9. FORECASTING INFLATION BY USING THE SUB-GROUPS OF BOTH CPI AND WPI: EVIDENCE FROM AUTO REGRESSION (AR) AND ARIMA MODELS

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Abstract

The undertaken study is conducted to forecast the inflation of Pakistan for the financial year FY2018-19 using two different time series techniques. In this research, we used consumer price index (CPI) and wholesale price index (WPI) with their sub-groups as inflation indicators for Pakistan. The undertaken research analyzes the proficiency of two important econometrics time series approaches such as Autoregressive (AR) with seasonal dummies, and Autoregressive integrated moving averaged (ARIMA) models by using root mean square (RMSE) criteria. In any economy, inflation and its forecasting are an imperative factor for the fiscal and monetary policies. The study is pertinent, as the forecasted figures of inflation start before the FY2018-19, which helps the policy makers to set the inflation target for FY2018-19. The month-to-month data has been considered for this study for the period from July 2008 to June 2018, and this research is concentrated on forecasting for the year 2018-19. In order to forecast CPI, we use 12 sub-groups and for WPI we use 5 sub-groups in both baskets for the 2007-08 base year. The result of this study reveals that the forecasted value of period average of CPI for the period FY2018-19 is 6.23 percent, however, for WPI is 8.96 percent.

Keywords: inflation forecasting; sub-groups of CPI; sub-groups of WPI; AR model with seasonal dummies; ARIMA model, RMSE technique

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1. Introduction

The only thing, which is certain about the future, is uncertainty. On the other hand, we cannot live with uncertainties. Therefore, we always try to convert the unknown elements of future into known facts as much as possible. This simulation is adopted in every field of study so as to make the decision-making activity more effective and accurate (Purwa et al., 2020). Keeping in view this significance of forecasting, the economic policy makers require certain models that enable them to look into the future and draw up the policies with precision and certainty. One of the most significant and uncertain economic elements is inflation that needs to be watched, analyzed and predicted before it gets too late for the policy makers (Vesna and Pejovic, 2021). According to the International Monetary Fund (IMF), the definition of inflation is: "Inflation is the rate of increase in prices over a given period of time" (Bokil and Schimmelpfennig, 2005, p. 10). On one hand, abrupt changes in inflation affect the standard of living of general public by eroding their purchasing power. On the other hand, it destroys the planning of the producers, sellers and government. Therefore, the uncertainty with regard to future inflation rate needs to be addressed by the policy makers so as to formulate effective monetary, fiscal and other policies (Jiranyakul, 2020).

In Pakistan, the country has experienced galloping and hyperinflation in the past. The reasons behind this were either the cost-push factors, such as oil prices, expensive electric power, devaluation of domestic currency or other demand-pull factors. It has been of great concern for the Central Bank to keep the inflation rate under control, and it has been under control for the last five years (Ghauri et al., 2019). However, the devaluation of the Pakistani Rupee (PKR) against the US dollar, the recent rise in oil prices, the unfavorable TORs of CPEC for Pakistan and some other factors are ringing the alarm for the policy makers pertaining to volatility in inflation rate. In this context, it has become inevitable for the regulator bodies to have an appropriate and accurate model of forecasting inflation rate. The previous literature pertaining to the exploration of determinants of inflation and inflation forecasting has relatively fewer studies on the context of Pakistan. However, there is no dearth of literature on this topic, which was carried out globally. In the Pakistani context, the important studies include Zhang et al. (2020), Štreimikienė et al. (2018), Haider and Hanif (2009), Bukhari and Feridun (2006), Riaz (2012), and Bokil and Schimmelpfennig (2006). However, Stock and Watson (2008), Antipin et al. (2014), Atkeson and Ohanian (2001), and Elliot and Timmermann (2008) have carried out their research studies in the context of US and Australia.

When we look at the previous studies, we reach the conclusion that the past researches on developed countries such as USA (Boubaker et al., 2020; Atkeson and Ohanian, 2001) have dominantly targeted overall regime of inflation. However, there are some exceptions to this, such as Vesna and Pejovic (2021), and Stock and Watson (2008), who have examined the progress of inflation forecasting models in segments. They explored different best performing models for different segments of time. As far as Pakistan is concerned, no research is found that investigates the inflation by using elements of forecasting CPI and WPI. In addition to this, the previous studies used a variety of modelling approaches that include vector auto regression models, single equation models and few other leading indicator models. However, it is relevant to note that none of the previous researches have compared different models in a single study. Keeping in view various inflation environments under development, in this paper we evaluated components of CPI and WPI, and forecasted inflation with different models, such as autoregressive and ARIMA (Guo et al., 2020; Gonçalves and Barreto-Souza, 2020).

In the recent past, the inflation has been higher and volatile in absolute sense in the Pakistani economy; thus, forecasting becomes a more difficult job in this scenario (Ghauri et al., 2019). In this paper, two inflation indicators, CPI and WPI, are used from July 2008 to April 2018. In order to forecast CPI, we use the CPI overall index and 12 sub-group indices. For WPI, we use the overall WPI index and 5 sub-groups indices of 2007-08 base year baskets . The weights composition of both CPI and WPI with base year 2007-08 has been used. The primary purpose of this research is to find out such a model of forecasting inflation rate for Pakistan that can reduce the future uncertainty and provide accurate outcomes. In this way, the policy makers would be able to use the forecasted rate of inflation and include this information in their policies.

To the best of our knowledge, there is no paper that uses components for forecasting CPI and WPI in the case of Pakistan. This study provides the basis to the government to take corrective measures in order to overcome inflation on the basis of CPI and WPI baskets. This paper is a value addition to the current literature on the considered topic; moreover, future studies may be conducted on the basis of this research paper for new perspectives on inflation and its implications. This study is helpful for other countries' researchers to explore their findings in the scenarios for their own economies. The study is also important to the policymakers of other developing countries.

2. Literature Review

The overview of past literature reveal that an extensive number of studies have brought into account the forecasting of variables related to macroeconomics and identified the progress of substitute model by incorporating out of sample forecasting (Ghoto, 2021; Ghauri et al., 2019). The significant econometric modeling used for inflation forecasting is the Philips curve model, univariate time series (ARIMA) model, interest rate model and the naive model (Işığıçok et al., 2020). Another approach is used to forecast inflation, i.e., the Philips Curve, whose study can be divided into different periods. Gordon (1982) was one of the first persons who studied the Philips Curve. He developed a triangle model that was helpful in forecasting fall in inflation during recession. Alderite and Capili (2020) and Stockton and Glassman (1987) have also made further attempts in this regard. The second period of study includes the researches that used different types of volatility in the coefficients of the Phillips curve, such as the slope and mean of the Euro area Philips curve. The prominent research studies in this respect are He et al. (2020) and Canova (2007). The last period included the literature that takes into consideration three measures of inflation and compares forecasts of different inflation measures: the GDP deflator, CPI-all and CPI-core inflation. Banbura and Mirza (2013) conducted research and made forecast for the GDP Deflator, long-run expectations of harmonized index of consumer price (HICP) and for the forecasting of HICP.

Fama and Gibbons (1984) have made initial attempt by using univariate model of real interest rate. They made a comparison between univariate and interest rate models and concluded that the later one is more precise. Eissa (2020), and Kenny, Meyler and Quinn (1998) have employed autoregressive integrated moving average (ARIMA) model to forecast inflation in the context of Ireland. They took into consideration two different methods to identify ARIMA, and they employed the objective penalty function technique, and the Box Jenkins approach (Ghazo, 2021). This research study helped in optimizing forecast performance by addressing multiple models for forecasting inflation in their country. Sekine (2001) also developed a model to forecast one-year inflation in Japan. He employed the equilibrium correction model (EqCM), and explored the long-run determinant of inflation. He concluded that the obtained EqCM would be able to perform for the structural model-based inflation forecasting, his approach was applicable widely in different countries.

Mohamed (2020) and Alles and Horton (1999) evaluated the progress of univariate time series, and interest rate models in forecasting inflation. Furthermore, the public survey of inflation forecast and error correction model were also used by Alles and Horton (1999). Both of these researches revealed that univariate model was found to be a satisfactory performer. A recent paper by Drachal (2020), Ghauri et al. (2019), and Štreimikienė et al. (2018) used both univariate and multivariate models for forecasting tax revenues of Pakistan. They used autoregressive model with seasonal dummies (AR model), autoregressive integrated moving average (ARIMA) model, vector autoregressive (VAR) model to forecast the tax revenues in Pakistan. They used three basic models to compare the forecasting of these time series models that include mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). They conclude that forecasting obtained from ARIMA model has minimum forecasting errors and, hence, considered to be the best model among the time series models analyzed in the paper. Two studies were carried by Saman and Pauna (2013) and Lee (2012) to evaluate the predictive performance of the naive model, univariate time series model and Philips Curve in forecasting inflation. He concluded that the efficiency of the univariate time series model was better than of the other two models. Few other studies, including Prüser (2021) and Ang et al. (2007) demonstrated that the univariate time series model (ARIMA) was proved to be either and outperformer, or equal performer as of the interest rate model or Philips curve for inflation forecasting in the case of the US economy.

Forecasting of macroeconomic variables with nonparametric methods mainly uses Artificial Neural Networks (ANNs). For the forecasting of inflation, Dadyan (2020), Mallick et al. (2020), Duzgun (2010), Binner et al. (2005) and Cameron (2000) have equated ANNs to ARIMA models. This strand of research finds that the sophisticated ANNs model tends to be better than or equal to ARIMA in performance in few of the cases. However, He et al. (2012) identified some contradictions and concluded that ANNs model is not better than the ARIMA model for making forecast of inflation in USA. Despite the dire need and interest in making forecast pertaining to macroeconomic variables in South Africa, not much effort have been made to compare economic techniques specifically to parametric and nonparametric models so as to give an indication on their suitability in making predictions (Guo, 2020). Woglom (2005) glares at the determinants of inflation forecasts and finds output gap, short term interest rate and import price inflation providing useful information in explaining inflation. On the other hand, Liu et al. (2009) have carried out their study by taking nominal short-term interest rate, inflation, and GDP growth rate, and for forecasting purposes they employed New Keynesian dynamic stochastic general equilibrium (NKDSGE) model in the context of South Africa. The authors compare the NKDSGE model with the classical and Bayesian VAR model and find the former model provides the best forecasting accuracy than the later models.

However, few have been carried out using alternative models of forecasting in South Africa. Khamis (2020), Gupta and Kabundi (2010) took into account five models that include Bayesian VAR model (BVAR), the small open economy new Keynesian dynamic stochastic general equilibrium (SOENKDSGE) model, small scale classical and Bayesian vector autoregressive model, and large scale dynamic factor (DFMs) models in order to forecast CPI inflation, growth rate of the nominal effective exchange rate, money market rate, and per capita growth rate. The large-scale BVAR model was proved to outperform the remaining models (Khan and Khan, 2020).

3. Material and Methods

3.1. Unit Root Test

The first purpose of this estimation is to test the unit root or to check the stationarity of data time series, as this is inevitable for conducting any higher and sophisticated econometric modeling. In order to conduct this test, we have numerous approaches to test the unit root; however, the Augmented Dickey-Fuller (1979, 1981) is the most popular approach to check the unit root. The simplified form of this test is expressed as follows:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{i=1}^{n} \alpha \Delta y_t + e_t \tag{1}$$

where: in Eq. (1), 'y' is a data series in time period 't', while, 'n' is known as the maximum number of lags, 'αo' refers to a constant value, whereas, the white noise error is regarded as 'e'.

3.2 The Autoregressive Integrated Moving Average Model (ARIMA Model)

3.2.1 ARMA Model

For the forecasting of future values in time series, the ARMA model is used. The ARMA model consists in two parts, the first is Autoregressive – AR (p), and second is Moving average – MA (q). Combining the ARMA (p, q) model we will get:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \phi_i X_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} \tag{2}$$

In Equation (2), the white noise error ε_t is usually presumed to be an independent, and uniformly distributed random variables (i, i, d) evaluated from the normal distribution with zero mean: $\varepsilon_t \sim N(0,\sigma^2)$ in which σ^2 is regarded as the variance.

3.2.2 ARIMA Model

The ARIMA model is derived from the ARMA, and it is the generalized shape of ARMA family. The ARIMA model is also known as the data concerned method (Qasim et al., 2020; Ghauri et al., 2019). Thus, the model AR (p) could be written as follows Eq. (4):

$$\varepsilon_t = \left(1 - \sum_{i=1}^{p} \phi_i L^i\right) X_t = \phi(L) X_t \tag{3}$$

where in Eq. (3) 'ϕ represents the polynomial function as: $\phi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i$.

The MA (q) model is given as in Eq. (4):

$$X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) = \theta(L)\varepsilon_t \tag{4}$$

where in Eq. (4) 'θ' denotes the polynomial function: $\theta(L) = 1 + \sum_{i=1}^{q} \theta_i L^i$.

Finally, we can write the combined model of ARMA (p, q) as in Eq. (5):

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \tag{5}$$

Or, more concisely, could be expressed as in Eq. (6):

$$\frac{\phi(L)}{\theta(L)} X_t = \varepsilon_t \tag{6}$$

3.4 Forecasting Error

As one knows, we encounter error in forecasting most of the time. Therefore, if we want to measure that error and bring about maximum possible accuracy in forecasting, the root mean square error (RMSE) technique is used. The mathematical expression for RMSE is shown in Eq. (7):

$$RMSE = \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{n} \qquad (7)$$

In Equation (15) 'n' means the forecasted numbers, and 'xi' refers to actual observed values; however, $\hat{x}_i$ denoted the forecasted values.

3.4. Data Collection

In this paper, two inflation indicators, CPI and WPI, were used from Jul 2008 to April 2018. Data were gathered from different issues of monthly bulletins of Pakistan Bureau of Statistics (PBS). For forecasting CPI, we use the CPI overall index and 12 sub-group indices and for WPI we use the overall WPI index and 5 sub-groups indices of 2007-08 base year baskets5. The weights composition of both CPI and WPI for 2007-08 base is reported in Table 1.

Table 1

The Weights Composition of Both CPI and WPI for the 2007–08 Base Year

Sub-groups of CPI (2007-08 base) Basket		Weights		Sub-groups of WPI (2007-08 base) Basket	Weights
G01	Food & Non-Alcoholic Beverages	34.8343	G1	Agriculture Forestry & Fishery Products	25.7674
G02	Alcoholic Beverages & Tobacco	1.4135	G2	Ores & Minerals, Electricity Gas & Water	12.0389
G03	Clothing & Footwear	7.5708	G3	Food Products, Beverages and Tobacco, Textiles, Apparel and Leather Products	31.1122
G04	Housing Water, Electric Power, Gas, Fuels	29.4149	G4	Other Transportable Goods Except Metal Products, Machinery and Equipment	22.3659
G05	Furnishing & Housing Equipment, Maintenance	4.2082	G5	Metal Product Machinery & Equipment	8.7156
G06	Health	2.1868			
G07	Transport	7.2023			
G08	Communication	3.2198			
G09	Recreation & Culture	2.0227			
G10	Education	3.9431			
G11	Restaurants & Hotels	1.2286			
G12	Miscellaneous	2.7550			

3.4 Data Analysis and Estimation Techniques

As already mentioned, the time series data used ranges from July 2008 to April 2018, including forecast inflation indicators CPI and WPI for Pakistan by taking its sub-groups indices. The study uses methods for forecasting inflation including Autoregressive integrated moving average (ARIMA), and Autoregressive (AR) with seasonal dummies approaches (natural log of all series). The empirical analysis for this paper starts with investigating the stationarity condition by using unit root test for the series. For checking the stationarity, we

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[5] *Sub-groups for CPI basket (base: 2007-08) are: G01 Food & Non-Alcoholic Beverages, G02 Alcoholic Beverages & Tobacco, G03 Clothing & Footwear, G04 Housing, Water, Electricity, Gas & other Fuel, G05 Furnished House Hold Equipment & Maintenance etc., G06 Health, G07.Transport, G08 Communication, G09 Recreation & Culture, G10 Education, G11, Restaurant & Hotels, G12 Miscellaneous*

employed Augmented Dickey-Fuller (ADF) (1979; 1981) and Philips Perron (1988) approaches. Both CPI and WPI with their sub-groups indices were estimated with the help of AR model along with seasonal dummies (Qasim et al., 2020; Khan and Khan, 2020; Zhang, 2013; Litterman, 1986; Doan, Litterman & Sims, 1984). Similarly, we estimated the ARIMA model for all series (Alderite and Capili, 2021; Štreimikienė et al., 2018; Ahmed et al., 2017; Zhang, 2013; Weiss, 1984; Box & Jenkins, 1976; Tiao & Box, 1975). Finally, by using both models we employed forecasting and ultimately compared the forecasting error of these models with the help of root mean squared error (RMSE) test (He et al., 2021; Štreimikienė et al., 2018; Ahmed et al., 2017; Zhang, 2013).

4. Empirical Data and Analysis

4.1 The Augmented Dickey-Fuller Approach

In this paper, we used the Augmented Dickey Fuller (ADF) and the Phillips Perron (PP) tests for checking the stationarity of the considered data series. Table 2a shows the result of the ADF test, which clearly indicates that the overall CPI and its sub-groups, G01 to G12, are stationary at 1st difference, i.e. they are I(1). For WPI and its sub-groups, G1 to G5 and overall WPI are stationary at 1st difference.

Table 2a

Stationarity of the Data Series (the ADF Test)

	ADF Test Statistics				
	At Level			At Ist Difference	
Variables	Value	P-value		Value	P-value
CPI					
G01	-1.3829	0.8612		-10.3371	0.0000
G02	-0.7805	0.9638		-9.0992	0.0000
G03	0.6315	0.9995		-9.1251	0.0000
G04	-2.3173	0.4210		-11.0214	0.0000
G05	-0.6949	0.9707		-3.8794	0.0159
G06	-1.2642	0.8917		-9.3736	0.0000
G07	-1.1508	0.9151		-8.7253	0.0000
G08	-2.0772	0.5528		-9.1697	0.0000
G09	-1.5397	0.8104		-10.6192	0.0000
G10	1.0804	0.9972		-2.8716	0.0521
G11	-0.5745	0.9785		-10.3167	0.0000
G12	-1.5321	0.8131		-10.5635	0.0000
Overall	-1.0088	0.9381		-10.9015	0.0000
WPI					
G1	-1.5952	0.7893		-8.3123	0.0000
G2	-0.7473	0.9666		-11.2417	0.0000
G3	-1.6474	0.7681		-10.8899	0.0000
G4	-1.4995	0.8246		-5.6992	0.0000
G5	-0.8058	0.9615		-6.6367	0.0000
Overall	-1.1875	0.9080		-6.6721	0.0000
Note: MacKinnon (1996) one-sided p-values at 1% level: -4.0370, at 5% level: -3.4480, at 10% level: --3.1491.					

Source: Authors' estimation.

Thus, we modeled all series with ARIMA model and AR model with seasonal dummies at 1st difference.Table 2b shows the results obtained with the PP test; this test also gives the same result as ADF; i.e., overall CPI and its sub-groups are all stationary at 1st difference and also overall WPI and its sub-groups are stationary at 1st difference.

Table 2b

Stationarity of the Data Series (the PP Test)

	Phillips-Perron Test Statistic				
	At Level			At Ist Difference	
Variables	Value	P-value		Value	P-value
CPI					
G01	-1.2114	0.9032		-11.1233	0.0000
G02	-1.0791	0.9275		-8.9985	0.0000
G03	0.0064	0.9960		-9.7749	0.0000
G04	-2.1296	0.5238		-15.3222	0.0000
G05	-0.5904	0.9776		-11.1549	0.0000
G06	-1.6018	0.7867		-9.4461	0.0000
G07	-1.2488	0.8951		-8.6260	0.0000
G08	-2.1940	0.4882		-9.1697	0.0000
G09	-1.5644	0.8012		-10.6206	0.0000
G10	1.2366	0.9983		-14.8164	0.0000
G11	-1.4410	0.8438		-10.3060	0.0000
G12	-1.5312	0.8134		-10.5633	0.0000
Overall	-0.9166	0.9499		-11.0587	0.0000
WPI					
G1	-1.7750	0.7108		-8.3123	0.0000
G2	-0.7170	0.9690		-11.2887	0.0000
G3	-1.6681	0.7593		-10.9388	0.0000
G4	-1.2488	0.8951		-5.3587	0.0001
G5	-0.8884	0.9531		-6.6136	0.0000
Overall	-1.1933	0.9069		-6.8004	0.0000
Note: MacKinnon (1996) one-sided p-values at 1% level: -4.0370, at 5% level: -3.4480, at 10% level: --3.1491.					

Source: Authors' estimation.

4.2. CPI Forecasting Using AR with Seasonal Dummies Model

12 sub-group indices of CPI and overall CPI index have been estimated by using the Autoregressive of different orders6 with seasonal dummies. After that, by using weighted average (using weights as given in Table 1) of forecasted values of 12 sub-group indices the overall CPI is also calculated. Table 3 shows the forecasted values of CPI inflation YoY for CPI and its 12 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 12 sub-group indices are 5.40% and 7.00%, respectively. However, when AR model with seasonal dummies is applied to overall CPI the YoY minimum and maximum inflation is 5.45% and 9.12%, respectively.

[6] *For G01 to G03 AR(1) model, G04 & G05 AR(2) model, G06 AR(11) model, G07 & G08 AR(1) model, G09 AR(3) model, G10 AR(6), G11 & G12 AR(1) and CPI overall AR(1) model are applied subject to statistical significance of the models.*

Table 3

Sub-group Wise Forecasted Value of CPI Inflation by Using the AR Model – YoY

Period	Overall#	Overall*	Sub-groups of CPI											
			G01	G02	G03	G04	G05	G06	G07	G08	G09	G10	G11	G12
Jul-18	5.45	5.59	3.82	2.38	6.60	4.92	5.86	5.67	14.33	0.50	6.29	12.97	5.24	7.04
Aug-18	6.38	6.27	5.39	4.20	7.13	4.56	6.87	5.97	14.67	0.29	6.77	13.49	6.07	7.55
Sep-18	6.13	6.29	5.27	5.07	7.68	4.09	7.16	6.28	15.45	0.50	7.28	14.04	6.01	8.17
Oct-18	5.77	6.18	5.39	5.07	7.98	3.88	7.61	6.87	15.69	0.32	7.53	9.36	5.94	9.48
Nov-18	6.34	6.44	6.05	5.25	8.13	3.69	8.14	7.16	15.07	0.61	7.71	9.85	6.59	9.66
Dec-18	7.07	6.78	7.37	5.41	8.43	3.27	8.94	6.43	12.63	0.76	7.72	10.36	7.57	9.88
Jan-19	7.46	6.52	6.62	5.42	8.21	3.83	8.40	6.69	10.63	1.23	7.58	10.90	7.76	9.45
Feb-19	9.01	7.00	8.11	4.76	8.50	3.25	8.89	6.29	10.63	1.56	7.82	11.32	8.52	10.32
Mar-19	9.12	6.48	7.84	4.30	8.54	2.70	9.10	6.69	9.61	1.49	7.17	6.53	9.22	10.48
Apr-19	7.78	5.40	7.54	4.84	6.71	0.76	7.61	6.54	9.97	1.23	3.57	4.76	8.64	8.08
May-19	7.66	6.14	8.40	6.31	7.98	0.41	8.35	6.95	10.27	2.33	5.21	9.64	8.91	8.60
Jun-19	7.48	5.65	7.58	6.80	8.24	-0.09	8.87	7.38	6.80	2.48	6.89	10.05	9.61	9.10
RMSE	0.0004		0.0057	0.0214	0.0074	0.0211	0.0059	0.0031	0.0136	0.0052	0.0141	0.0116	0.0031	0.0127

#: Forecasting of CPI by using AR with seasonal dummies model.
**: weighted average.*

Source: Authors' estimation.

4.3. WPI Forecasting Using AR with Seasonal Dummies Model

Autoregressive of order one with seasonal dummies to G1, G3, G4, G5 and overall WPI index, whereas for G2 autoregressive of order 15 are estimated. After that, by using weighted average (using weights as given in Table 1) of forecasted values of 5 sub-group indices the WPI overall is also calculated. Table 4 shows the forecasted values of WPI YoY inflation for WPI and its 5 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 5 sub-group indices are 6.82% and 10.41%, respectively. However, when AR model with seasonal dummies is applied to overall WPI the YoY minimum and maximum inflation is 8.14% and 10.63%, respectively.

Table 4

Sub-group Wise Forecasted Value of the WPI Inflation by Using the AR Model – YoY

Period	Overall#	Overall*	Sub-groups of WPI				
			G01	G02	G03	G04	G05
Jul-18	9.25	9.56	7.19	0.20	8.57	23.91	6.06
Aug-18	10.18	10.07	8.41	-0.53	8.17	26.02	6.26
Sep-18	10.63	10.41	8.38	-0.96	9.26	25.94	6.96
Oct-18	10.46	10.18	7.61	-1.45	9.98	24.74	7.35
Nov-18	10.05	9.69	7.18	-1.88	9.96	22.56	7.86
Dec-18	9.40	9.18	6.15	-2.58	10.17	21.35	8.20
Jan-19	8.53	8.09	4.89	-0.87	8.83	18.42	7.95
Feb-19	9.05	8.50	7.67	-1.15	9.62	14.57	8.26
Mar-19	9.55	8.82	8.36	-1.40	10.33	14.17	8.20
Apr-19	9.60	8.73	8.80	-1.82	9.91	14.18	7.55
May-19	8.86	7.73	7.98	-2.35	9.18	11.61	7.63
Jun-19	8.14	6.82	8.57	-2.92	8.53	7.61	6.86
RMSE	0.0064		0.0057	0.0036	0.0064	0.0269	0.0056
*#: Forecasting of CPI by using AR with seasonal dummies model *: weighted average*.							

Source: Authors' estimation.

4.4 CPI Forecasting Using the ARMA/ARIMA Model

Different orders of autoregressive processes and moving average processes are applied in order to get statistically significant ARMA/ARIMA model to 12 sub-group indices of CPI and overall CPI index. After that, by using weighted average of forecasted values of 12 sub-group indices the CPI overall is also calculated. Table 5 shows the forecasted values of CPI inflation YoY for overall CPI and its 12 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 12 sub-group indices is 5.48% and 7.69%, respectively. However, when ARIMA model is applied to overall CPI the YoY minimum and maximum inflation is 5.45% and 8.07%, respectively.

Table 5

Sub-group Wise Forecasted Value of the CPI Inflation by Using the ARIMA Model – YoY

Period	Overall#	Overall*	Sub-groups of CPI											
			G01	G02	G03	G04	G05	G06	G07	G08	G09	G10	G11	G12
Jul-18	5.45	5.45	3.82	0.41	6.60	4.42	5.86	5.67	14.33	0.50	6.25	12.97	5.24	7.04
Aug-18	6.70	6.39	4.95	0.44	7.07	5.73	6.76	6.18	15.81	0.55	7.14	12.01	5.95	7.18
Sep-18	6.15	6.13	3.84	0.74	7.64	5.92	6.91	6.38	15.36	0.83	6.85	13.24	5.24	7.12
Oct-18	5.82	5.87	3.96	0.91	7.81	5.14	7.54	6.88	14.83	1.03	6.99	9.49	4.72	8.01
Nov-18	5.95	6.42	4.24	1.12	8.42	6.46	7.97	7.36	14.50	1.18	7.85	9.26	5.22	7.57
Dec-18	6.49	6.98	5.43	1.24	8.89	6.61	8.49	6.85	14.28	1.40	7.53	9.35	5.36	7.86
Jan-19	7.04	6.87	5.64	1.23	8.54	6.07	8.31	7.14	13.00	1.63	7.37	10.68	5.41	7.51
Feb-19	7.90	7.69	6.67	1.27	9.12	7.38	8.90	6.72	12.33	1.77	7.45	10.94	6.11	8.42
Mar-19	8.07	7.39	6.34	1.37	9.04	7.52	8.78	7.08	11.35	1.92	6.78	7.08	6.24	8.64
Apr-19	6.67	6.07	5.34	1.64	7.56	5.37	7.72	6.86	11.50	1.94	3.88	4.98	5.77	6.36
May-19	6.62	6.79	5.90	1.82	8.27	6.60	8.51	7.19	11.03	2.17	4.38	6.17	5.92	6.92
Jun-19	6.52	6.53	5.30	1.71	8.42	6.75	8.52	7.54	8.32	2.43	5.68	6.55	6.27	7.50
RMSE	0.0074		0.0065	0.0156	0.0113	0.0067	0.0074	0.0025	0.0149	0.0021	0.0373	0.0119	0.0049	0.0132

*#: Forecasting of CPI by using ARIMA model *: weighted average.*

Source: Authors' estimation.

4.5 WPI Forecasting Using the ARMA/ARIMA Model

Different orders of autoregressive processes and moving average processes are applied in order to get statistically significant ARMA/ARIMA model to 5 sub-group indices of WPI and overall WPI index. After that, by using weighted average of forecasted values of 5 sub-group indices the WPI overall is also calculated. Table 6 shows the forecasted values of WPI YoY inflation for WPI and its 5 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 5 sub-group indices is 5.50% and 9.48%, respectively. However, when ARIMA model is applied to overall WPI the YoY minimum and maximum inflation is 8.53% and 11.00%, respectively.

Table 6

Sub-group Wise Forecasted Value of the WPI Inflation by Using the ARIMA Model – YoY

Period	Overall#	Overall*	Sub-groups of WPI				
			G01	G02	G03	G04	G05
Jul-18	9.28	8.91	6.97	0.91	6.43	23.98	5.99
Aug-18	10.06	9.13	8.06	0.99	5.46	25.10	6.21
Sep-18	10.75	9.48	8.14	1.33	6.03	25.26	6.88
Oct-18	10.56	9.29	7.94	1.60	5.74	24.47	7.45
Nov-18	10.71	9.34	9.40	2.01	5.23	22.52	7.97
Dec-18	11.00	9.39	10.23	2.09	4.92	21.59	8.54
Jan-19	9.75	7.86	8.33	2.55	3.14	18.77	8.89
Feb-19	10.58	8.45	11.84	3.14	3.36	15.13	9.43
Mar-19	10.95	8.59	11.96	3.87	3.49	14.83	9.69
Apr-19	10.20	7.64	10.21	4.30	2.53	14.17	8.53
May-19	9.47	6.67	9.67	4.67	1.29	11.70	8.27
Jun-19	8.53	5.50	9.41	4.96	0.12	7.89	7.77
RMSE	0.0094		0.0114	0.0040	0.0093	0.0256	0.0091
*#: Forecasting of WPI by using ARIMA model *: weighted average.*							

Source: Authors' estimation.

4.6. Forecasting on the Basis of RMSE

When comparing the AR model with seasonal dummies and the ARIMA model by using minimum criteria of root mean square error (RMSE), the majority forecasted values (7 out of 12) of CPI sub-groups indices supported the AR model with seasonal dummies and the remaining 5 sub-groups supported the ARIMA model. By applying both models to overall CPI index gives results in favor of the AR model with seasonal dummies (for detailed results see Table 3 and Table 4). When comparing the AR model with seasonal dummies and the ARIMA model by using minimum criteria of root mean square error (RMSE), the forecasted values for 4 out of 5 sub-groups of WPI supported the AR model with seasonal dummies and only 1 (G4) supported the ARIMA model. By applying both models to overall WPI index gives results in favor of the AR model with seasonal dummies (for detailed results see Table 5 and Table 6).

5. Results and Discussions

The findings of the ADF and PP tests clearly indicate that the overall CPI and its sub-groups, G01 to G12, are stationary at 1st difference. For WPI and its sub-groups, G1 to G5 and overall WPI are stationary at 1st difference also. Similar outcomes are shown by the previous literature such as (He et al., 2021; Ghauri et al., 2019; Boubaker et al., 2020). The findings of 12 sub-group indices of CPI and overall CPI index show the forecasted values of CPI inflation for CPI and its 12 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 12 sub-group indices are 5.40% and 7.00%, respectively. However, when AR model with seasonal dummies is applied to overall CPI the YoY minimum and maximum inflation is 5.45% and 9.12%, respectively. These results are in lined with the previous literature, for instance (Dadyan, 2020; Zhang, 2013; Litterman, 1986; Doan, Litterman & Sims, 1984). The findings of Autoregressive of order one with seasonal dummies to G1, G3, G4, G5 and overall WPI index, whereas for G2 autoregressive of order 15 show the forecasted values of WPI YoY inflation for WPI and its 5 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 5 sub-group indices are 6.82% and 10.41%, respectively. However, when AR model with seasonal dummies is applied to overall WPI the YoY minimum and maximum inflation is 8.14% and 10.63%, respectively. The findings are consistent with the previous studies such as (Qasim et al., 2020; Khan and Khan, 2020; Litterman, 1986; Doan, Litterman & Sims, 1984).

The findings show the forecasted values of CPI inflation for overall CPI and its 12 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 12 sub-group indices is 5.48% and 7.69%, respectively. However, when ARIMA model is applied to overall CPI the YoY minimum and maximum inflation is 5.45% and 8.07%, respectively. The previous literature also demonstrated the similar outcomes (Gonçalves and Barreto-Souza, 2020; Ghoto, 2021; Štreimikienė et al., 2018; Ahmed et al., 2017; Weiss, 1984; Box & Jenkins, 1976; Tiao & Box, 1975). The findings show the forecasted values of WPI inflation for WPI and its 5 sub-groups. For FY2018-19, the minimum and maximum YoY inflation for weighted average of forecasted values of 5 sub-group indices is 5.50% and 9.48%, respectively. However, when ARIMA model is applied to overall WPI the YoY minimum and maximum inflation is 8.53% and 11.00%, respectively. The findings are consistent with the previous literature, for instance (Alderite and Capili, 2021; Štreimikienė et al., 2018; Ahmed et al., 2017; Zhang, 2013; Weiss, 1984; Box & Jenkins, 1976; Tiao & Box, 1975). When comparing the AR model with seasonal dummies and the ARIMA model by using minimum criteria of root mean square error (RMSE), the majority forecasted values (7 out of 12) of CPI sub-groups indices supported the AR model with seasonal dummies and the remaining 5 sub-groups supported the ARIMA model. By applying both models to overall CPI index gives results in favor of the AR model with seasonal dummies. When comparing the AR model with seasonal dummies and the ARIMA model by using minimum criteria of root mean square error (RMSE), the forecasted values for 4 out of 5 sub-groups of WPI supported the AR model with seasonal dummies and only 1 (G4) supported the ARIMA model. By applying both models to overall WPI index gives results in favor of the AR model with seasonal dummies. Previous literature also exhibited the similar results in which the criteria of root mean square error (RMSE) demonstrated the superiority of the AR model with seasonal dummies (Vesna and Pejovic, 2021; Guo et al., 2020; Liu et al., 2009; Zhang, 2013; Doan, Litterman & Sims, 1984). However, previous literature also supported the ARIMA model such as (Zhang et al., 2020; Štreimikienė et al., 2018; Ghauri et al., 2019; Ahmed et al., 2017).

6. Conclusions

The research objective was to forecast the inflation of Pakistan for FY2018-19 using two different time series techniques. We use both wholesale price index (WPI), and consumer price index (CPI) with their sub-groups as inflation indicators for Pakistan. The research further analyzed the efficiency of these two time series with techniques such as: Autoregressive integrated moving average (ARIMA), and Autoregressive (AR) with seasonal dummies by using root mean square (RMSE) criteria. When comparing the AR model with seasonal dummies and the ARIMA model by using minimum criteria of root mean square error (RMSE), the majority of forecasted values (7 out of 12) of CPI sub-groups indices supported the AR model with seasonal dummies and the remaining 5 supported the ARIMA model. By applying both models to overall CPI index gives results in favor of the AR model with seasonal dummies. However, when comparing the AR model with seasonal dummies and the ARIMA model by using minimum criteria of root mean square error (RMSE), 4 forecasted values out of 5 sub-groups of WPI supported the AR model with seasonal dummies and only 1 (G4) supported the ARIMA model. By applying both models to overall WPI index gives results in favor of the AR model with seasonal dummies. Moreover, the result of this study revealed that forecasted values of CPI and WPI for the period of FY2018-19 (period average) are 6.23 percent and 8.96 percent, respectively.

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