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Research Article

IMPACT OF IMPLEMENTATION OF GST ON INFLATION WITH SPECIAL REFERENCE TO CONSUMER PRICE INDEX FOR INDUSTRIAL WORKERS IN INDIA

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Abstract: In India, the implementation of Goods and Service Tax (GST) has influenced an entire economy with the help of many economic indicators. One of the major economic indicators affected by the GST is inflation. This article has made an attempt to assess the impact of the implementation of GST on inflation in India through an empirical study using the Consumer Price Index for Industrial Workers (CPI-IW) data from January-2013 to September-2018. Time series intervention analysis has done through transfer function-noise models and Box-Jenkins methodology. The empirical study shows that the implementation of GST has affected inflation positively.

Keywords: GST, Inflation, ARIMA, Intervention Analysis, ACF and PACF

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Introduction

On 29th March 2017, the GST act has been passed by LokSabha accordingly it is implemented right from July 1, 2017. GST is an indirect tax which is replaced by multiple taxes like service tax, sales tax, VAT tax, etc imposed both by state and central governments of India. As per the experiences of different countries of the world, GST has brought multidimensional impact throughout the world. Few countries like Canada, Australia, China, Japan and Singapore experienced the positive impact. Whereas, some of the prominent countries like Greece, New Zealand, Thailand, Portugal, and Vietnam have experienced a reduction in the inflation rate. In this chapter, an attempt has been made to assess the impact of the implementation of GST on inflation in India through an empirical study using the Consumer Price Index (CPI-IW) data. Many of the researchers from economics, finance and business management [1-4] have studied the impact of the implementation of GST on inflation through naive statistical methods and fundamental theories of their respective domains. Hence, we the statisticians want to explore results of the implementation of GST on inflation through time series intervention analysis. ARIMA modeling is usually used in modeling time series data. Nevertheless, when the time series under study is disturbed by some external events such as strikes, legislation, and inclusion of new environmental regulations. Consequently, the ARIMA model's forecasting performances can be affected. However, it can be improved by applying appropriate techniques such as ARIMA-Intervention model. In various areas ARIMA intervention analysis has been intensively applied in order to recognize and measure event impacts [5-21]. Few are applied ARIMA intervention analysis on inflation series [22-24].

Material and Methods

The data considered for this study are monthly data of the Consumer Price Index for Industrial Workers by a year-on-year increase (in percentage) from Jan-2013 to Sept-2018 obtained from EPWRF India Time Series website. For intervention analysis, the entire data are broadly grouped into two categories pre-intervention periods and post-intervention periods. Initially, the pre-intervention time series is fitted using the ARIMA model. ARIMA intervention model is applied on account of assessing the impact of the intervention on the interested time series [5,11,16].

The general form of Seasonal ARIMA *(p,d,q)(P,D,Q)** is:

$$N_t = \frac{\theta_q(B)\Theta_Q(B^s)}{\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D}\epsilon_t$$

Where, $\Phi_P(B)$, $\phi_p(B)$, Θ_Q and $\theta_q(B)$ are seasonal and non-seasonal AR and MA operators respectively.

P,Q,D, p,q,d are order of seasonal and non-seasonal AR, MA and differencing operators respectively.

B is backshift operator and ε_t is white noise term

The general intervention model can be expressed as:

$$Y_t = \frac{\omega_s(B)}{\delta_r(B)}B^b\, I_t + N_t$$

Where, N_t is SARIMA model.

$\omega_s(B)B^b/\delta_r(B)$ is a transfer function with delay component.

I_t is an indicator variable.

Analysis and Discussion

We begin data analysis by examining the inflation data. The preliminary analysis starts with plotting a monthly inflation rate to understand the patterns and behaviours of the data. From [Fig-1] we can observe that from January-2013 to June-2017 there is a downward trend. From July-2017 the direction of the trend changes to upward. It may depict a slight seasonal pattern in the series, which is not quite clear and further seasonal identification plots can confirm the same. It also shows variance stability.

Modelling the Pre-intervention Inflation Series

[Fig-2] displays the autocorrelation plot of the pre-intervention monthly inflation rate series, it also presents a typical pattern for a nonstationary series with a slow decline in the size of the autocorrelations. The slow decline in the ACF as the number of lags increase is because of the trend, while the "sinusoidal" shape is due to the seasonality. [Fig-3] shows the partial autocorrelation plot of the pre-intervention monthly inflation rate series, it depicts a nonstationary series with a high spike close to 1 at the first lag.

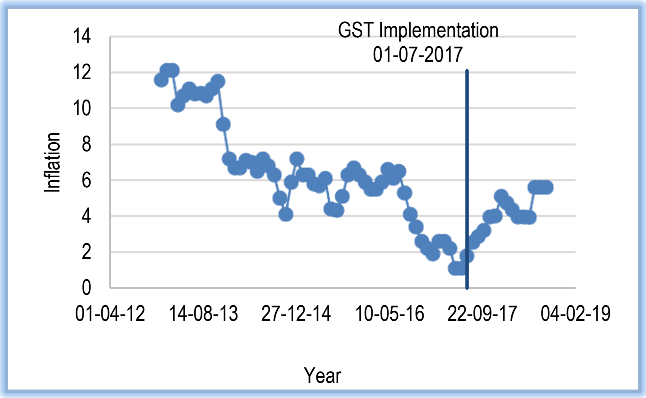

Fig-1 Time series plot of monthly Inflation rate for industrial workers (CPI-IW) of the India from January-2013 to September-2018.

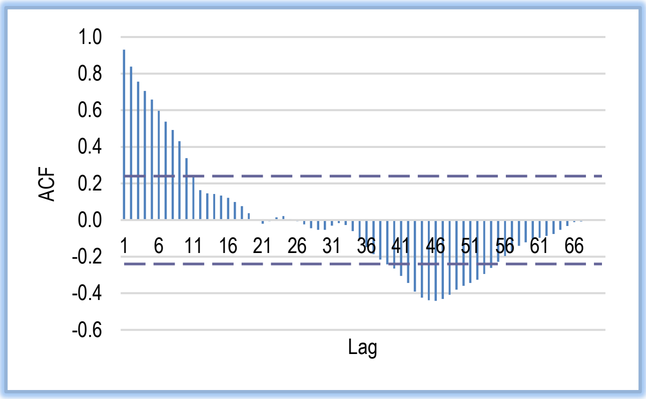

Fig-2 ACF plot of pre-intervention monthly Inflation rate (CPI-IW) of the India

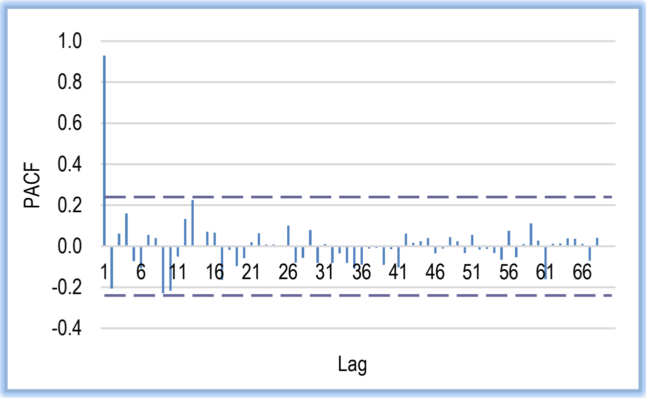

Fig-3 PACF plot of pre-intervention monthly Inflation rate (CPI-IW) of the India

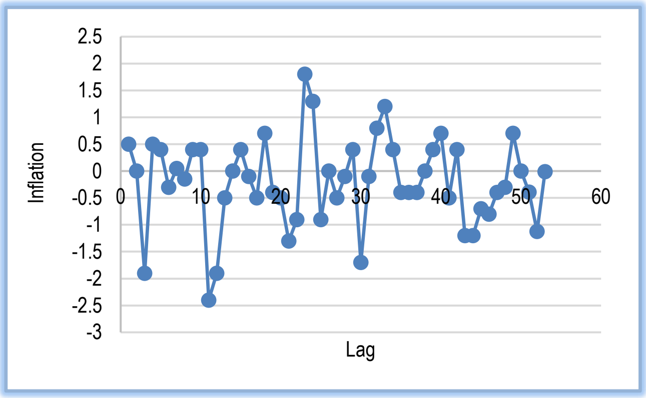

Fig-4 Time series plot of first-differenced pre-intervention series

Unit Root test

One way to figure out more objectively whether differencing is necessary is to employ a unit root test. These are the tests of stationarity that are developed for determining whether differencing is needed. Several unit root tests are present, which are based upon different assumptions. In our analysis, we employ the KPSS test as a unit root test.

Table-1 KPSS Test for pre-intervention series

Test Statistic	Lag Order	P-Value
0.2552	1	0.01

The test statistic value of 0.2552 with a p-value of 0.01, which is lower than the 0.05 (5 % level of significance), which indicates that the null hypothesis is rejected. In other words, the data are not stationary. Therefore, we can difference the data, and apply the test again. [Fig-4] depicts the time series plot of the first-differenced pre-intervention series, it is noticed that the series has no trend. The first differencing has made the series appear relatively stationary.

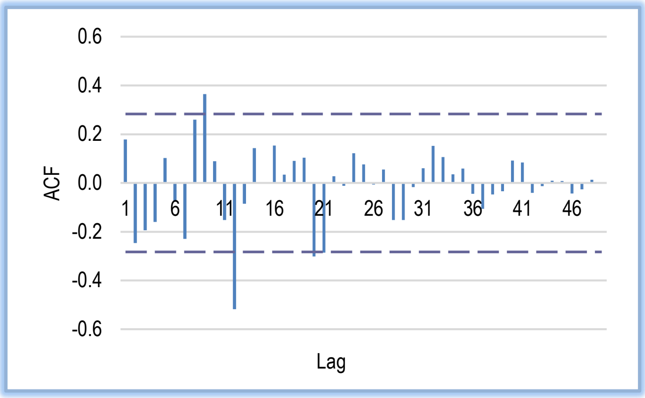

Fig-5 ACF plot of first differenced pre-intervention series.

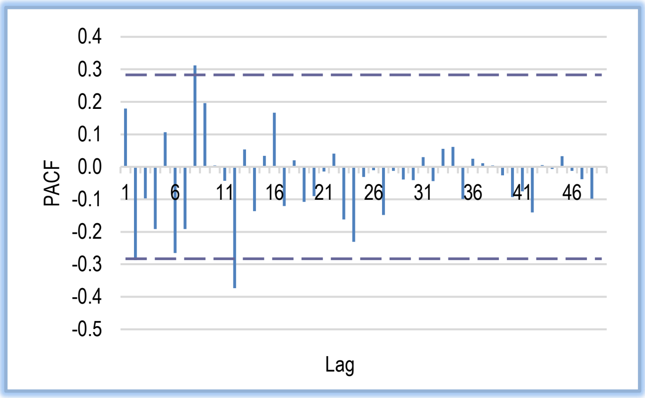

Fig-6 PACF plot of first differenced pre-intervention series.

The [Fig-5] and [Fig-6] display the ACF and PACF plots of first differenced pre-intervention series. From [Fig-5] and [Fig-6], it is noticed that there is no proof of the existence of non-stationarity in the series. Post first differencing we apply one more time, unit root tests to examine the stationarity of the differenced series.

Table-2 KPSS Test for differenced pre-intervention series

Test Statistic	Lag Order	P-Value
2.1767	1	0.01

At this point, the test statistic value of 2.1767 with a p-value of 0.01, which is much greater than the critical value of 0.05, thus we could expect for stationary data. Therefore, we can come to a decision that the differenced data are stationary.

Fitting a SARIMA model using pre-intervention series

The model identification procedure wherein the form and order of provisional models are chosen from the sample ACF and PACF of the differenced pre-intervention inflation rate series after the unit root tests have been confirmed to be stationary. Based on [Fig-5] and [Fig-6], it can be observed that there are no significant spikes at beginning few lags and no exponential decay of the early few lags. Therefore, we can conclude that the orders of non-seasonal AR and MA components are zero. There is a single significant spike at seasonal lag (lag 12) in both the ACF and PACF. Based on the ACF and PACF plots, we identified two models, they are SARIMA (0,1,0) (1,0,0)12 and SARIMA (0,1,0) 0,0,1)12.

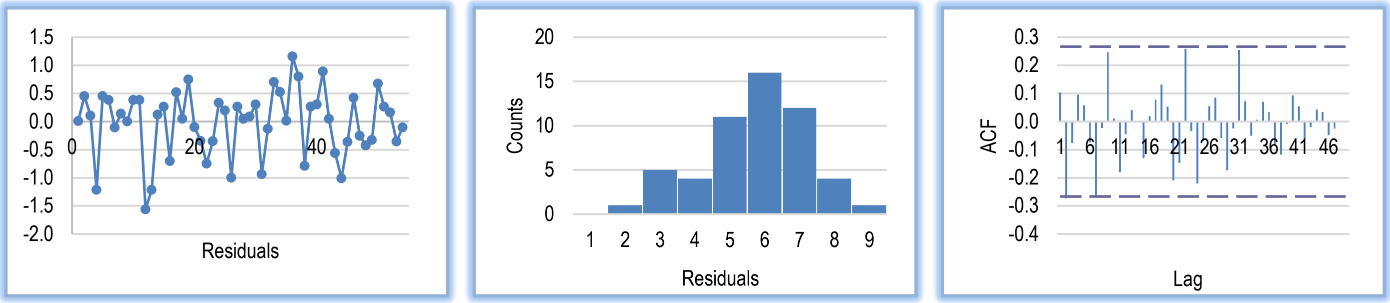

Fig-7 Residual plots for ARIMA model

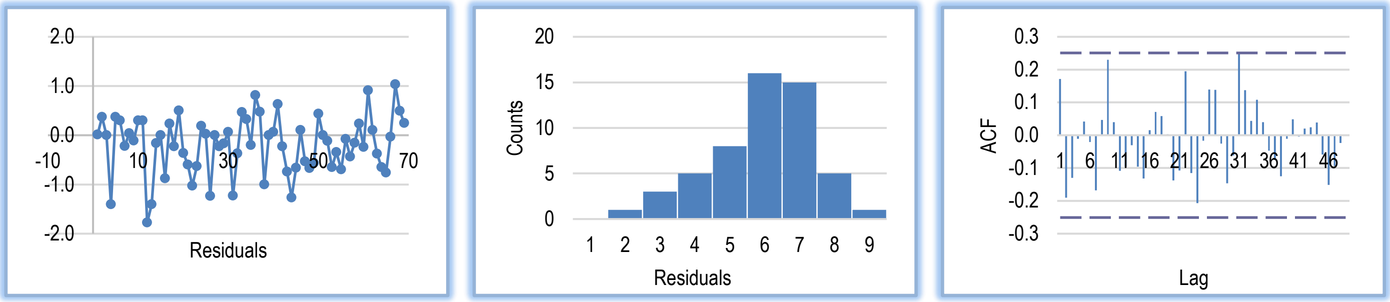

Fig-8 Residual plots for ARIMA Intervention model

Estimation of the model parameters

At this juncture, the parameters of the selected SARIMA(0, 1, 0)(1,0,0)12 model is estimated employing the maximum likelihood estimation method. In reference to the AIC and BIC criteria, this model is excellent among all the plausible estimated seasonal ARIMA models that are statistically significant. The outcomes from the estimated model are therefore presented in [Table-3].

Table-3 Parameter estimates for SARIMA (0,1,0)(1,0,0)[12] model

Type	Estimate	Standard Error	Z-Value	P-Value
C=Constant	-0.1531	0.0515	-2.9756	0.0029
SAR(1)(Φ_1)	-0.7195	0.0927	-7.7615	8.39E-15
σ^2	0.3473			

From [Table-3], both Intercept and Seasonal AR (1) are found to be statistically significant since their p-value of z-test are less than 0.05. Furthermore, the coefficient of the seasonal AR parameter estimate was found to confirm to the bounds of stationary since its respective value lies between-1 & 1.

Hence, the fitted Seasonal ARIMA (0, 1, 0)(1,0,0)12 model can be written as

$$\hat{\Phi}_1(B^{12})(1-B)N_t = C$$

Diagnostic checking of the fitted SARIMA model of pre-intervention series

Diagnostic checking of the fitted ARIMA model has been performed by using test Portmanteau Ljung Box test and different diagnostic plots.

[Fig-7] is composed of the line plot, ACF plot, and histogram of the residuals of the fitted SARIMA(0,1,0)(1,0,0)[12] model respectively. The line plot of the residuals obviously shows that the residuals seem to be randomly scattered about zero, no proof exists that the error terms are correlated with one another as well as no proof of the existence of an outlier. The ACF plot of the residuals depicts no proof of a significant spike in the ACF plot (the spikes are within the threshold limits) pointing out that the residuals appear to be uncorrelated. Lastly, the histogram plot of the residual shows that the residual terms are normally distributed.

From [Table-4], the p-value for the Ljung-Box test is higher than the chosen critical value of 0.05 and hence we fail to discard the null hypothesis and come to the conclusion that the residuals of the pre-intervention inflation-rate series model follow a white noise process.

Table-4 Ljung Box Test for pre-intervention series

Test Statistic	Degrees of Freedom	P-Value
15.092	8.8	0.0815

Modelling the Full Inflation Series

To formulate the intervention model, it quite needs to hypothesize the effect that the execution of GST may have had on the rate of inflation. Probably the easiest scenario in which the level of the inflation time series is supposed to permanently altered. So this is in par with hypothesizing that the intervention effect is a change in the inflation rate. Hence the input series should be a step function.

$$S_t = \begin{cases} 0 & t = 1,2,\dots,54 \\ 1 & t = 55,56,\dots,69. \end{cases}$$

Estimation of the Intervention model

$$Y_t = \hat{\omega}_0 S_t^{(55)} + \frac{1}{\hat{\Phi}_1(B^{12})(1-B)}$$

Table-5 Parameter estimates for SARIMA(0,1,0)(1,0,0)[12] intervention model

Type	Estimate	Standard Error	Z-Value
SAR(1)(Φ_1)	-0.6717	0.0927	-7.2452
ω	1.6728	0.5100	-3.2803
σ^2	0.3737		

From [Table-5], the coefficient of the estimated parameter for the seasonal AR (1) component is considerably differ from zero since its p-value of z-test is lower than 0.05, while the estimated Seasonal AR(1) coefficient again strictly conforms to the bounds of stationarity. The estimate of the impact parameter (ω) of 1.6728 is interpreted as the magnitude of the impact of the implementation of GST. Its positive sign indicates an increase in the inflation series as a result of GST and its corresponding p-value of the z-test indicates decline is statistically significant.

Diagnostic checking of the Intervention model

Figure is consists of the line plot, ACF plot and histogram of the residuals of the fitted SARIMA(0,1,0)(1,0,0)[12] intervention model respectively. The line plot of the residuals clearly depicts that the residuals look to be randomly scattered about zero, no proof exists that the error terms are correlated with one another as well as no proof of the existence of an outlier. The ACF plot of the residuals depicts no proof of a considerable spike outside the limits in the ACF plot pointing out that the residuals appear to be uncorrelated. Finally, the histogram plot of the residual depicts that the residual terms are normally distributed.

Table-6 Ljung Box Test for Full-intervention series

Test Statistic	Degrees of Freedom	P-Value
13.056	8	0.1099

From [Table-6], the p-value for the Ljung-Box test for white noise is 0.1099 which is higher than the chosen critical value of 0.05 and hence we fail to discard the null hypothesis and come to the conclusion that the residuals of the full intervention inflation-rate series model are white noise.

Conclusion

In this paper, in order to assess the impact of GST on inflation, an ARIMA intervention analysis has been applied. Based on the empirical analysis results, it is concluded that the ARIMA model for pre-intervention series and the ARIMA intervention model for the full series are statistically significant and from both portmanteau test and analysis of the residual plots, it could be stated that, both pre-intervention and full intervention models are adequate. Finally, the investigator arrived at a conclusion of saying that the implementation of GST, as an intervention on inflation has a significant and permanent positive impact.

Application of research: The ARIMA intervention model is applied on account of assessing the impact of the intervention on the interested time series (Agricultural, Economic, medical data *etc*).

Research Category: Time Series, Econometrics

Abbreviations: GST: Goods and Service Tax
ACF: Autocorrelation Function
PACF: Partial Autocorrelation Function
ARIMA: Autoregressive Integrated Moving Average.

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Cultivar / Variety / Breed name: Nil

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Ethical Committee Approval Number: Nil

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