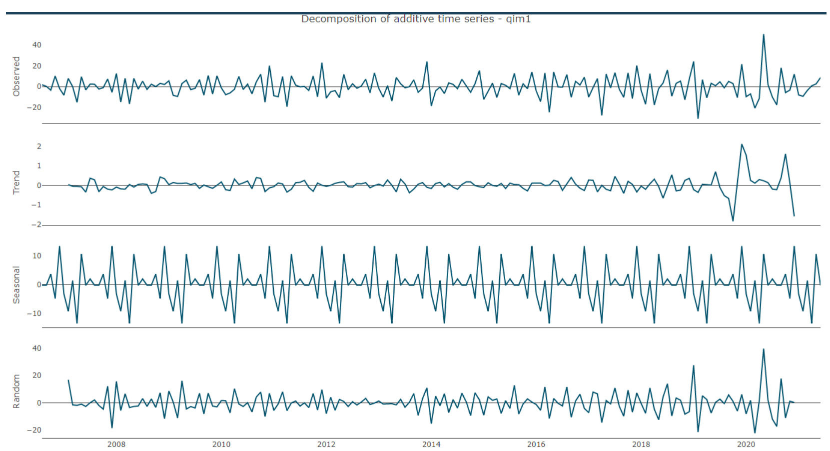


Figure 4.4: Variable of interest "QIM" after stationarity

Chapter 5

Results And Discussion

The analysis for this research was performed using five popular models O.L.S, A.R.I.M.A, V.E.C, V.A.R, and S.V.A.R below are the outputs and results obtained from these models

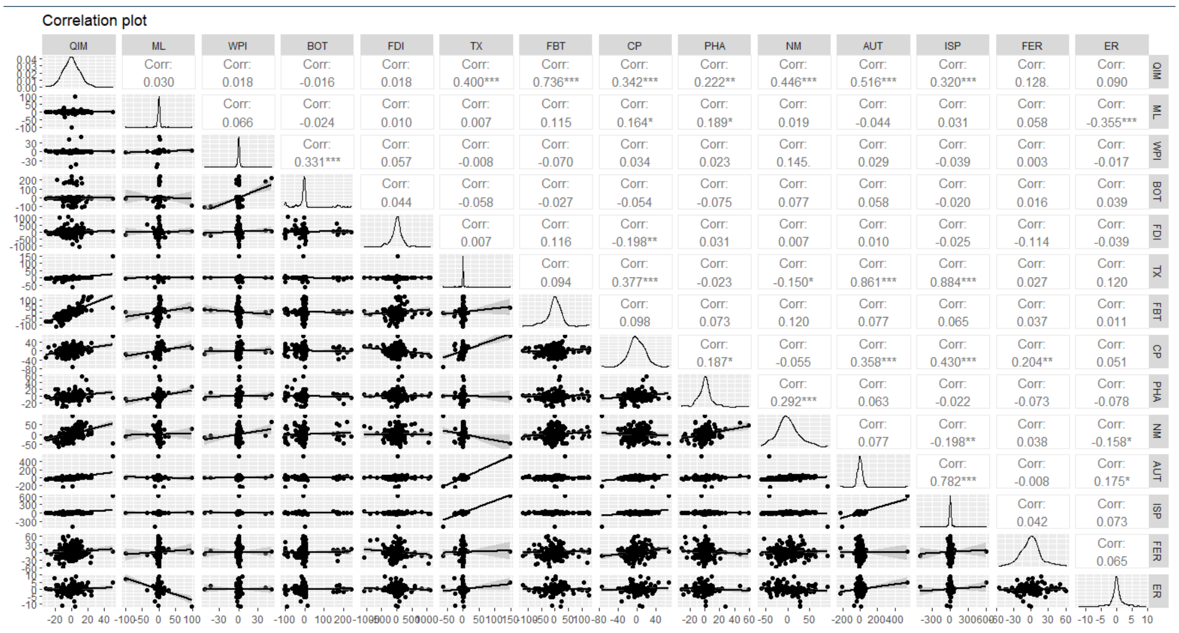


Figure 5.1: The correlation plot between all variables

In the figure 5.1 we observe 3 things, 1: Distribution of the variables (on the diagonal). 2: Correlation factor (above the diagonal). 3: Scatterplots for every variable against the other (below the diagonal). The starred correlation values show that these variables are statistically significant. Normally the correlation values are divided into 3 ranges, weak, moderate, and highly correlated for the threshold values of less than 0.3, greater than and less than 0.7, and above 0.7 respectively. If we look at the main diagonal we see the distribution of each variable. Our variable of interest, QIM is seen to be following a somewhat (mesokurtic) normal symmetrical behavior but it is also slightly positively skewed from the bottom. This depicts the relation of QIM with itself. Scatterplot identifies outlies and extremes if any.

We performed O.L.S regression to check individual relations between QIM and the rest of the variables that were selected. It is evident from the results of the O.L.S regression that TX, FBT, CP, PHA, NM, AUT, and ISP are statistically significant and positively affect the QIM.

Variable	Coefficient	Variable	Coefficient
ML	0.02	PHA	0.22**
WPI	0.02	NM	0.18**
BOT	-0.00	AUT	0.10***
FDI	0.00	ISP	0.05***
TX	0.33***	FER	0.07
FBT	0.20***	ER	0.37
CP	0.20***		

Table 5.1: Regression coefficients for O.L.S
(significance level 0.01),*(significance level 0.001)

The table above enlists the regression coefficients and their respective significance levels. The results tell us that TX, FBT, CP, AUT, and ISP are highly important for QIM with significance level of 0.001, similarly, PHA and NM are also important with a significance level of 0.01. The rest of the variables do not show any notable significance or association.

In A.R.I.M.A the best fitted model: S.A.R.I.M.A(0,0,2)(2,0,0)[12] with zero mean

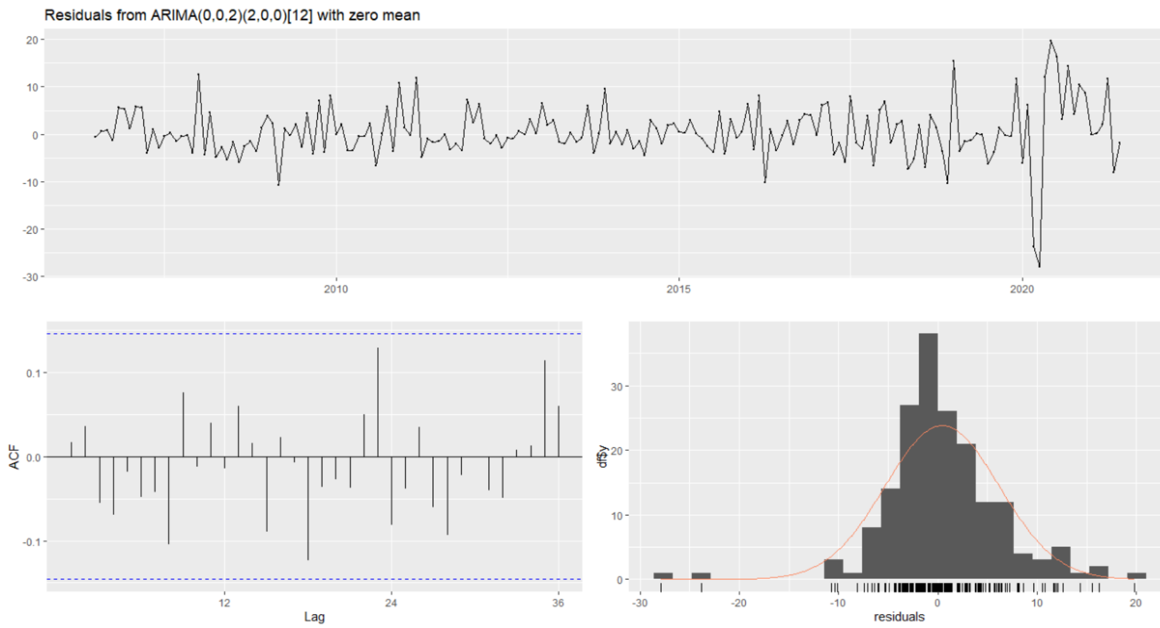


Figure 5.2: This figure shows the residuals for the A.R.I.M.A model

In figure 5.2 we see that the residuals for the A.R.I.M.A are spread over the plane with their mean equal to zero, the ACF plot also shows no favor to the possibility of autocorrelation. Box.Ljung test aids the regression results as it verifies that there is no trend in the series.

The term S.A.R.I.M.A refers to a certain extension of A.R.I.M.A model which caters to the component of seasonality. As already mentioned before, our data was collected monthly hence the [12] refers to the yearly cycle/season.

Application of V.E.C model revealed that there is no evidence found for a long-term relationship between QIM and independent variables as the error correction terms are all insignificant. In the short-run a negative significant relationship between ML and QIM at lag orders "7", "8", and "9". While NM shows a positive significant relation with QIM at "7th" lag order and FDI, FBT, and NM are significant and positively related with QIM on lag order "9", likewise TX, FBT, and NM also show a positive significant relation at the "8th" lag.

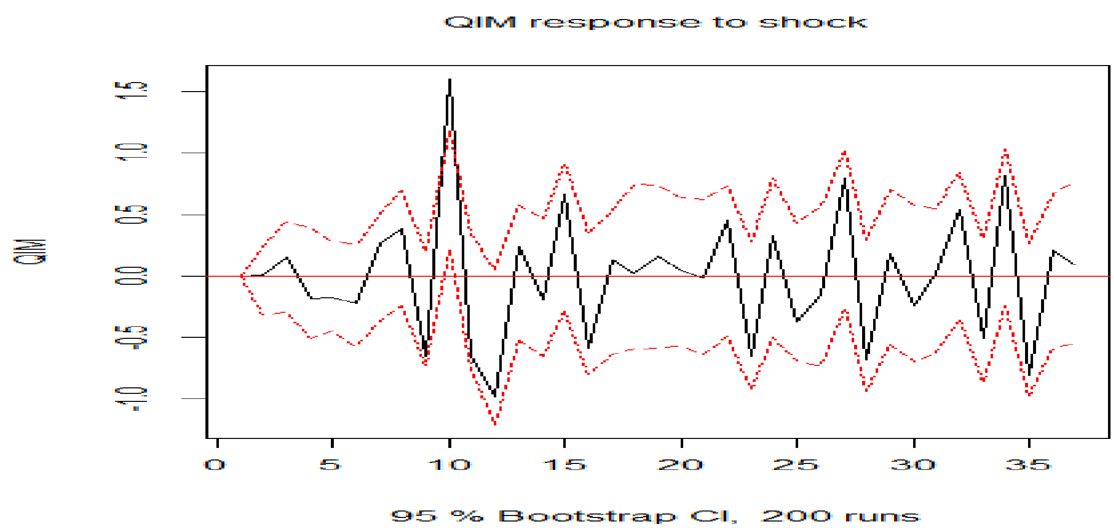
QIM	1.00	NM	-0.13
ML	0.05	AUT	-0.07
WPI	-0.02	ISP	0.01
BOT	0.00	FER	-0.03
FDI	0.00	ER	-0.15
TX	-0.06	FBT	-0.18
PHA	-0.04	CP	-0.08

Table 5.2: Cointegrating vector with coefficients for V.E.C model

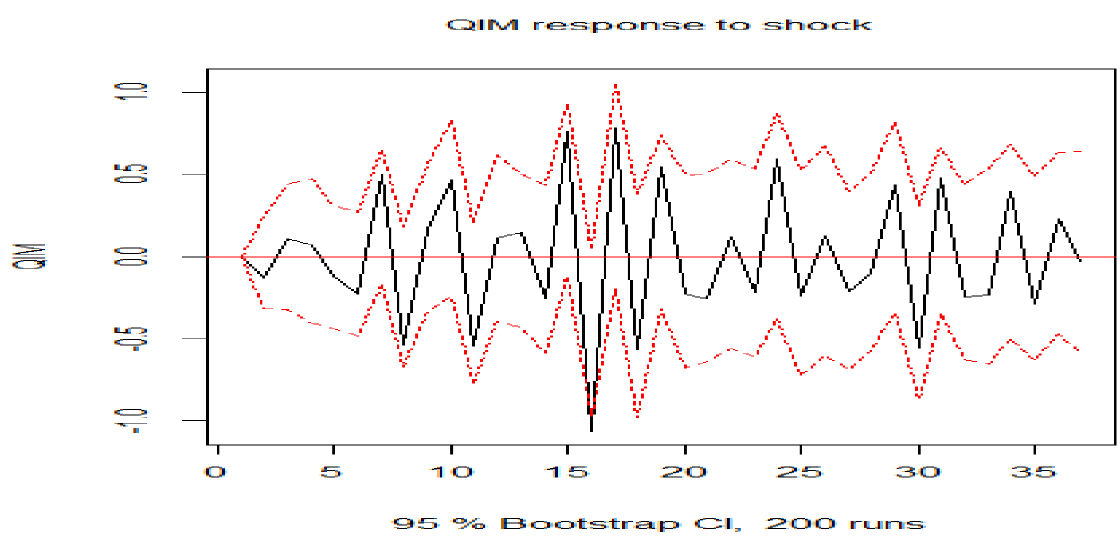
Eq QIM	QIM -1	ML -1	WPI -1	BOT -1		
	0.54	-0.31	0.95	0.08		
	FDI -1	TX -1	FBT -1	CP -1	PHA -1	NM -1
	0.00	1.61	0.47	-1.59	1.88	0.70
	AUT -1	ISP -1	FER -1	ER -1	QIM -2	ML -2
	-0.59	0.28	-0.74	1.35	-0.65	-0.29
	WPI -2	BOT -2	FDI -2	TX -2	FBT -2	CP -2
	0.85	0.06	0.00	1.60	0.62	-1.49
	PHA -2	NM -2	AUT -2	ISP -2	FER -2	ER -2
	1.96	0.67	-0.47	0.25	-0.58	0.65
	QIM -3	ML -3	WPI -3	BOT -3	FDI -3	TX -3
	-2.49	-0.32	0.74	0.04	0.01	1.74
	FBT -3	CP -3	PHA -3	NM -3	AUT -3	ISP -3
	0.94	-1.30	2.05	0.83	-0.36	0.24
	FER -3	ER -3	QIM -4	ML -4	WPI -4	BOT -4
	-0.40	1.45	-3.11	-0.23	0.62	0.11
	FDI -4	TX -4	FBT -4	CP -4	PHA -4	NM -4
	0.01	1.81	1.04	-1.09	1.86	0.88
	AUT -4	ISP -4	FER -4	ER -4	QIM -5	ML -5
	-0.29	0.26	-0.27	1.83	-2.78	-0.24
	WPI -5	BOT -5	FDI -5	TX -5	FBT -5	CP -5
	0.53	0.17	0.01	1.97	0.93	-0.89
	PHA -5	NM -5	AUT -5	ISP -5	FER -5	ER -5
	1.41	0.83	-0.24	0.17	-0.26	1.84
	QIM -6	ML -6	WPI -6	BOT -6	FDI -6	TX -6
	-2.32	-0.44	0.61	0.09	0.01	1.69
	FBT -6	CP -6	PHA -6	NM -6	AUT -6	ISP -6
	0.77	-0.61	0.91	0.73	-0.17	0.05
	FER -6	ER -6	QIM -7	ML -7	WPI -7	BOT -7
	-0.18	0.77	-1.79	-0.52.	0.44	0.03
	FDI -7	TX -7	FBT -7	CP -7	PHA -7	NM -7
	0.00	1.40	0.55	-0.32	0.40	0.61.
	AUT -7	ISP -7	FER -7	ER -7	QIM -8	ML -8
	-0.15	-0.02	-0.11	0.51	-1.93*	-0.57**
	WPI -8	BOT -8	FDI -8	TX -8	FBT -8	CP -8
	0.20	0.00	0.00	1.08.	0.54*	-0.03
	PHA -8	NM -8	AUT -8	ISP -8	FER -8	ER -8
	0.04	0.44*	-0.07	-0.09	-0.05	0.48
	QIM -9	ML -9	WPI -9	BOT -9	FDI -9	TX -9
	-1.18**	-0.42***	0.09	-0.01	0.00.	0.14
	FBT -9	CP -9	PHA -9	NM -9	AUT -9	ISP -9
	0.29*	0.07	0.05	0.18*	0.06	-0.05
	FER -9	ER -9				
	-0.05	-0.01				

Table 5.3: Regression estimates for QIM from V.E.C model at their respective lags

IRFs for V.E.C model



(a)

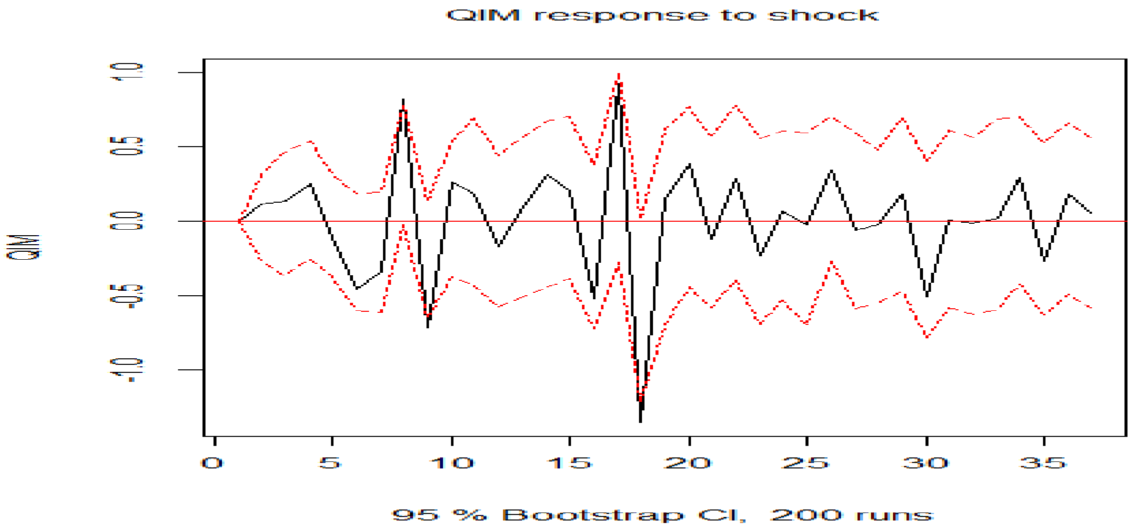


(b)

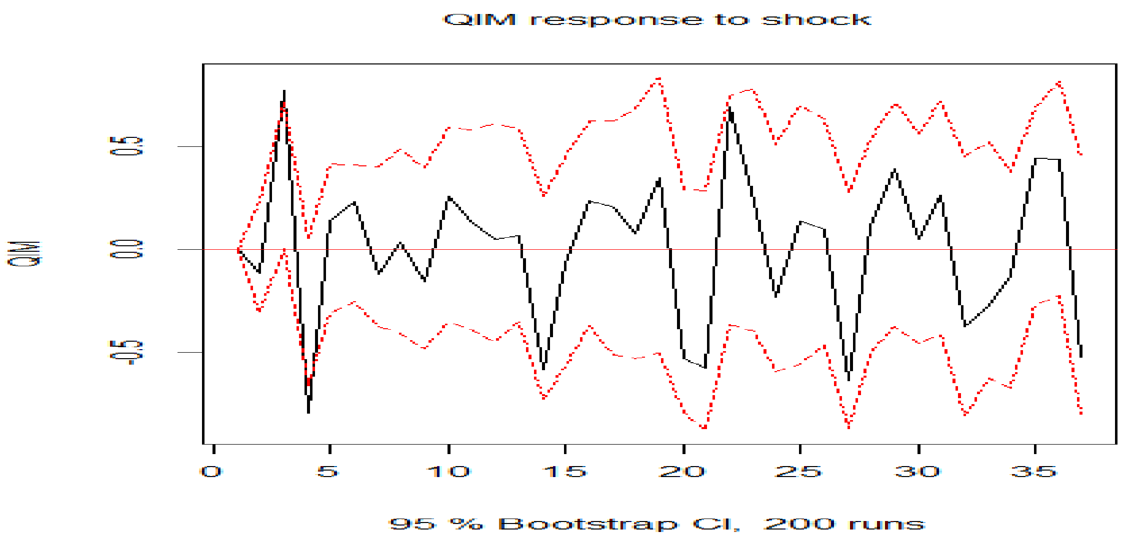
Figure 5.3: (a)IRF: ML vs QIM (b) IRF: WPI vs QIM

In picture (a), it is observed that according to the V.E.C model, a shock to ML at first has no instant effect but then it boosts the QIM then it will go up and down a cyclic pattern but at the end, it will have a downward trend.

Whereas In picture (b), it is observed that according to the V.E.C model, a shock to WPI at first has no instant effect but then it has a negative effect but then it boosts the QIM, then it will go up and down a cyclic pattern but at the end, it will have a downward trend.



(a)

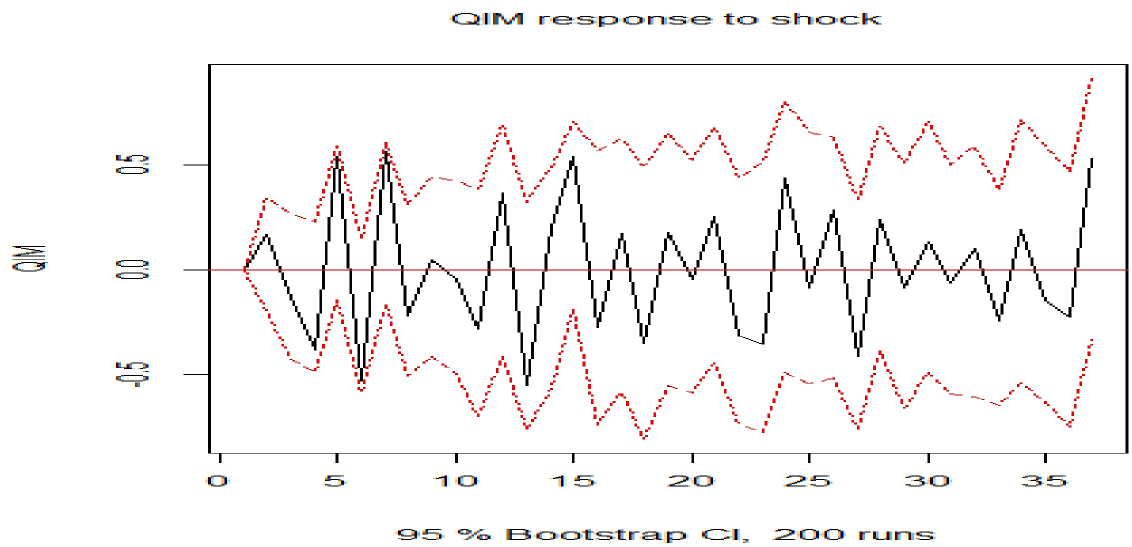


(b)

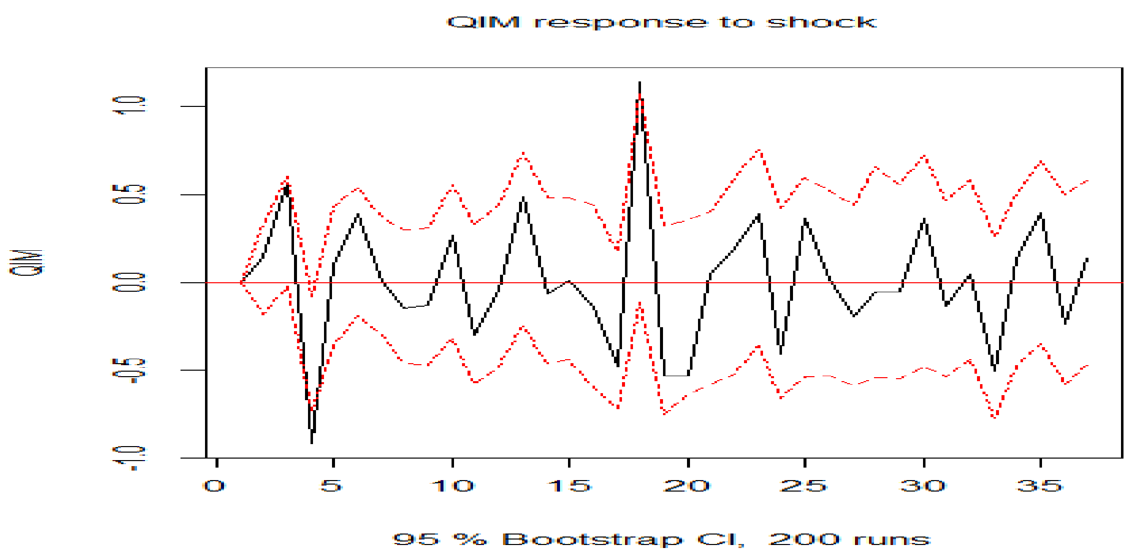
Figure 5.4: (a)IRF: BOT vs QIM (b) IRF: FDI vs QIM

In picture (a), it is observed that according to the V.E.C model, a shock to BOT first at first has no instant effect but then it has a positive increasing effect but then it deflates the QIM then it will go up and down a cyclic pattern but at the end, it will have a downward trend.

Whereas in picture (b), it is observed that according to the V.E.C model, a shock to FDI at first has no instant effect but then it has a slightly negative effect but then it boosts the QIM then it will go up and down a cyclic pattern but at the end, it will have a severe downward trend.



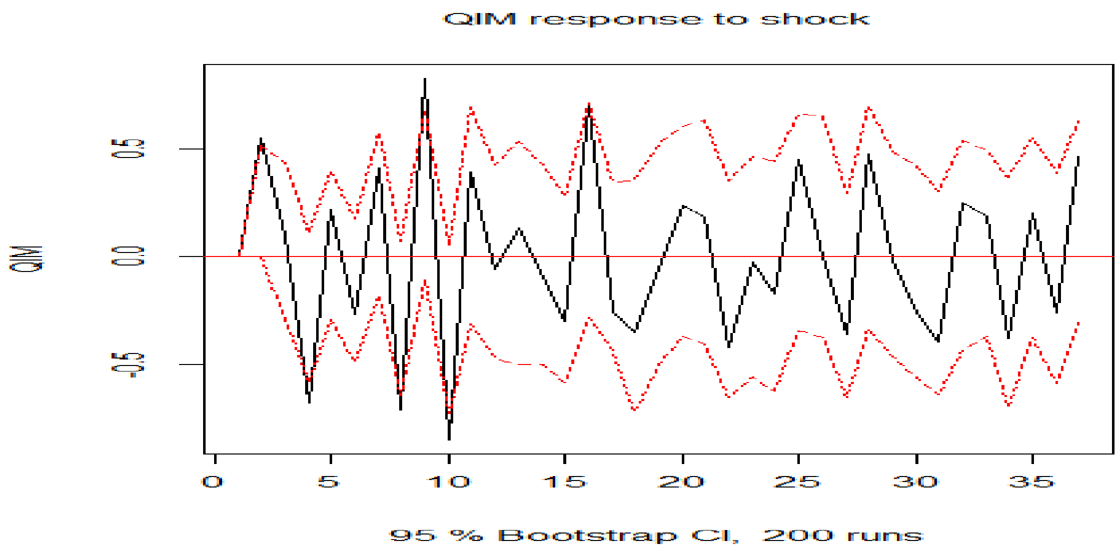
(a)



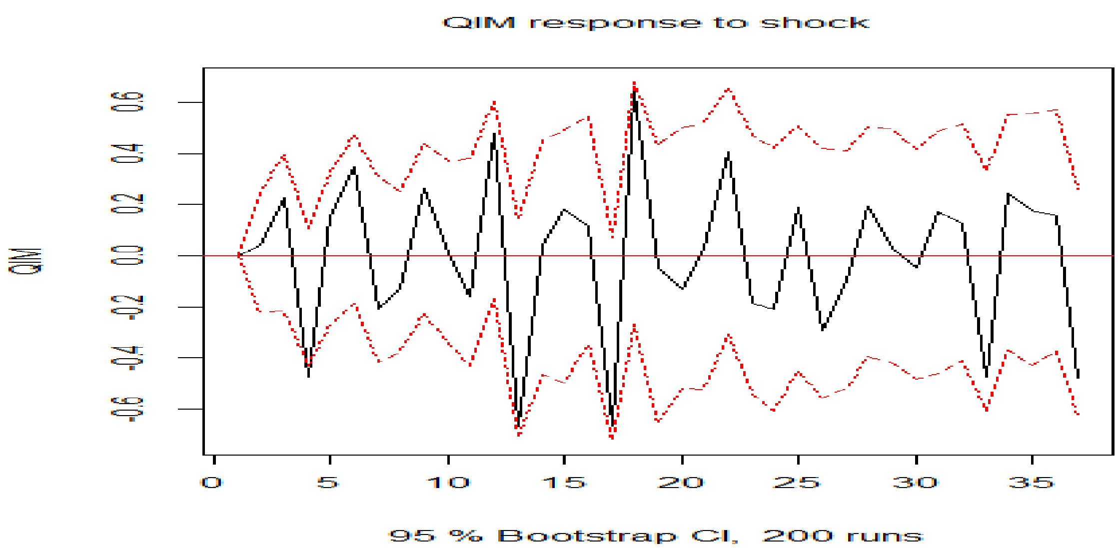
(b)

Figure 5.5: (a)IRF: TX vs QIM (b) IRF: FBT vs QIM

In picture (a), it is observed that according to the V.E.C model, a shock to TX at first has no instant effect but then it has a positive effect on QIM but then it will go up and down in a cyclic pattern but at the end, it will have a strong positive trend. Whereas In picture (b), it is observed that according to the V.E.C model, a shock to FBT at first has no instant effect but then it has a positive effect on QIM but then it will go up and down but in the end, it will have a positive trend.



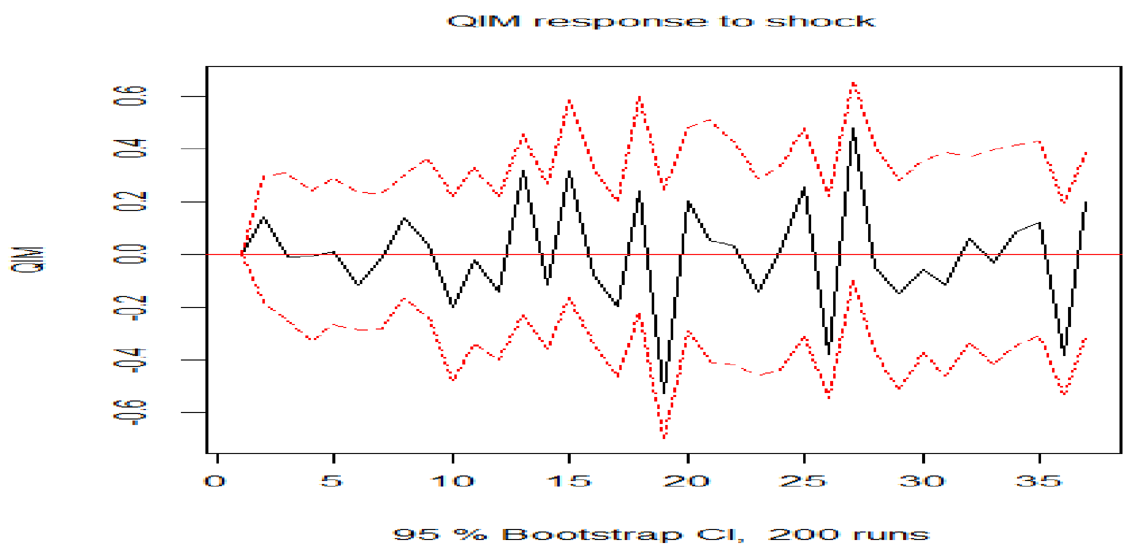
(a)



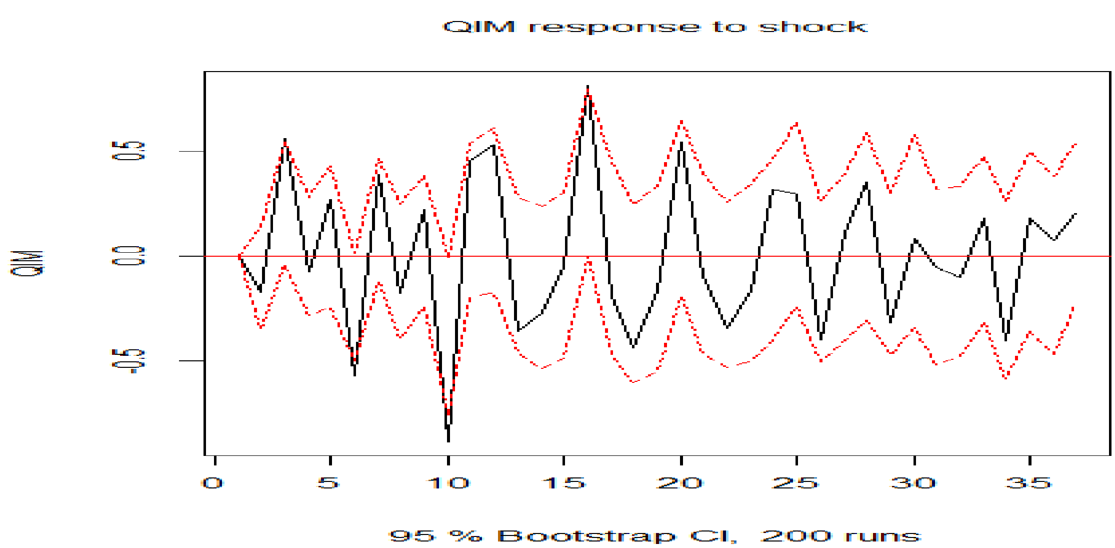
(b)

Figure 5.6: (a)IRF: CP vs QIM (b) IRF: PHA vs QIM

In picture (a), it is observed that according to the V.E.C model, a shock to CP at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend. Whereas In picture (b), it is observed that according to the V.E.C model, a shock to PHA at first has no instant effect but then it has a positive effect on QIM but then it will go up and down in a cyclic pattern but at the end, it will have a strong negative trend.



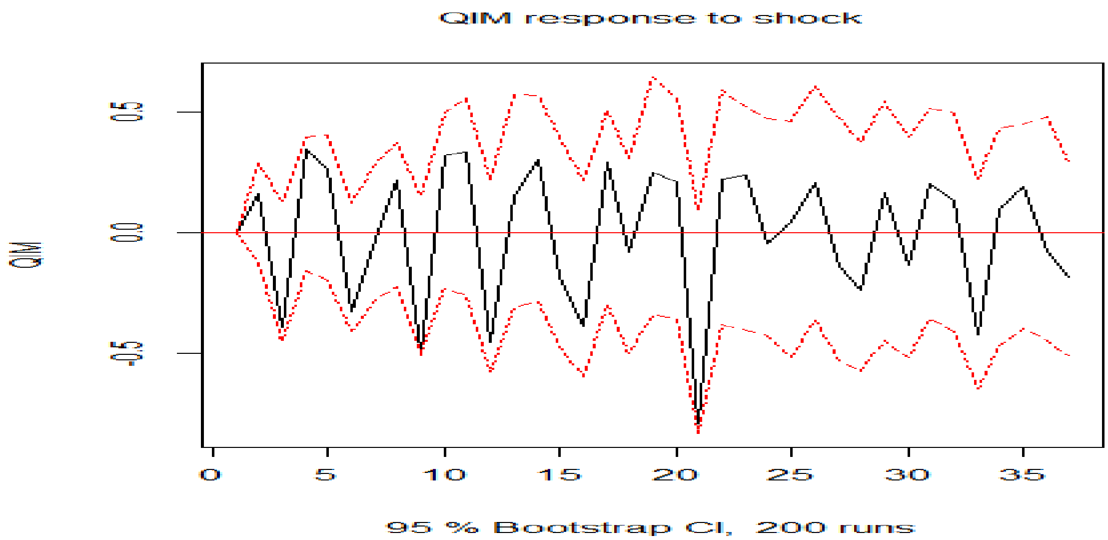
(a)



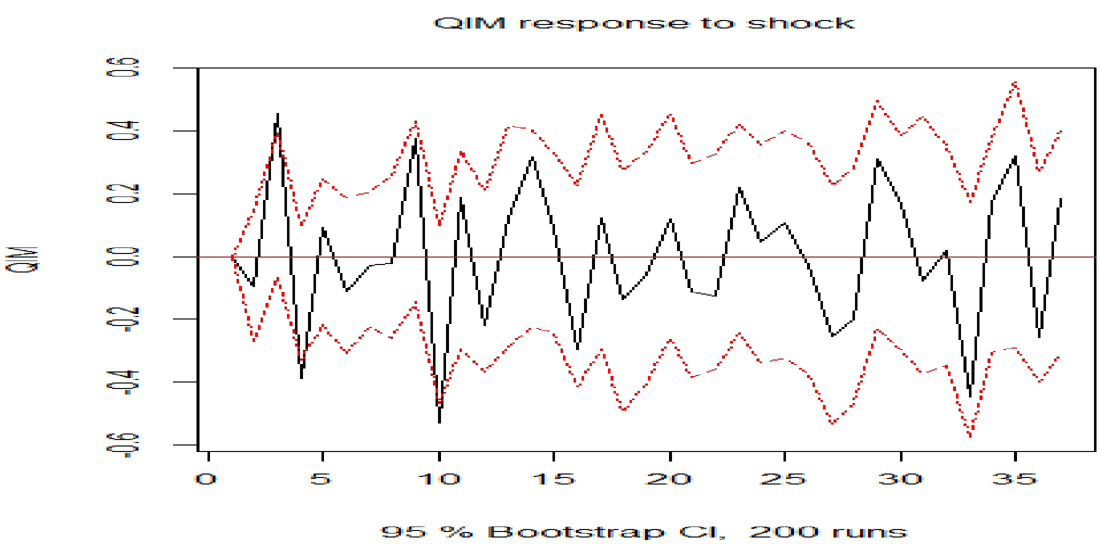
(b)

Figure 5.7: (a)IRF: NM vs QIM (b) IRF: AUT vs QIM

In picture (a), it is observed that according to the V.E.C model, a shock to NM at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend. Whereas In picture (b), it is observed that according to the V.E.C model, a shock to AUT at first has no instant effect but then it has a slightly negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a slightly positive trend.



(a)



(b)

Figure 5.8: (a)IRF: ISP vs QIM (b) IRF: FER vs QIM

In picture (a), it is observed that according to the V.E.C model, a shock to ISP at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend. Whereas In picture (b), it is observed that according to the V.E.C model, a shock to FER at first has no instant effect but then it has a slightly negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend.

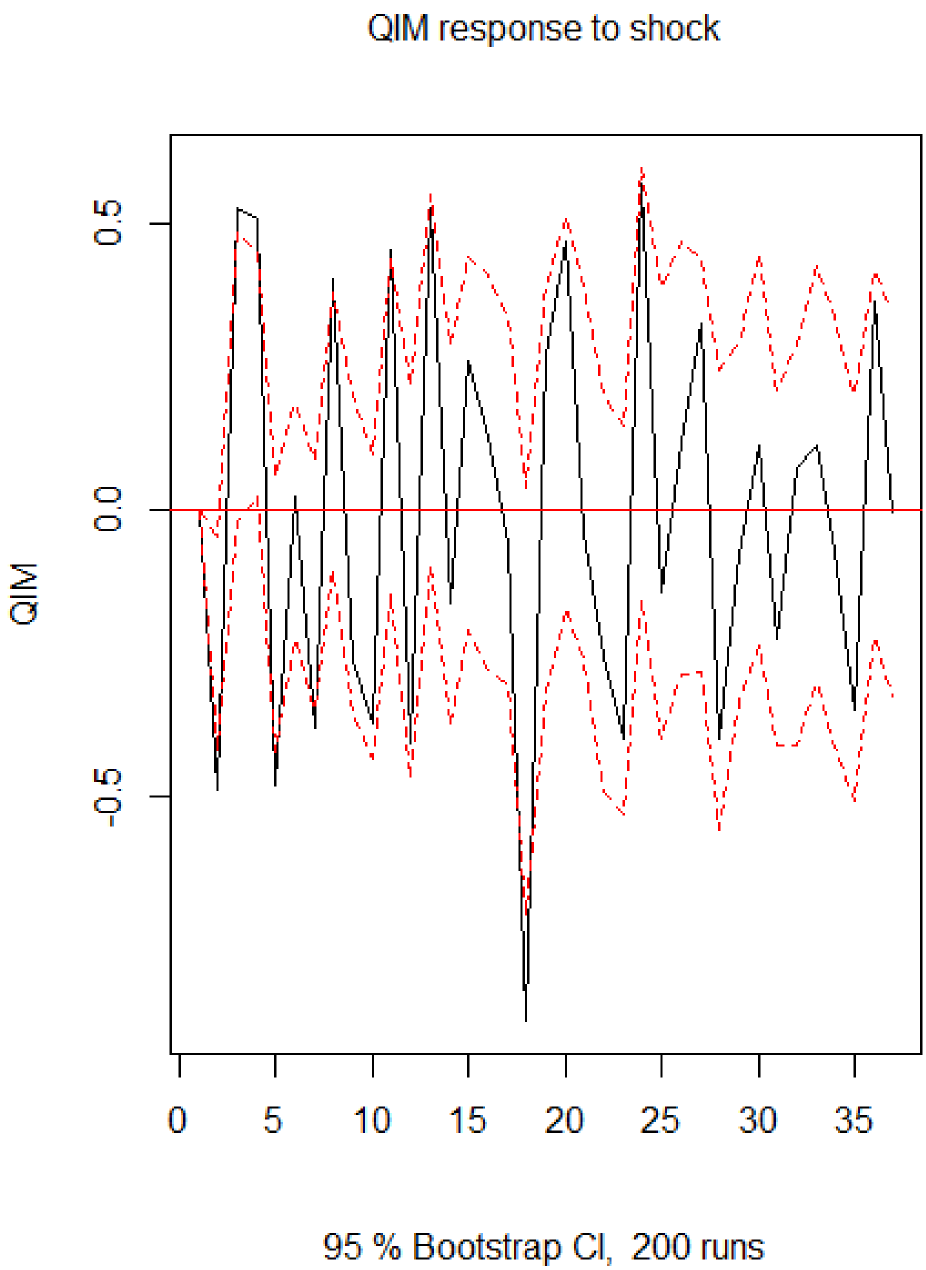


Figure 5.9: This figure shows the IRF for QIM on shock from ER in the V.E.C model

It is observed in figure 5.9 that a shock to ER at first has no instant effect but then it has a strong negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend.

QIM = QIM.l1 + ML.l1 + WPI.l1 + BOT.l1 + FDI.l1 + TX.l1 + FBT.l1 + CP.l1 + PHA.l1 + NM.l1 + AUT.l1 + ISP.l1 + FER.l1 + ER.l1 + QIM.l2 + ML.l2 + WPI.l2 + BOT.l2 + FDI.l2 + TX.l2 + FBT.l2 + CP.l2 + PHA.l2 + NM.l2 + AUT.l2 + ISP.l2 + FER.l2 + ER.l2 + QIM.l3 + ML.l3 + WPI.l3 + BOT.l3 + FDI.l3 + TX.l3 + FBT.l3 + CP.l3 + PHA.l3 + NM.l3 + AUT.l3 + ISP.l3 + FER.l3 + ER.l3 + QIM.l4 + ML.l4 + WPI.l4 + BOT.l4 + FDI.l4 + TX.l4 + FBT.l4 + CP.l4 + PHA.l4 + NM.l4 + AUT.l4 + ISP.l4 + FER.l4 + ER.l4 + QIM.l5 + ML.l5 + WPI.l5 + BOT.l5 + FDI.l5 + TX.l5 + FBT.l5 + CP.l5 + PHA.l5 + NM.l5 + AUT.l5 + ISP.l5 + FER.l5 + ER.l5 + QIM.l6 + ML.l6 + WPI.l6 + BOT.l6 + FDI.l6 + TX.l6 + FBT.l6 + CP.l6 + PHA.l6 + NM.l6 + AUT.l6 + ISP.l6 + FER.l6 + ER.l6 + QIM.l7 + ML.l7 + WPI.l7 + BOT.l7 + FDI.l7 + TX.l7 + FBT.l7 + CP.l7 + PHA.l7 + NM.l7 + AUT.l7 + ISP.l7 + FER.l7 + ER.l7 + QIM.l8 + ML.l8 + WPI.l8 + BOT.l8 + FDI.l8 + TX.l8 + FBT.l8 + CP.l8 + PHA.l8 + NM.l8 + AUT.l8 + ISP.l8 + FER.l8 + ER.l8 + QIM.l9 + ML.l9 + WPI.l9 + BOT.l9 + FDI.l9 + TX.l9 + FBT.l9 + CP.l9 + PHA.l9 + NM.l9 + AUT.l9 + ISP.l9 + FER.l9 + ER.l9 + QIM.l10 + ML.l10 + WPI.l10 + BOT.l10 + FDI.l10 + TX.l10 + FBT.l10 + CP.l10 + PHA.l10 + NM.l10 + AUT.l10 + ISP.l10 + FER.l10 + ER.l10 + const

Observations	169
R2	0.98
Adjusted R2	0.91
Residual Std. Error	3.06 (df = 28)
F Statistic	14.34*** (df = 140; 28)

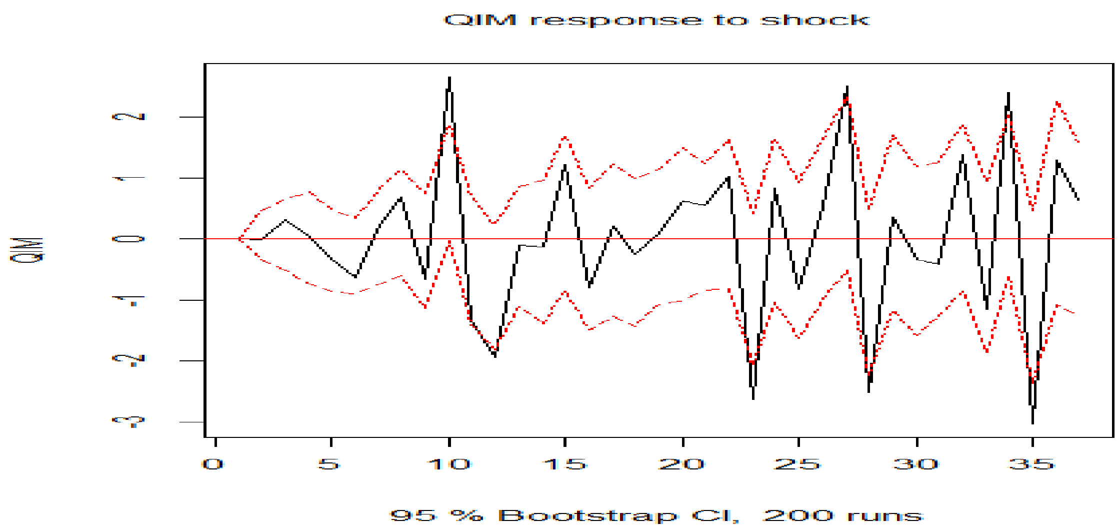
Table 5.4: This is the regression equation and estimation errors for QIM from V.A.R model

QIM.l1	-0.94**	QIM.l3	-1.92***	QIM.l5	0.15	QIM.l7	0.40	QIM.l9	0.67
ML.l1	-0.01	ML.l3	-0.02	ML.l5	0.00	ML.l7	-0.07	ML.l9	0.15
WPI.l1	-0.11	WPI.l3	-0.10	WPI.l5	-0.08	WPI.l7	-0.15	WPI.l9	-0.10
BOT.l1	0.01	BOT.l3	-0.00	BOT.l5	0.08	BOT.l7	-0.04	BOT.l9	-0.01
FDI.l1	-0.00	FDI.l3	0.00	FDI.l5	0.00	FDI.l7	-0.00	FDI.l9	-0.00
TX.l1	-0.24	TX.l3	0.25	TX.l5	0.35	TX.l7	-0.12	TX.l9	-0.85**
FBT.l1	-0.06	FBT.l3	0.31**	FBT.l5	-0.10	FBT.l7	-0.21	FBT.l9	-0.24*
CP.l1	-0.02	CP.l3	0.16	CP.l5	0.18	CP.l7	0.28*	CP.l9	0.11
PHA.l1	0.00	PHA.l3	0.10	PHA.l5	-0.44*	PHA.l7	-0.52*	PHA.l9	-0.00
NM.l1	-0.00	NM.l3	0.19	NM.l5	0.02	NM.l7	-0.05	NM.l9	-0.23*
AUT.l1	0.07	AUT.l3	0.10	AUT.l5	0.02	AUT.l7	0.01	AUT.l9	0.13**
ISP.l1	0.04	ISP.l3	-0.01	ISP.l5	-0.08	ISP.l7	-0.09	ISP.l9	0.02
FER.l1	0.03	FER.l3	0.16	FER.l5	-0.00	FER.l7	0.05	FER.l9	-0.01
ER.l1	-0.54	ER.l3	0.81*	ER.l5	0.09	ER.l7	-0.23	ER.l9	-0.48
QIM.l2	-1.25**	QIM.l4	-0.77	QIM.l6	0.29	QIM.l8	-0.21	QIM.l10	1.15**
ML.l2	0.02	ML.l4	0.10	ML.l6	-0.19	ML.l8	-0.05	ML.l10	0.42***
WPI.l2	-0.10	WPI.l4	-0.13	WPI.l6	0.08	WPI.l8	-0.23*	WPI.l10	-0.09
BOT.l2	-0.01	BOT.l4	0.08	BOT.l6	-0.05	BOT.l8	-0.02	BOT.l10	0.01
FDI.l2	0.00	FDI.l4	0.00	FDI.l6	-0.00	FDI.l8	0.00	FDI.l10	-0.00*
TX.l2	0.04	TX.l4	0.23	TX.l6	-0.07	TX.l8	-0.15	TX.l10	-0.11
FBT.l2	0.13	FBT.l4	0.10	FBT.l6	-0.14	FBT.l8	0.00	FBT.l10	-0.29**
CP.l2	0.08	CP.l4	0.2	CP.l6	0.26	CP.l8	0.28*	CP.l10	-0.07
PHA.l2	0.09	PHA.l4	-0.18	PHA.l6	-0.51*	PHA.l8	-0.37	PHA.l10	-0.05
NM.l2	-0.00	NM.l4	0.10	NM.l6	-0.03	NM.l8	-0.11	NM.l10	-0.17**
AUT.l2	0.11	AUT.l4	0.06	AUT.l6	0.05	AUT.l8	0.05	AUT.l10	-0.06
ISP.l2	-0.02	ISP.l4	0.02	ISP.l6	-0.11	ISP.l8	-0.07	ISP.l10	0.04
FER.l2	0.14	FER.l4	0.10	FER.l6	0.04	FER.l8	0.03	FER.l10	0.05
ER.l2	-0.69	ER.l4	0.448	ER.l6	-0.99**	ER.l8	-0.01	ER.l10	0.01
const	-0.04								

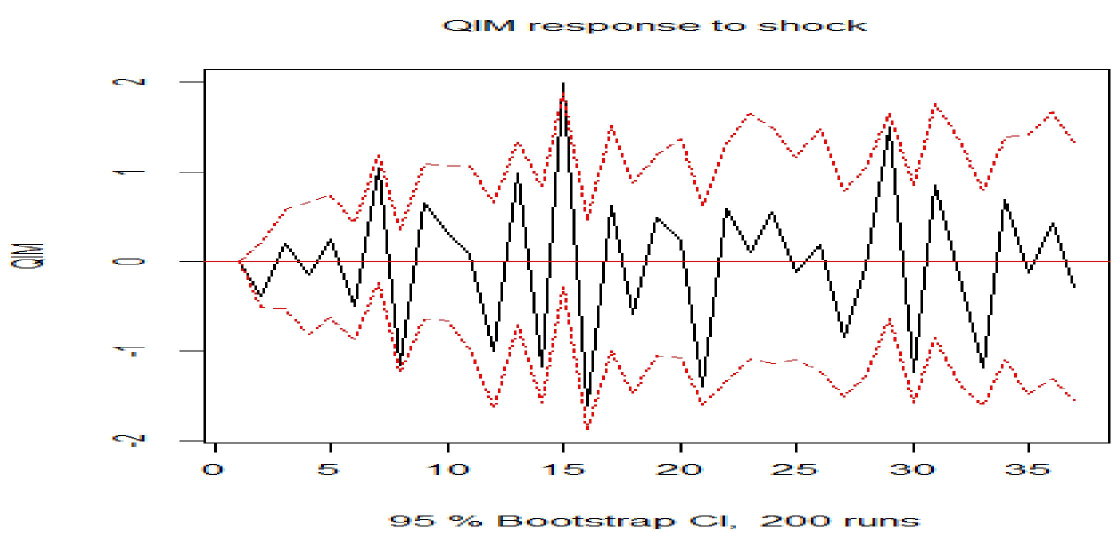
Table 5.5: These are the estimation results for V.A.R at the respective lag orders *=p<0.1 **=p<0.05 ***=p<0.01

According to the results of V.A.R model, at the lag value of "10" ML shows a strong positive and significant effect on our variable of interest on the other hand NM, FBT and FDI show a negative but significant effect. At lag order "9" AUT shows positive and TX, FBT, and NM show negative and significant relation.At lag "8" CP and WPI and at lag "7" CP and PHA show mild positive and negative significant relation with QIM respectively. For the lag value "6" PHA and ER show mild negative significant effect, at lag order "5" PHA displays a negative significant effect and lastly for lag order "3" ER and FBT show a positive and significant effect on the value of QIM. The rest variables on all lag orders are insignificant.

IRFs for V.A.R model

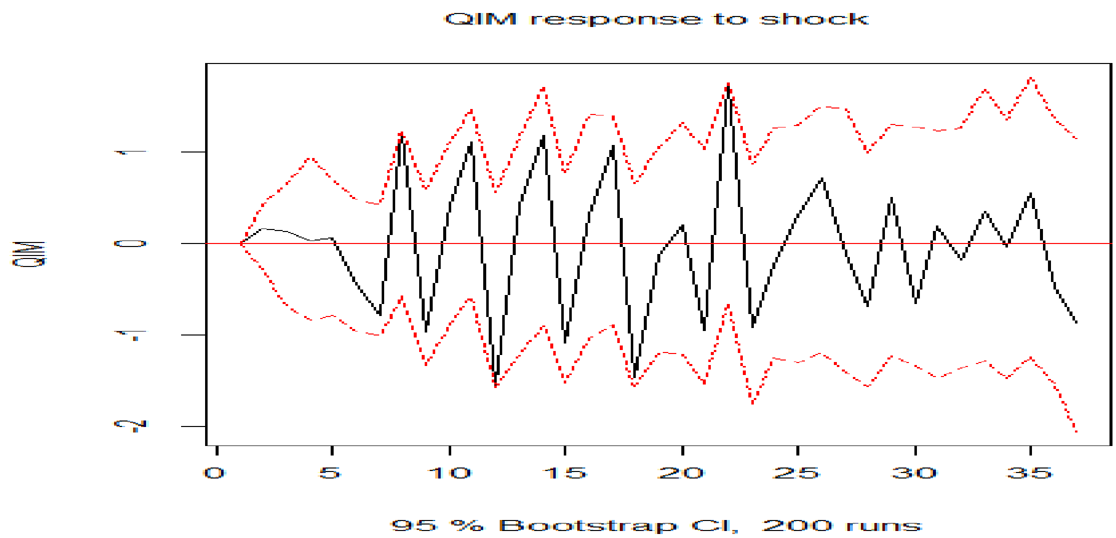


(a)

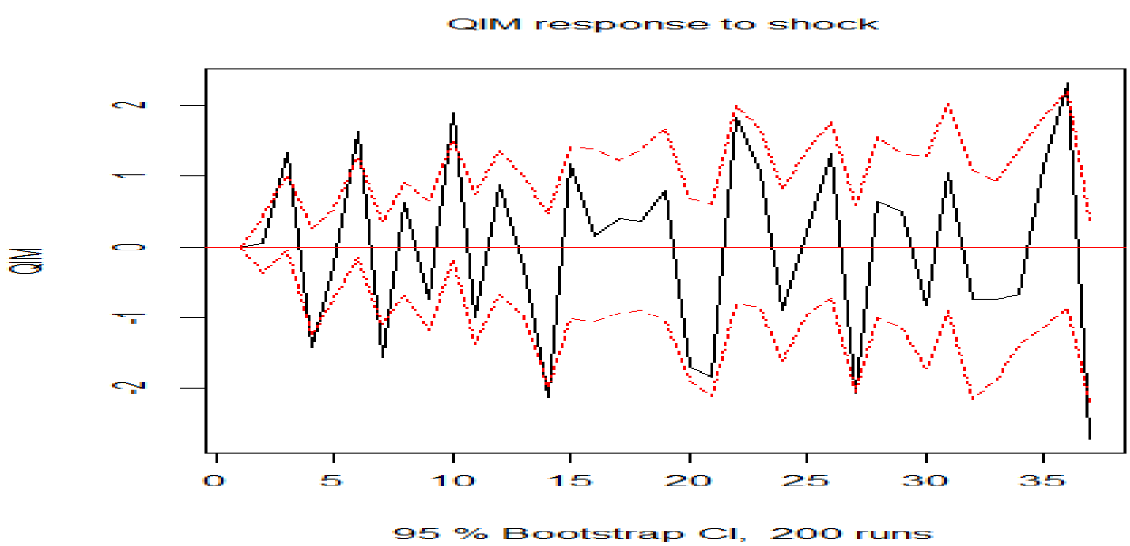


(b)

Figure 5.10: (a)IRF: ML vs QIM (b) IRF: WPI vs QIM
In picture (a), it is observed that according to the V.A.R model, a shock to ML at first has no instant effect on QIM in the start but then it will go up and down a cyclic pattern but at the end, it will have a slightly negative trend.
Whereas In picture (b), it is observed that according to the V.A.R model, a shock to WPI at first has no instant effect but then it has a strong negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend.

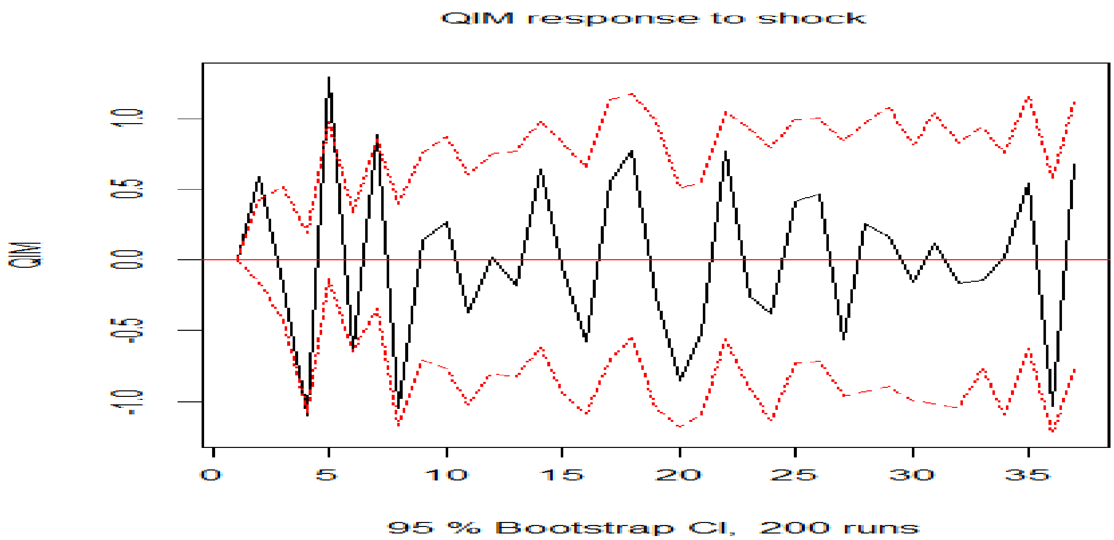


(a)

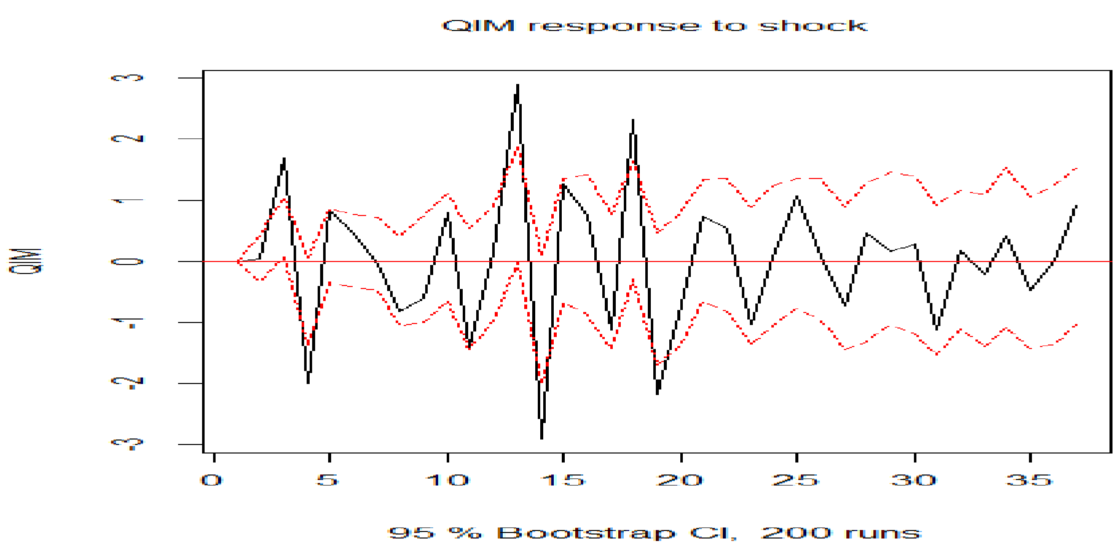


(b)

Figure 5.11: (a)IRF: BOT vs QIM (b) IRF: FDI vs QIM
In picture (a), it is observed that according to the V.A.R model, a shock to BOT at first has no instant effect but then it has a slightly positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a negative trend. Whereas in picture (b), it is observed that according to the V.A.R model, a shock to FDI at first has no instant effect but then it has a strong positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend.



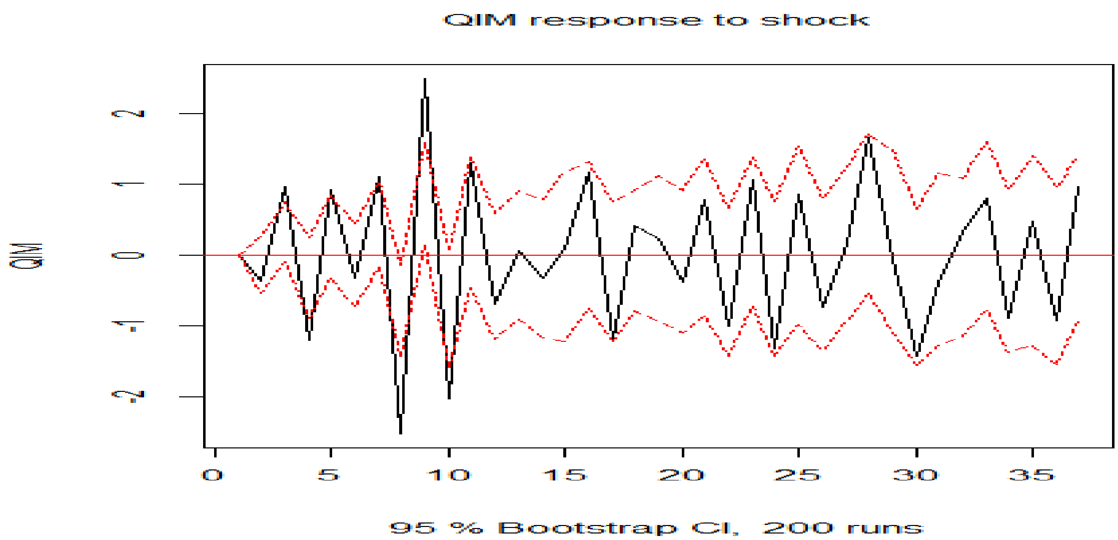
(a)



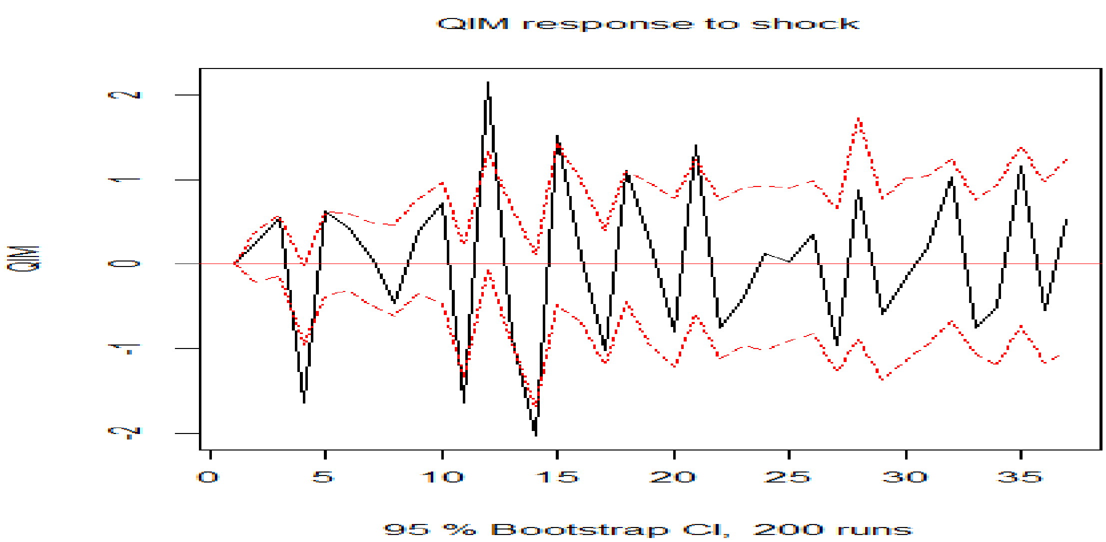
(b)

Figure 5.12: (a)IRF: TX vs QIM (b) IRF: FBT vs QIM

In picture (a), it is observed that according to the V.A.R model, a shock to TX at first has no instant effect but then it has positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend. Whereas in picture (b), it is observed that according to the V.A.R model, a shock to FBT at first has no instant effect but then it has a strong positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a positive trend.



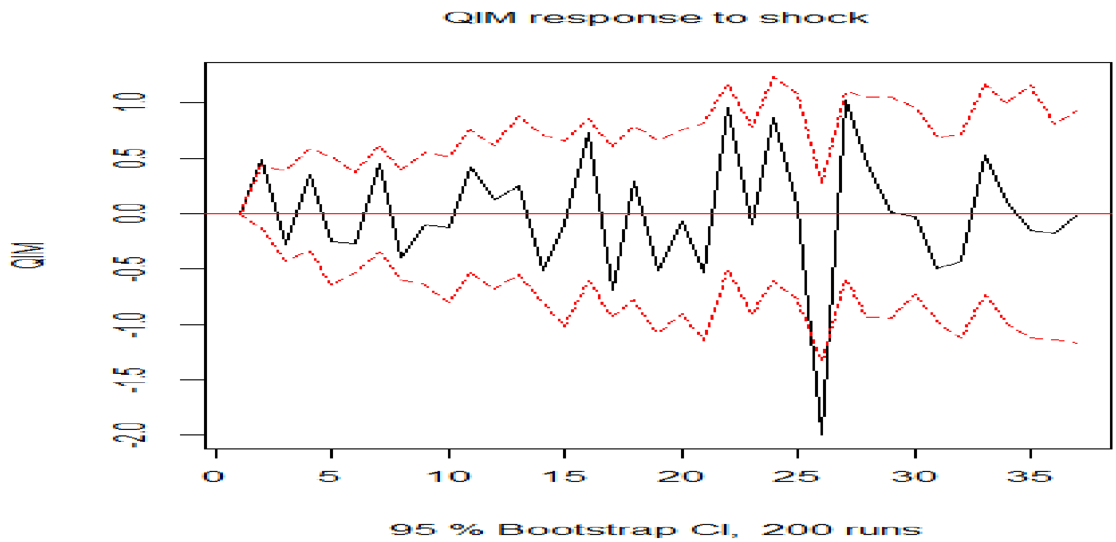
(a)



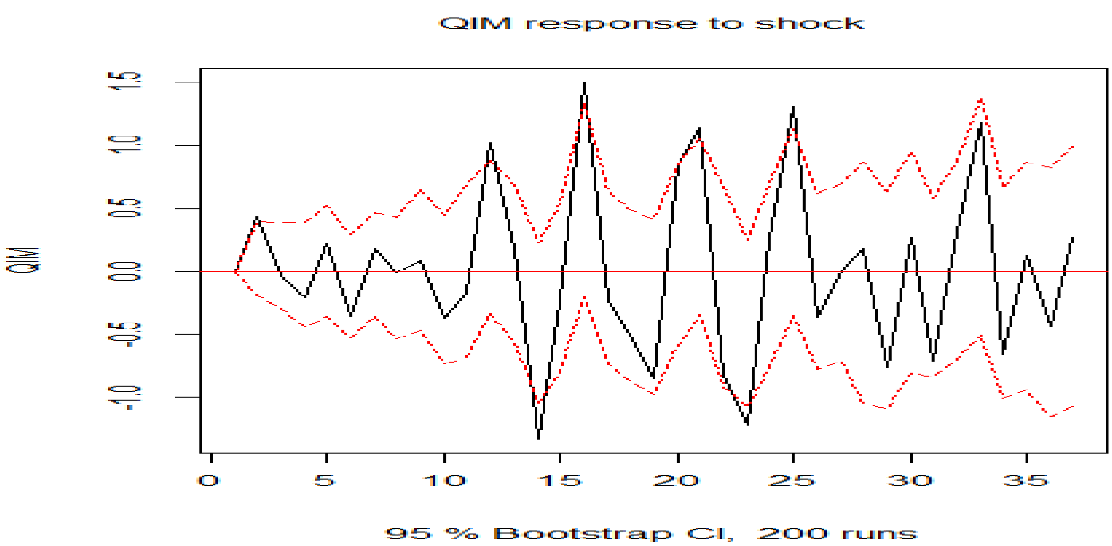
(b)

Figure 5.13: (a)IRF: CP vs QIM (b) IRF: PHA vs QIM

In picture (a), it is observed that according to the V.A.R model, a shock to CP at first has no instant effect but then it has a negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend. Whereas in picture (b), it is observed that according to the V.A.R model, a shock to PHA at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend.



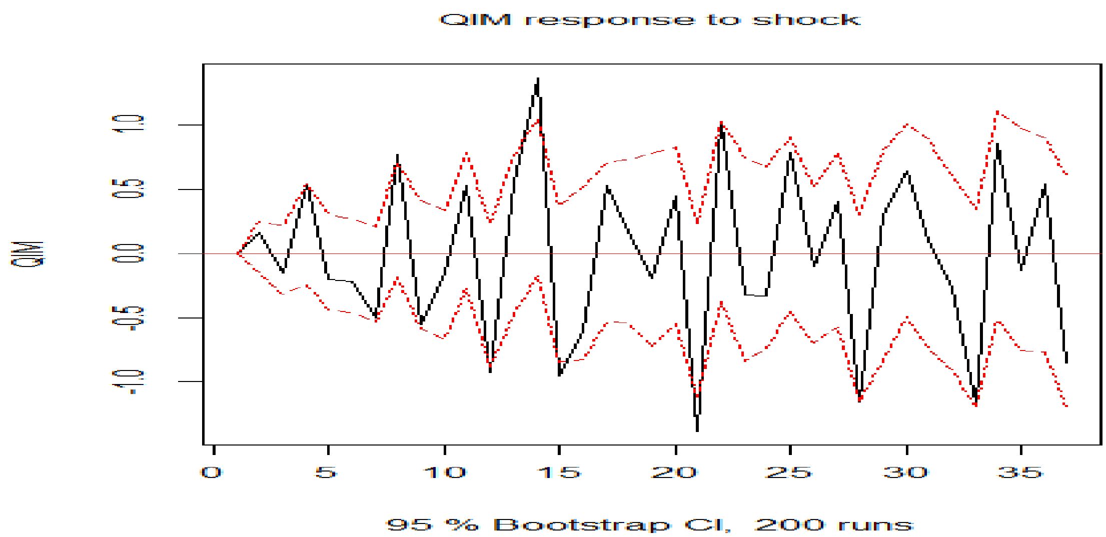
(a)



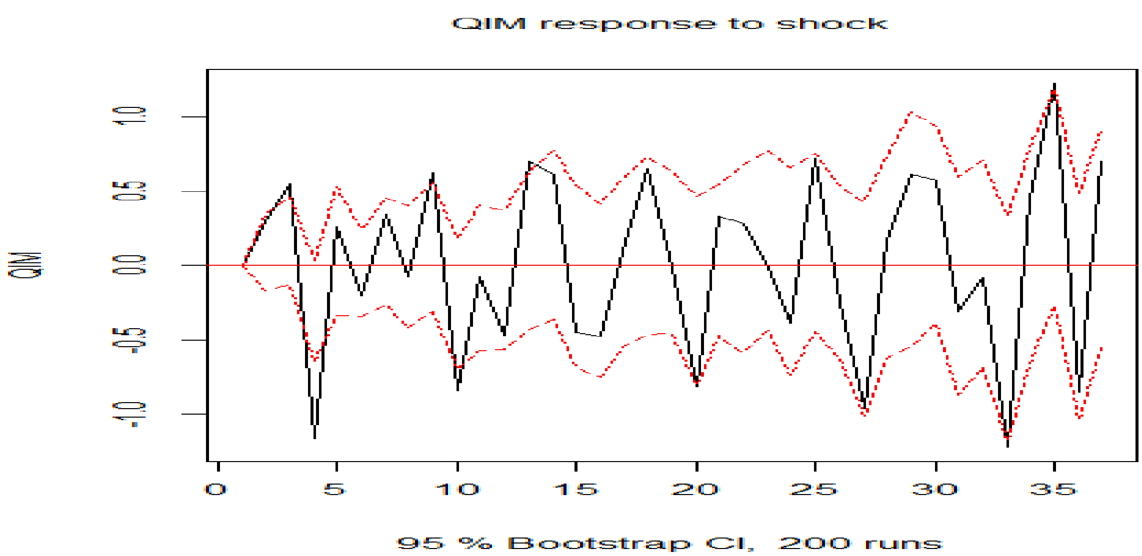
(b)

Figure 5.14: (a)IRF: NM vs QIM (b) IRF: AUT vs QIM

In picture (a), it is observed that according to the V.A.R model, a shock to NM at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a slightly positive trend. Whereas in picture (b), it is observed that according to the V.A.R model, a shock to AUT at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a positive trend.



(a)



(b)

Figure 5.15: (a)IRF: ISP vs QIM (b) IRF: FER vs QIM

In picture (a), it is observed that according to the V.A.R model, a shock to ISP at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend. Whereas in picture (b), it is observed that according to the V.A.R model, a shock to FER at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend.

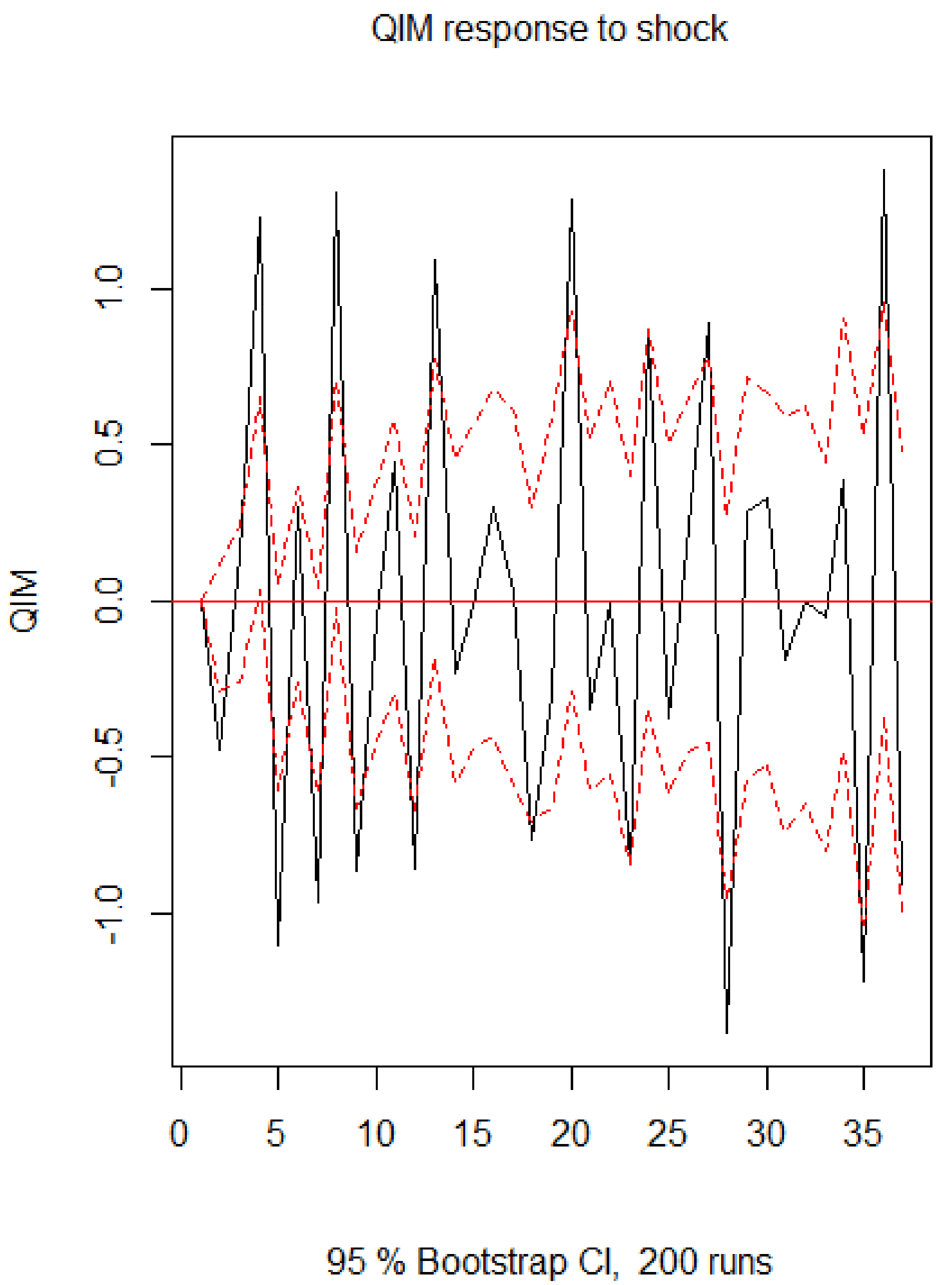
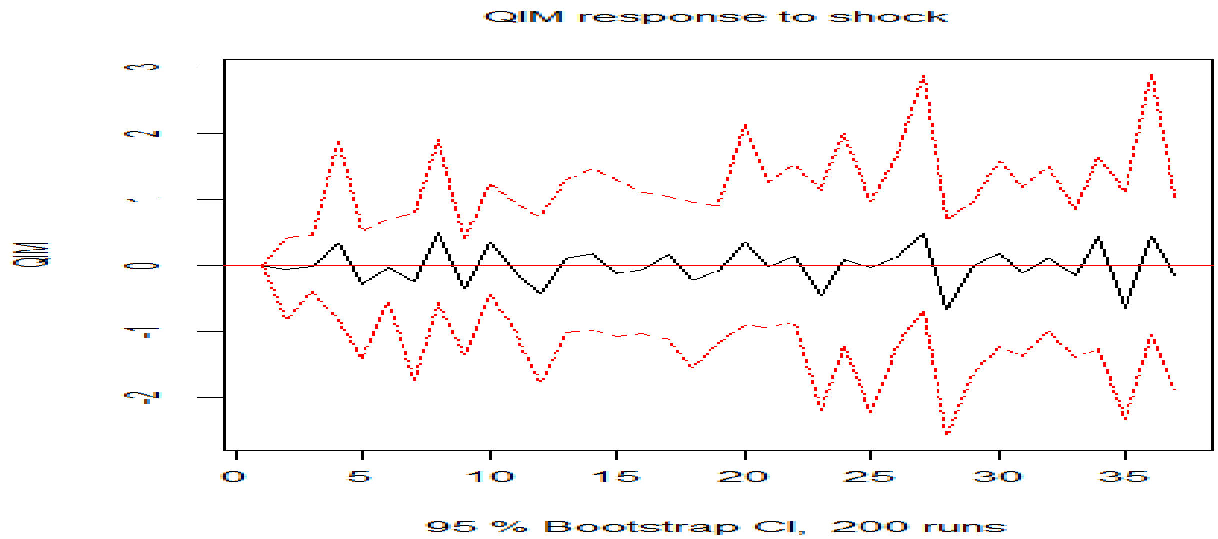
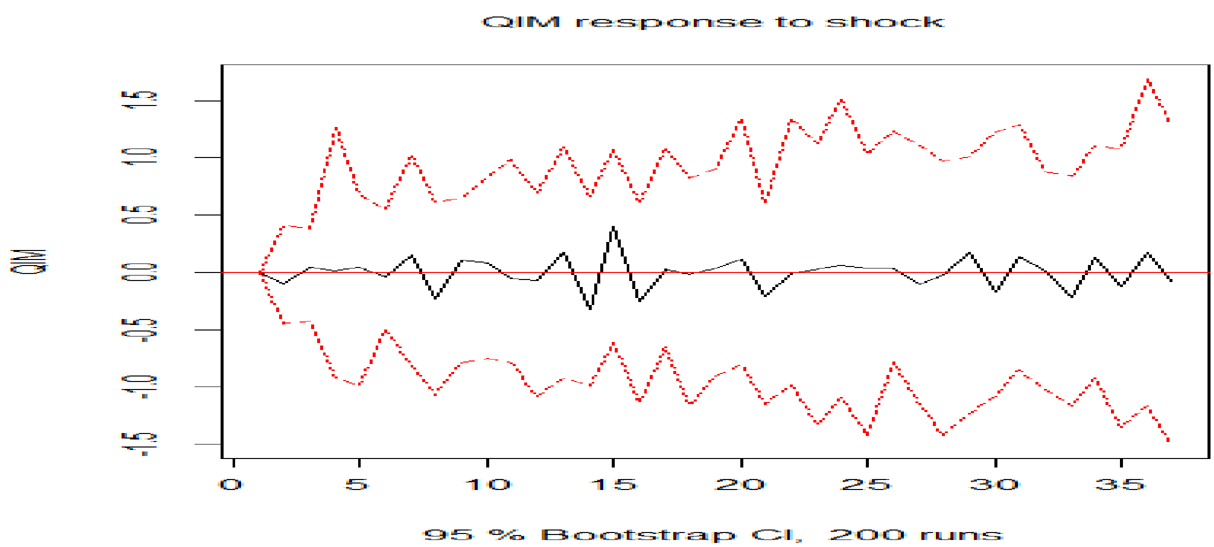


Figure 5.16: This figure shows the IRF for QIM on shock from ER in the V.A.R model It is observed in figure 5.23 that a shock to ER at first has no instant effect but then it has a negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend.

IRFs for S.V.A.R model



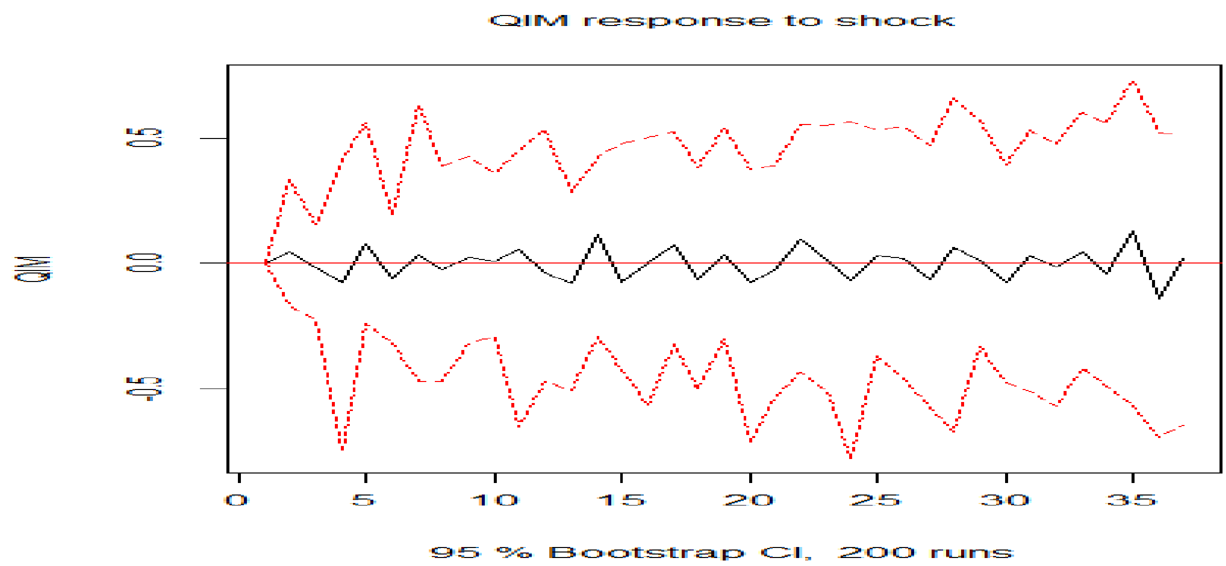
(a)



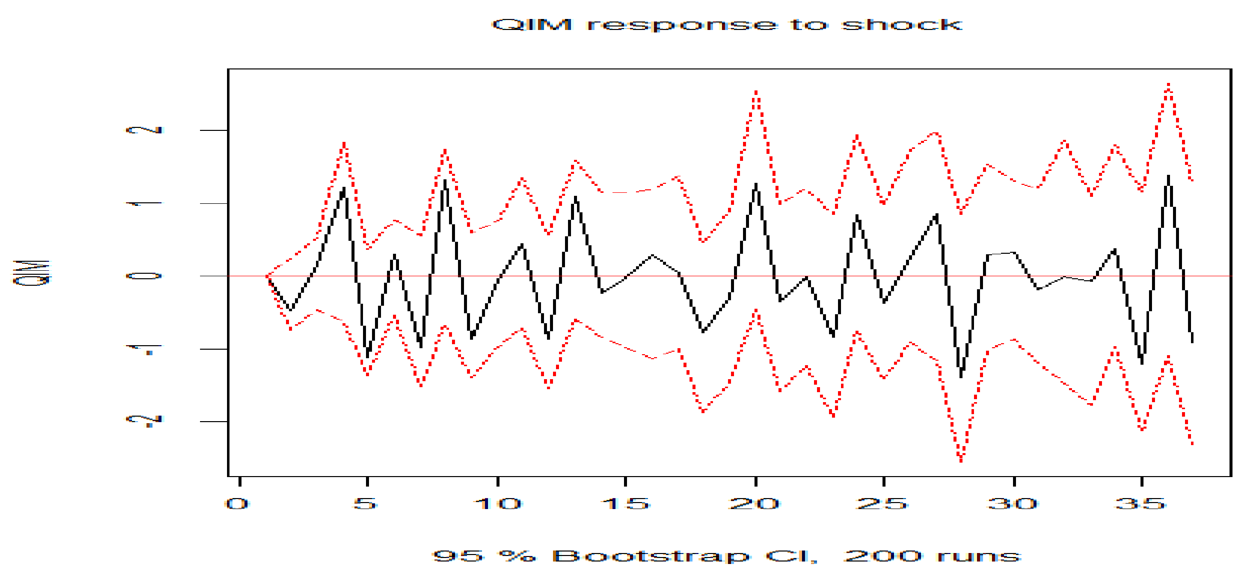
(b)

Figure 5.17: (a)IRF: ML vs QIM (b) IRF: WPI vs QIM

In picture (a), it is observed that according to the S.V.A.R model, a shock to ML at first has no instant effect but then it has slightly positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a negative trend. Whereas in picture (b), it is observed that according to the S.V.A.R model, a shock to WPI at first has no instant effect but then it has slightly negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a negative trend.



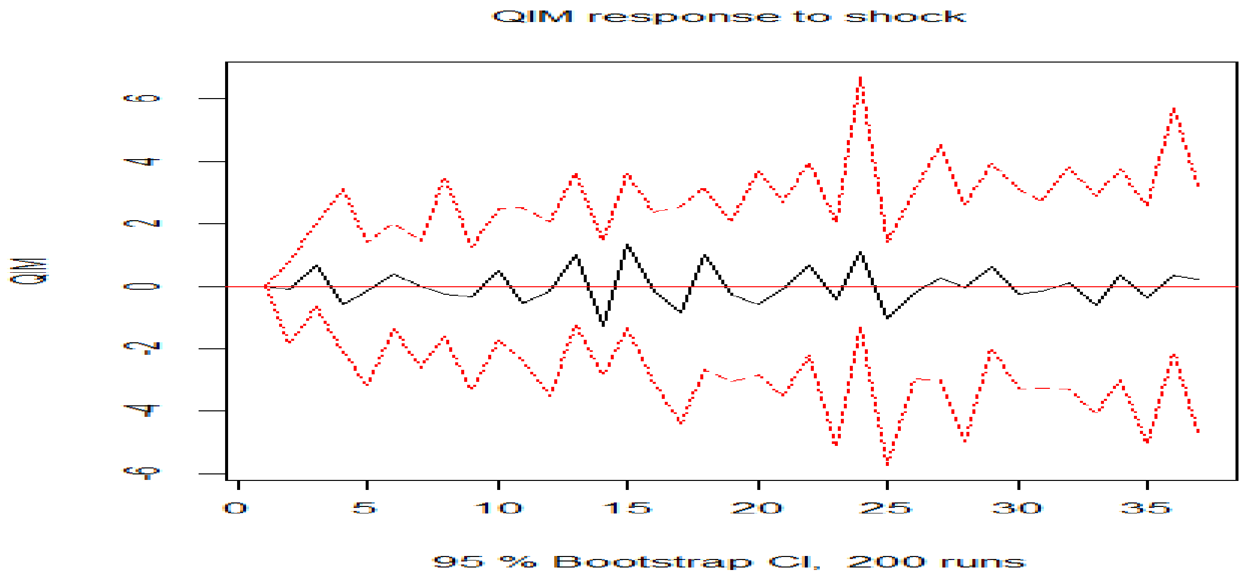
(a)



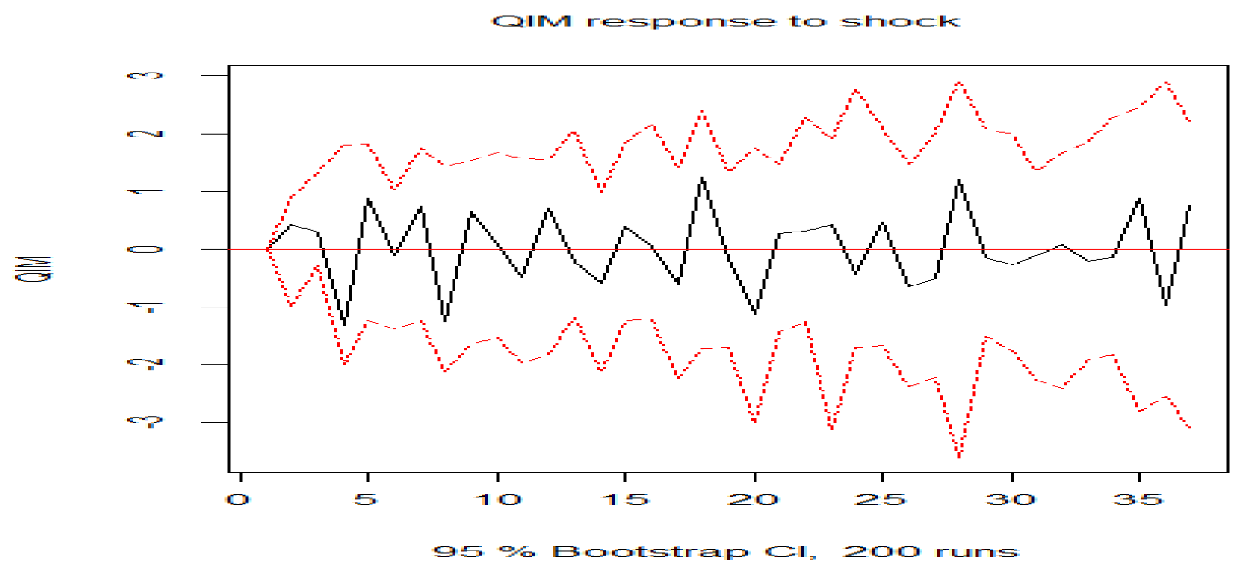
(b)

Figure 5.18: (a)IRF: BOT vs QIM (b) IRF: FDI vs QIM

In picture (a), it is observed that according to the S.V.A.R model, a shock to BOT at first has no instant effect but then it has a slightly positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a positive trend. Whereas in picture (b), it is observed that according to the S.V.A.R model, a shock to FDI at first has no instant effect but then it has a negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend.



(a)

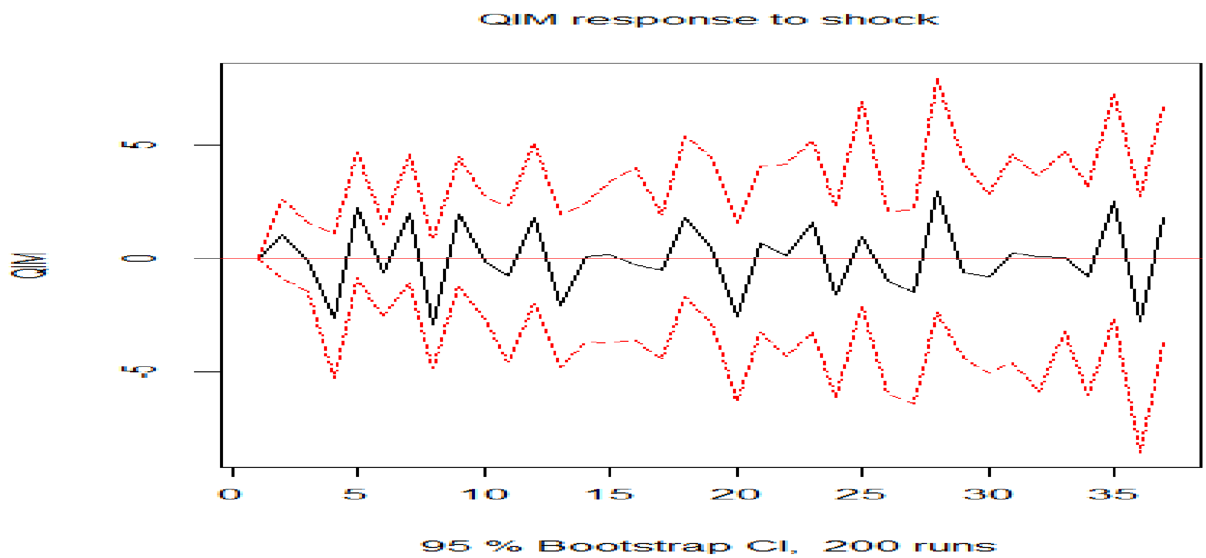


(b)

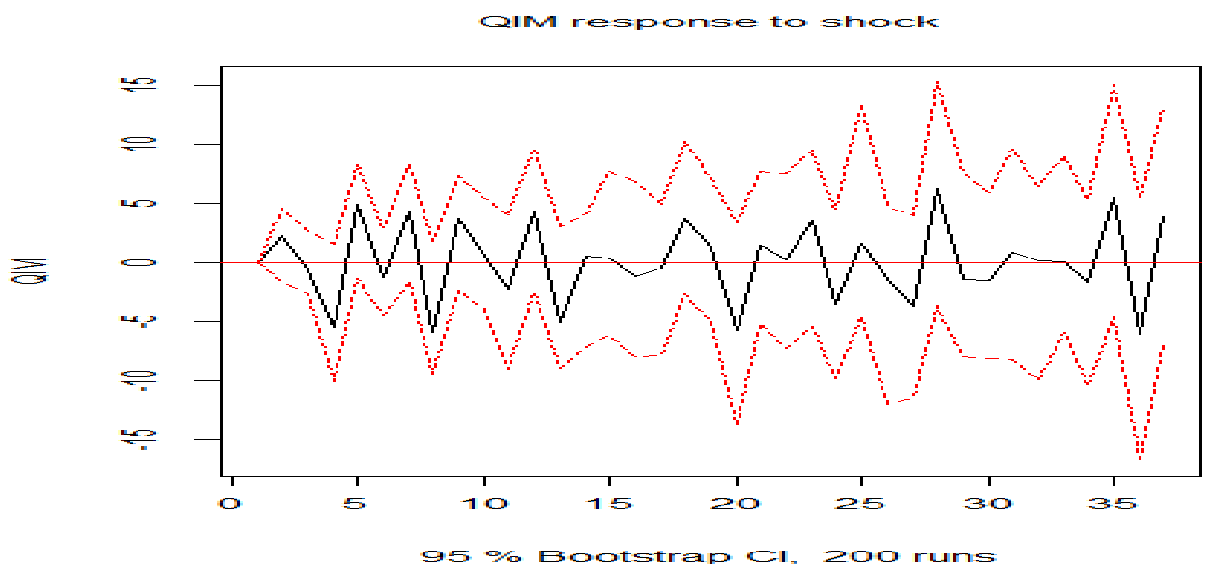
Figure 5.19: (a)IRF: TX vs QIM (b) IRF: FBT vs QIM

In picture (a), it is observed that according to the S.V.A.R model, a shock to TX at first has no instant effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a slightly negative trend.

Whereas In the picture on the right side it is observed that according to the S.V.A.R model, a shock to FBT at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend.

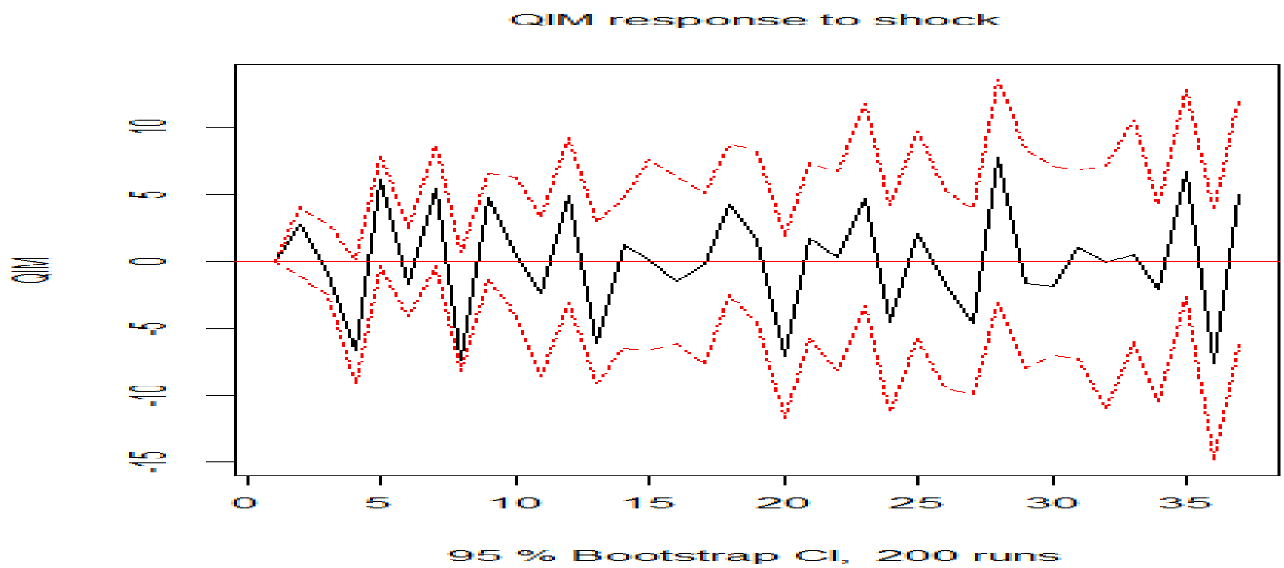


(a)

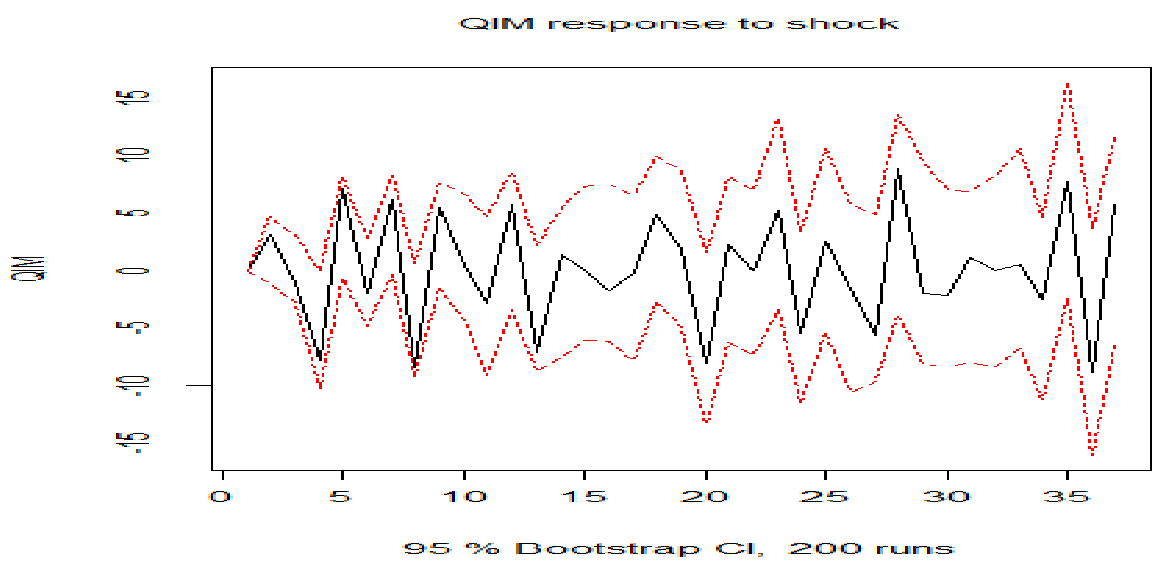


(b)

Figure 5.20: (a)IRF: CP vs QIM (b) IRF: PHA vs QIM
In picture (a), it is observed that according to the S.V.A.R model, a shock to CP at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend. Whereas In picture (b), it is observed that according to the S.V.A.R model, a shock to PHA at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend.



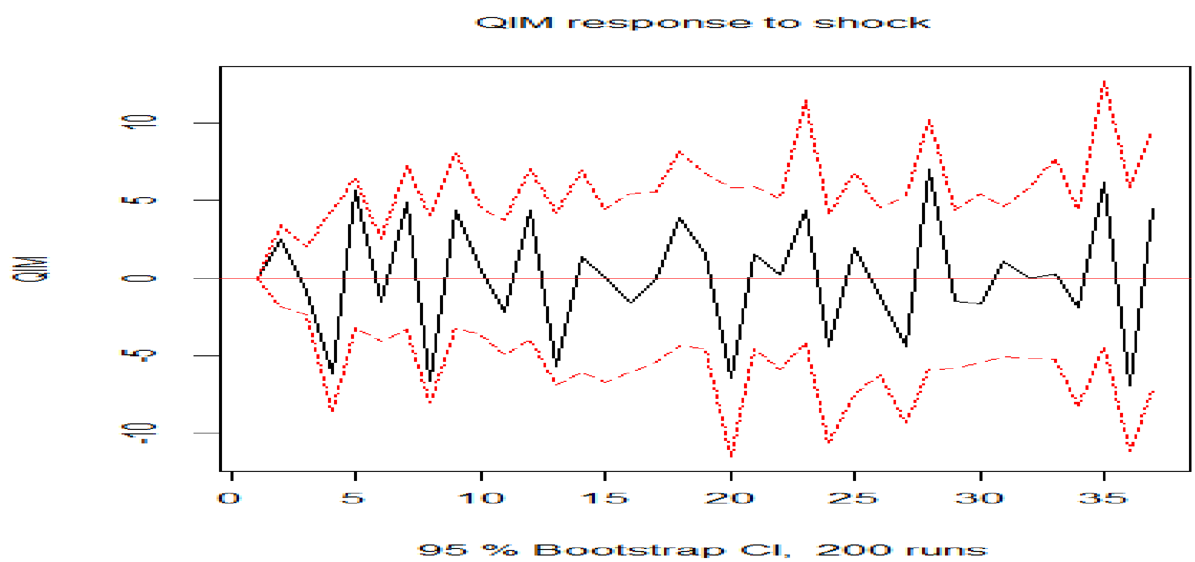
(a)



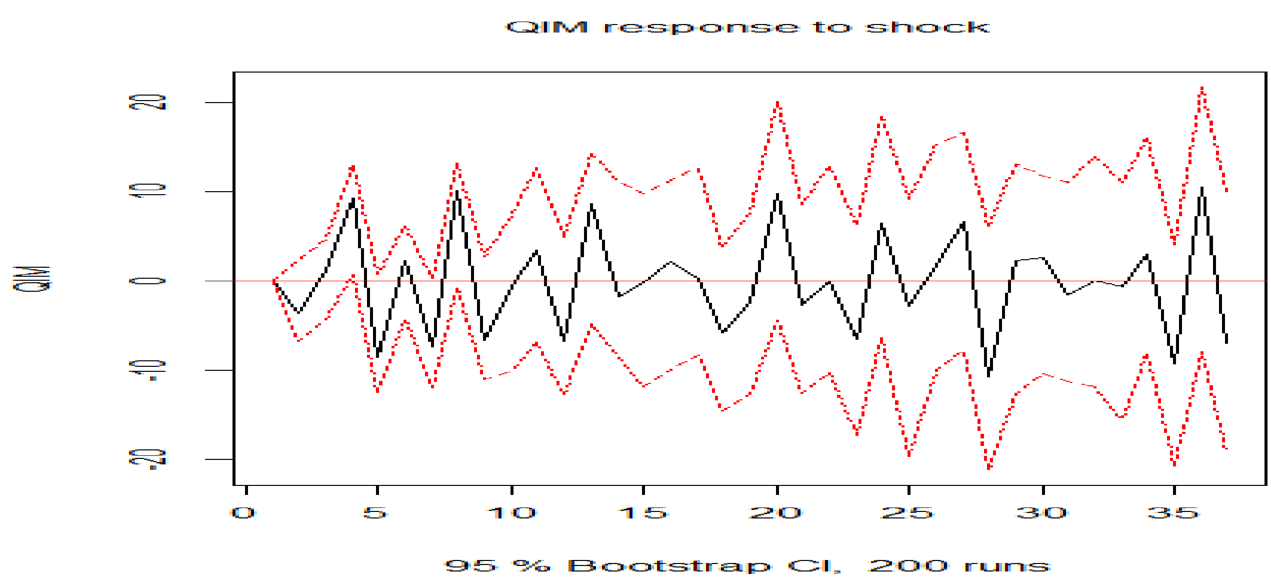
(b)

Figure 5.21: (a)IRF: NM vs QIM (b) IRF: AUT vs QIM

In picture (a), it is observed that according to the S.V.A.R model, a shock to NM at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend. Whereas in picture (b), it is observed that according to the S.V.A.R model, a shock to AUT at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend.



(a)



(b)

Figure 5.22: (a)IRF: ISP vs QIM (b) IRF: FER vs QIM

In picture (a), it is observed that according to the S.V.A.R model, a shock to ISP at first has no instant effect but then it has a positive effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong positive trend. Whereas in picture (b), it is observed that according to the S.V.A.R model, a shock to FER at first has no instant effect but then it has a negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend.

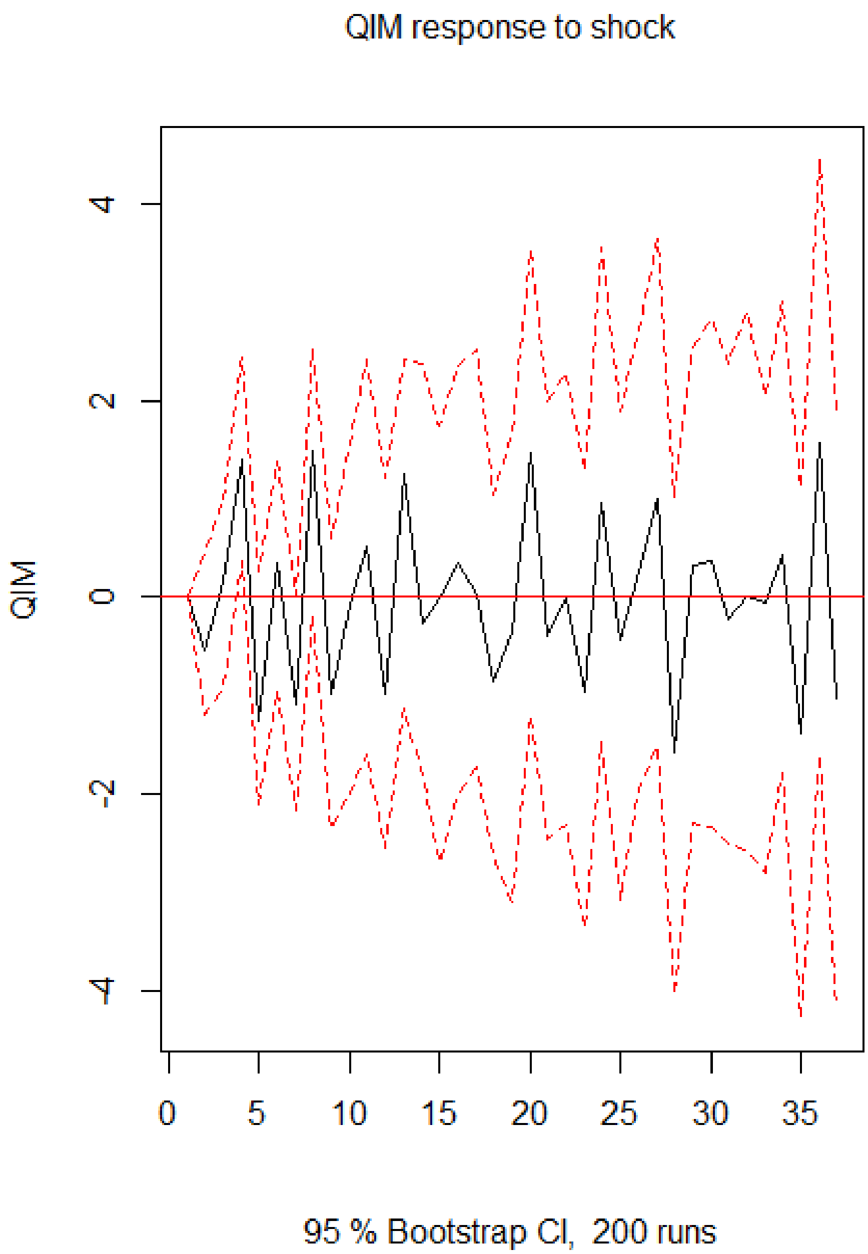


Figure 5.23: This figure shows the IRF for QIM on shock from ER in the S.V.A.R model

It is observed in figure 5.23 that a shock to ER at first has no instant effect but then it has a negative effect on QIM but then it will go up and down a cyclic pattern but at the end, it will have a strong negative trend.

Forecasts

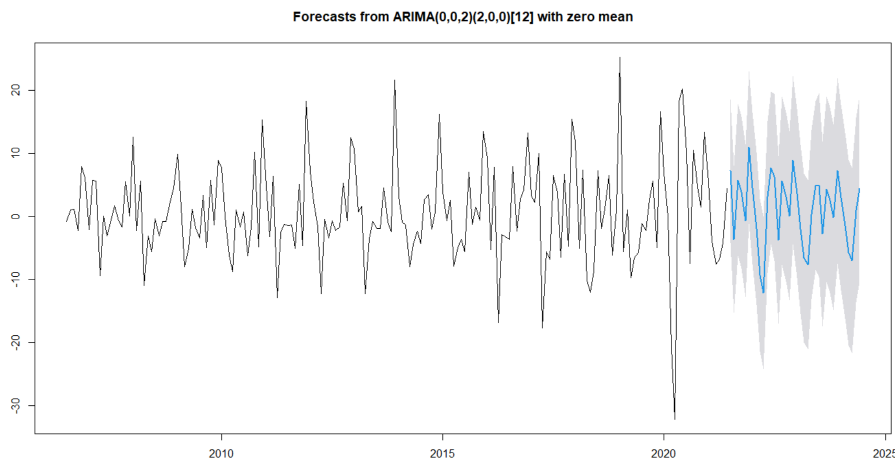


Figure 5.24: This figure shows the forecast obtained from A.R.I.M.A

It is observed in figure 5.24 that according to the A.R.I.M.A model next thirty-six months will yield a relatively low QIM. This means that unless we plan our policies in favor of the factors that boost QIM, at the current rate we will not make any progress.

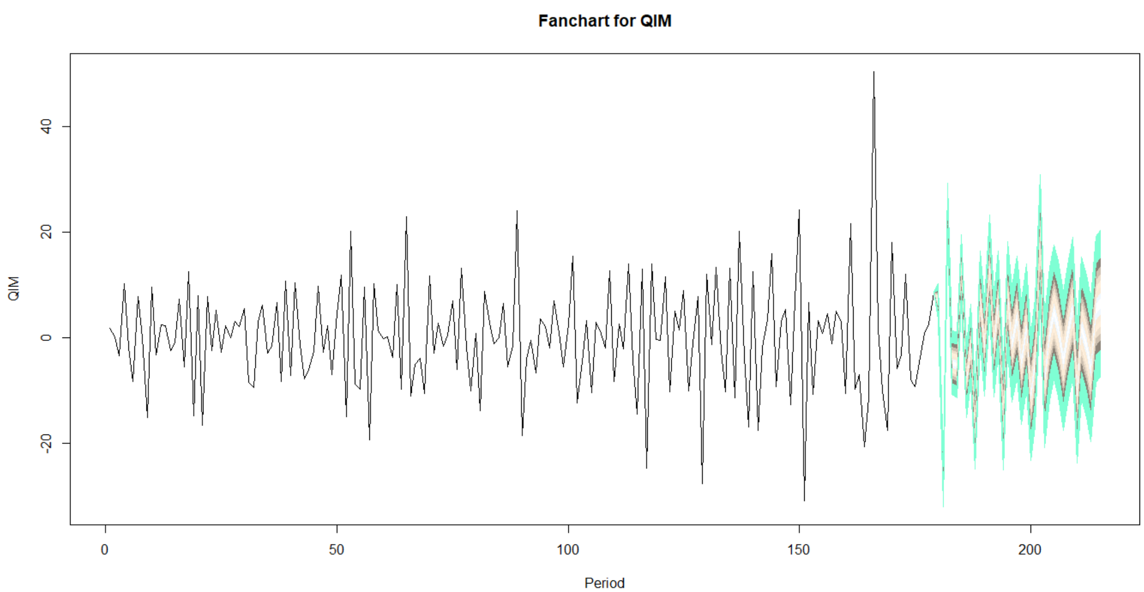


Figure 5.25: This figure shows the forecast obtained from V.E.C

It is observed in figure 5.25 that according to the V.E.C model next thirty-six months will yield a slightly increased QIM. This means that at the current rate we will move in a progressive pattern.

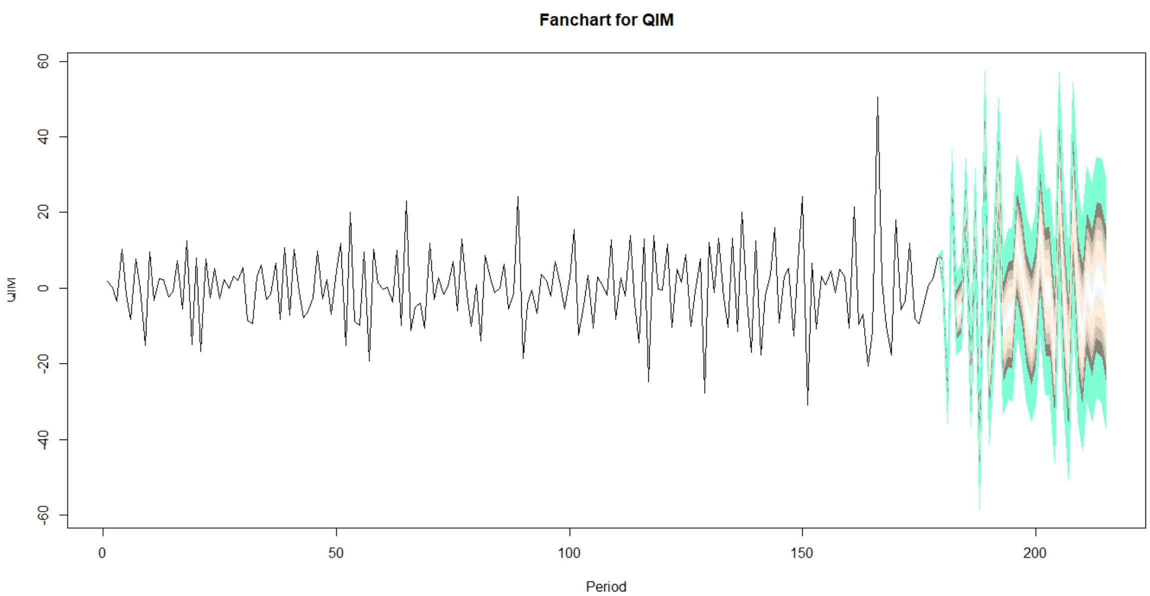


Figure 5.26: This figure shows the forecast obtained from V.A.R

It is observed in figure 5.24 that according to the V.A.R model next thirty-six months will yield a relatively low QIM. This means that unless we plan our policies in favor of the factors that boost QIM, at the current rate we will not make any progress.

Date	V.A.R	A.R.I.M.A	V.E.C
Jul-21	4.9870819	7.25980722	6.8400217
Aug-21	-28.3536522	-3.64348826	-27.3616694
Sep-21	28.1653686	5.79101227	23.9643576
Oct-21	-6.9906469	3.83108897	-4.7564082
Nov-21	-4.7589506	-0.67653690	-5.1439008
Dec-21	22.3913176	10.99469851	12.9648166
Jan-22	-24.1708022	4.49254143	-8.2243566
Feb-22	17.5511301	-1.89131592	-1.2656776
Mar-22	-43.2649785	-9.35962418	-16.820651
Apr-22	40.5715543	-12.14140092	7.5463565
May-22	-23.6995922	3.06597492	-1.9377165
Jun-22	0.4505681	7.70930009	13.7280902
Jul-22	30.5138298	6.25733626	-1.499457
Aug-22	-11.7981778	-3.80554115	6.5946162
Sep-22	-6.8924113	5.68281965	-14.9833135
Oct-22	-6.7984862	3.14770747	7.7336143
Nov-22	11.6878026	0.07882667	-1.330941
Dec-22	4.5784155	8.95167224	3.9047182
Jan-23	-5.597882	3.63617708	-4.8010184
Feb-23	-10.521407	-1.98871690	2.1436872
Mar-23	-4.9117324	-6.56079404	-11.1734124
Apr-23	15.5315459	-7.66878978	-4.6508526
May-23	-0.9818649	0.29975802	18.6139054
Jun-23	-0.8001128	4.90731593	-8.2852751
Jul-23	-18.6452363	4.99018605	0.7695934
Aug-23	28.8302739	-2.82149453	4.8944058
Sep-23	-1.6447622	4.31017604	1.7333299
Oct-23	-20.9769908	2.55980083	-4.4595437
Nov-23	24.3299688	-0.14950353	0.7486572
Dec-23	-4.9491926	7.30727745	5.7594682
Jan-24	-12.4105676	2.97554627	-10.4560179
Feb-24	1.4251997	-1.47095348	1.868969
Mar-24	-3.8972404	-5.71548238	-1.5532024
Apr-24	2.9427717	-7.01285518	-5.9984937
May-24	2.0694464	0.99069740	5.4321815
Jun-24	-4.0221782	4.47096688	6.3931565

Table 5.6: The forecasted values of QIM for the next 36 months

Model Preformance

Lastly, we evaluated the performance of our models to judge their power in forecasting and compared them using various error statistics, namely, mean error (ME), mean average error (MAE), mean square error (MSE), root mean squared error (RMSE), and normalized root mean squared error (NRMSE).

	V.A.R	A.R.I.M.A	V.E.C
ME	-2.83	-0.53	-2.53
MAE	25.92	6.09	14.73
MSE	989.72	65.29	324.60
RMSE	31.46	8.08	18.02
NRMSE	315.80	81.10	180.80

Table 5.7: Model validation results

The results from all of the measures of error state that A.R.I.M.A was the best-performing model for our data because it has the least error value. If we are to compare the V.A.R and V.E.C models, the results favor the results from the V.E.C model.

Chapter 6

Conclusion

This study focused on the variables affecting the growth of the quantum index of manufacturing in Pakistan. V.A.R, A.R.I.M.A, and V.E.C models were applied to the monthly time series data for the years 2006-07 to 2020-21 assuming the base year at 2005-06. From the results that we obtained, it is evident that the large-scale manufacturing industry is highly reliant on manufacturing loans, automobiles, coke and petroleum, food beverages and tobacco, exchange rate, foreign direct investment, non-metallic minerals, and the textile industry (in the short run). Results also depict that there is a certain level of error and uncertainty which is mainly because the data could not be obtained from the firms directly, but from secondary sources of information. Hence the possibility of data being biased or altered can not be ruled out. Much deeper analysis with much stronger sources is required to study this sector more efficiently.

It is advisable for the policymakers to focus on such policies that will boost the production of automobiles, coke and petroleum, food beverages and tobacco non-metallic minerals, and the textile industry, and increase manufacturing loans and foreign direct investment, these policies can be in the form of subsidies and relief packages to the manufacturers of these sectors. One key factor is found to be the exchange rate (pkr vs usd), lowering the difference between the two currencies will benefit the manufacturing sector. This will increase the growth of the economy as well in the long run.

Chapter 7

Limitations and Notes

The scarcity of literature related to this is a serious limitation, along with the unavailability of actual production data directly from firms. The application of neural networks to the problem can do wonders for us in this field.

Part of this research was presented at the 19th International Conference on Statistical Sciences organized by the Islamic Society of Statistical Sciences. The research was later on published in the proceedings of the conference http://www.isoss.net/proceedings.php. A snapshot of the conference and the publication has been provided in the appendix for reference.

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Appendix A

Appendix

A.1 Estimation results for S.V.A.R

	QIM	ML	WPI	BOT	FDI	TX	FBT	CP	PHA	NM	AUT	ISP	FER	ER
QIM	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
ML	0.06	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
WPI	0.07	0.01	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
BOT	0.09	-0.02	-0.09	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
FDI	0.85	1.02	0.34	-0.44	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
TX	0.10	0.04	0.05	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
FBT	-0.11	0.02	0.02	-0.07	-0.00	-0.68	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0
CP	0.01	-0.11	-0.02	0.10	0.01	-0.55	-0.40	1.00	0.00	0.00	0.00	0.00	0.00	0
PHA	-0.01	-0.00	-0.02	-0.11	-0.00	-0.20	-0.48	-0.78	1.00	0.00	0.00	0.00	0.00	0
NM	0.00	0.07	-0.01	0.14	0.03	0.17	-0.04	-0.08	-0.79	1.00	0.00	0.00	0.00	0
AUT	0.01	-0.07	-0.03	-0.09	0.00	-0.05	0.15	-0.01	-0.52	-0.72	1.00	0.00	0.00	0
ISP	0.00	0.08	0.03	-0.04	-0.00	-0.18	-0.10	0.04	0.08	-0.31	-0.72	1.00	0.00	0
FER	-0.02	0.00	-0.09	-0.05	-0.02	-0.62	-0.24	-0.24	-0.44	0.00	0.53	0.37	1.00	0
ER	-0.68	-0.91	0.05	0.41	-0.49	1.72	-0.05	0.01	0.54	-0.58	-1.20	1.94	-6.77	1

A.2 Covariance matrix for S.V.A.R

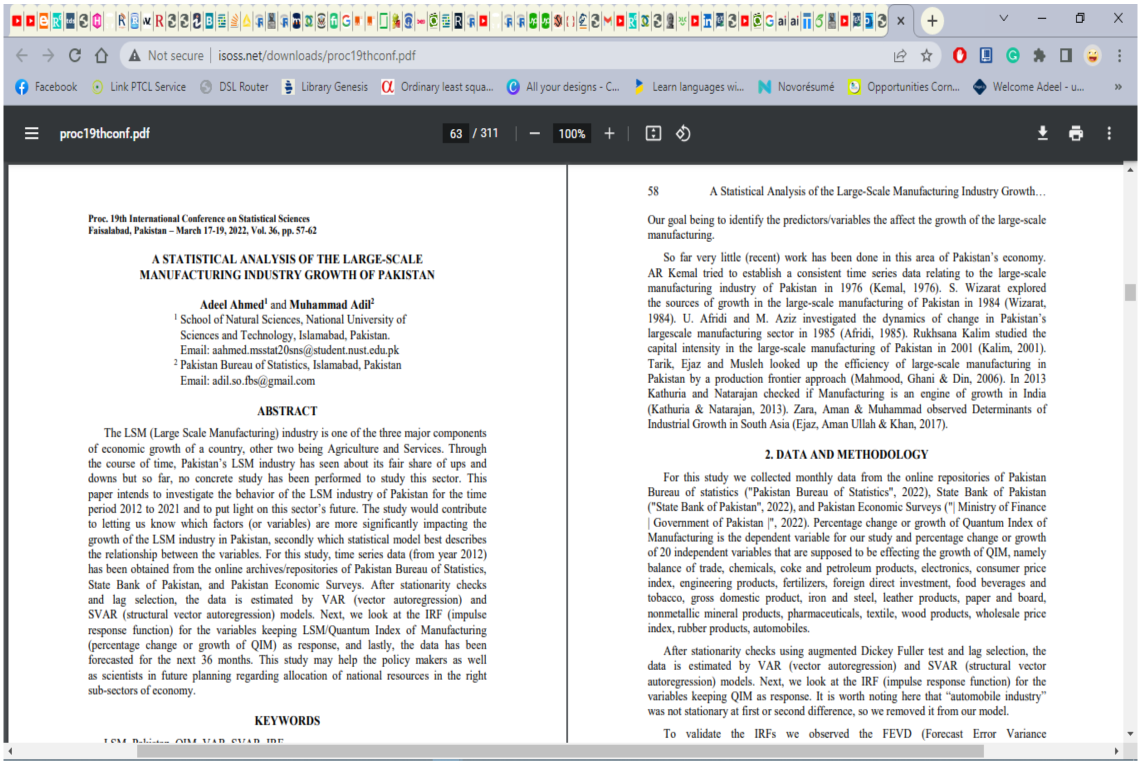
	QIM	ML	WPI	BOT	FDI	TX	FBT	CP	PHA	NM	AUT	ISP	FER	ER
QIM	100.00	-6.34	-7.19	-9.90	-80.64	-9.41	4.22	-3.10	-3.20	2.98	-3.49	-2.28	-5.49	9.79
ML	-6.34	100.40	-1.25	2.51	-95.70	-3.37	-6.13	8.71	3.21	-0.55	11.04	-3.05	-7.43	11.37
WPI	-7.19	-1.25	100.54	9.76	-23.02	-4.90	-5.57	-2.71	-2.17	-0.50	3.57	-1.70	1.58	0.29
BOT	-9.90	2.51	9.76	101.84	47.41	-0.14	6.34	-8.00	9.26	-9.51	6.87	6.59	4.91	-5.21
FDI	-80.64	-95.70	-23.02	47.41	295.47	12.84	7.64	-10.69	3.67	-10.18	-10.65	4.47	19.41	66.10
TX	-9.41	-3.37	-4.90	-0.14	12.84	101.36	69.01	83.76	119.73	86.45	119.70	126.64	41.71	-8.95
FBT	4.22	-6.13	-5.57	6.34	7.64	69.01	148.84	96.86	162.46	130.10	159.45	168.23	26.54	-81.22
CP	-3.10	8.71	-2.71	-8.00	-10.69	83.76	96.86	187.78	209.83	171.82	224.52	215.84	12.82	-213.60
PHA	-3.20	3.21	-2.17	9.26	3.67	119.73	162.46	209.83	368.29	292.97	387.57	373.01	-17.84	-609.60
NM	2.98	-0.55	-0.50	-9.51	-10.18	86.45	130.10	171.83	292.97	338.20	381.74	381.10	-90.80	-1000.89
AUT	-3.49	11.04	3.57	6.87	-10.65	119.70	159.45	224.52	387.57	381.74	562.96	524.66	-157.40	-1596.19
ISP	-2.28	-3.05	-1.70	6.59	4.47	126.64	168.23	215.84	373.01	381.10	524.66	601.96	-168.69	-1877.16
FER	-5.49	-7.43	1.58	4.91	19.41	41.71	26.54	12.82	-17.84	-90.80	-157.40	-168.69	276.32	1891.91
ER	9.79	11.37	0.29	-5.21	66.10	-8.95	-81.22	-213.60	-609.60	-1000.89	-1596.19	-1877.16	1891.91	14446.94

A.3 Standard errors for the estimation results for S.V.A.R

	QIM	ML	WPI	OT	FDI	TX	FBT	CP	PHA	NM	AUT	ISP	FER	ER
QIM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
ML	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
WPI	0.07	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
BOT	0.07	0.07	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
FDI	0.07	0.07	0.07	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
TX	0.10	0.11	0.08	0.08	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
FBT	0.10	0.11	0.08	0.08	0.07	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
CP	0.10	0.11	0.08	0.08	0.07	0.09	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0
PHA	0.10	0.11	0.08	0.08	0.07	0.10	0.08	0.07	0.00	0.00	0.00	0.00	0.00	0
NM	0.10	0.11	0.08	0.08	0.07	0.10	0.09	0.09	0.07	0.00	0.00	0.00	0.00	0
AUT	0.10	0.11	0.08	0.08	0.07	0.10	0.09	0.09	0.09	0.07	0.00	0.00	0.00	0
ISP	0.10	0.11	0.08	0.08	0.07	0.10	0.09	0.09	0.10	0.09	0.07	0.00	0.00	0
FER	0.10	0.11	0.08	0.08	0.07	0.10	0.09	0.09	0.10	0.09	0.09	0.07	0.00	0
ER	0.10	0.11	0.08	0.08	0.07	0.11	0.09	0.09	0.11	0.09	0.10	0.08	0.07	0

A.4 Publication Snapshot

The conference was held from march 17-19 2022 at the University of Agriculture, Faisalabad, Pakistan.



Proc. 19th International Conference on Statistical Sciences
Faisalabad, Pakistan – March 17-19, 2022, Vol. 36, pp. 57-62

A STATISTICAL ANALYSIS OF THE LARGE-SCALE MANUFACTURING INDUSTRY GROWTH OF PAKISTAN

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ABSTRACT

The LSM (Large Scale Manufacturing) industry is one of the three major components of economic growth of a country, other two being Agriculture and Services. Through the course of time, Pakistan's LSM industry has seen about its fair share of ups and downs but so far, no concrete study has been performed to study this sector. This paper intends to investigate the behavior of the LSM industry of Pakistan for the time period 2012 to 2021 and to put light on this sector's future. The study would contribute to letting us know which factors (or variables) are more significantly impacting the growth of the LSM industry in Pakistan, secondly which statistical model best describes the relationship between the variables. For this study, time series data (from year 2012) has been obtained from the online archives/repositories of Pakistan Bureau of Statistics, State Bank of Pakistan, and Pakistan Economic Surveys. After stationarity checks and lag selection, the data is estimated by VAR (vector autoregression) and SVAR (structural vector autoregression) models. Next, we look at the IRF (impulse response function) for the variables keeping LSM/Quantum Index of Manufacturing (percentage change or growth of QIM) as response, and lastly, the data has been forecasted for the next 36 months. This study may help the policy makers as well as scientists in future planning regarding allocation of national resources in the right sub-sectors of economy.

KEYWORDS

58 A Statistical Analysis of the Large-Scale Manufacturing Industry Growth…

Our goal being to identify the predictors/variables the affect the growth of the large-scale manufacturing.

So far very little (recent) work has been done in this area of Pakistan's economy. AR Kemal tried to establish a consistent time series data relating to the large-scale manufacturing industry of Pakistan in 1976 (Kemal, 1976). S. Wizarat explored the sources of growth in the large-scale manufacturing of Pakistan in 1984 (Wizarat, 1984). U. Afridi and M. Aziz investigated the dynamics of change in Pakistan's largescale manufacturing sector in 1985 (Afridi, 1985). Rukhsana Kalim studied the capital intensity in the large-scale manufacturing of Pakistan in 2001 (Kalim, 2001). Tarik, Ejaz and Musleh looked up the efficiency of large-scale manufacturing in Pakistan by a production frontier approach (Mahmood, Ghani & Din, 2006). In 2013 Kathuria and Natarajan checked if Manufacturing is an engine of growth in India (Kathuria & Natarajan, 2013). Zara, Aman & Muhammad observed Determinants of Industrial Growth in South Asia (Ejaz, Aman Ullah & Khan, 2017).

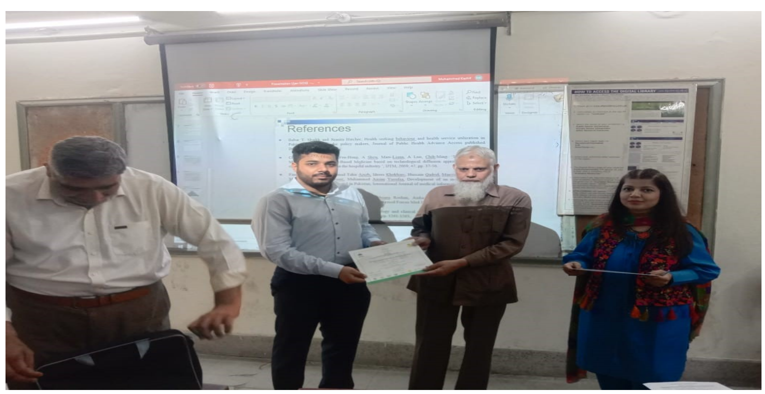
2. DATA AND METHODOLOGY

For this study we collected monthly data from the online repositories of Pakistan Bureau of statistics ("Pakistan Bureau of Statistics", 2022), State Bank of Pakistan ("State Bank of Pakistan", 2022), and Pakistan Economic Surveys ("| Ministry of Finance | Government of Pakistan |", 2022). Percentage change or growth of Quantum Index of Manufacturing is the dependent variable for our study and percentage change or growth of 20 independent variables that are supposed to be effecting the growth of QIM, namely balance of trade, chemicals, coke and petroleum products, electronics, consumer price index, engineering products, fertilizers, foreign direct investment, food beverages and tobacco, gross domestic product, iron and steel, leather products, paper and board, nonmetallic mineral products, pharmaceuticals, textile, wood products, wholesale price index, rubber products, automobiles.

After stationarity checks using augmented Dickey Fuller test and lag selection, the data is estimated by VAR (vector autoregression) and SVAR (structural vector autoregression) models. Next, we look at the IRF (impulse response function) for the variables keeping QIM as response. It is worth noting here that "automobile industry" was not stationary at first or second difference, so we removed it from our model.

To validate the IRFs we observed the FEVD (Forecast Error Variance

(a)



(b)

A.5 forecasted values of QIM calculated from our models compared with the original for the first 11 months of the forecast

Date	Actual QIM	V.A.R	A.R.I.M.A	V.E.C
Jul-21	-5.16773	4.9870819	7.25980722	6.8400217
Aug-21	2.104499	-28.3536522	-3.64348826	-27.3616694
Sep-21	0.355366	28.1653686	5.79101227	23.9643576
Oct-21	2.33711	-6.9906469	3.83108897	-4.7564082
Nov-21	2.00692	- 4.7589506	-0.67653690	-5.1439008
Dec-21	16.75712	22.3913176	10.99469851	12.9648166
Jan-22	8.367228	-24.1708022	4.49254143	-8.2243566
Feb-22	-2.30563	17.5511301	-1.89131592	-1.2656776
Mar-22	8.726674	-43.2649785	-9.35962418	-16.820651
Apr-22	-22.9177	40.5715543	-12.14140092	7.5463565
May-22	3.339882	-23.6995922	3.06597492	-1.9377165