# Dynamic Model for Price of Wheat in Bangladesh

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**Abstract**

Wheat is the second staple food of Bangladesh. In this paper we constructed a dynamic model for wheat price. Basically we constructed a single equation autoregressive integrated moving average (ARIMA) model of the price (quarterly wholesale wheat price). Standard ARIMA analysis rests on the simplifying assumption that the time series is stationary. So, at first stationary of the series is checked. An ARIMA (1,1,0) $(2,1,1)_4$ model is constructed based on the autocorrelation and partial autocorrelation functions. Finally, forecasts are made based on the model developed.

**Keywords:** Stationary, Autoregression, RMSFE, ARIMA

## 1. Introduction

Bangladesh is one of the most densely populated countries on earth. Food is a basic human need and plays a crucial role in the agro-based economy of Bangladesh, where a large proportion of the income of the population is allocated to food. The demand for cereal crop is constantly rising in Bangladesh with nearly 2.3 million people being added each year to its population of about 150 million. Cereal crop production increases must be achieved at a faster rate than in most other countries, while the land planted to cereal crop is not expanding. In addition, Bangladesh is faced with production constraints such as drought, lack of irrigation facilities, flooding and salinity of soils, coupled with fluctuating commercial cereal crop prices (Morris, *et. al.,* 1997). Karim (1997) reported that Bangladesh had annual food deficit of around 1.5 million metric tons, varying from year to year. Price difference is not only determined by the seasonal pattern it also depends on atmospheric changes (Shahabuddin and Dorosh, 1998). The analysis and forecasting of commodity prices continue to be important not only for utilizing commodity markets, but also for understanding their relationships to financial markets in a global context. Recent research in this area has been concerned with the underlying time series or structural character of prices (Tomek and Myers, 1993). Several studies have analyzed price relationships in the international wheat market (Gilmour and Fawcett 1987, Goodwin and Schroeder 1991, Goodwin 1992, Goodwin and Smith 1995).

In this paper we want to construct a seasonal autoregressive integrated moving average model of monthly wheat price (wholesale) in Bangladesh. An ARIMA process corresponds to the population mechanism that generates the time series. A model is based on sample data. Any ARIMA model build is a useful approximation of the true but unobservable underlying process. If a model is a good approximation of a process, the model tends to mimic the behavior of the process. Thus forecast from the model may provide useful information about future values of the series. Standard ARIMA analysis rests on the simplifying assumption that the process that generated a single time series is stationary.

## 2. Data source

In this work we are interested to construct ARIMA model for quarterly wholesale wheat price ($Z_t$) of Bangladesh for the periods 1984q3-2008q4. We took monthly time series data of 1984 (July) - 1995 (December), which are taken from the reliable publication "Agricultural Year Book" is published by Bangladesh Bureau of Statistics (BBS) and 1996 (January)-2008 (December) Agricultural Marketing Department, Bangladesh. We get wheat price in taka per quintal. Finally quarterly data is made by taking three month average.

## 3. Methodology

A general ARIMA (p, d, q) process may be written in a compact way using the following definitions:

$\nabla^d = (1-B)^d$ (the d-order differencing operator)

$\phi(B) = (1-\phi_1 B-\phi_2 B^2-\phi_3 B^3 - \ldots\ldots\ldots\ldots\ldots - \phi_p B^p)$ (the p-order AR operator)

$\theta(B)= (1-\theta_1 B-\theta_2 B^2-\theta_3 B^3- \ldots\ldots\ldots\ldots\ldots - \theta_q B^q)$ (the q-order MA operator)

Using these definitions, the general ARIMA (p, d, q) process is

$$\phi(B)\nabla^d Z_t = C+ \theta(B)\, b_t \qquad (3.1)$$

ARIMA models can also represent seasonal (or other periodic) and combined seasonal and nonseasonal patterns. A nonseasonal part of an ARIMA pattern expressed as in (3.1), but suppose the seasonal part is not represented yet in the process. Therefore the random shock series is not uncorrelated but instead is a series (denoted $b_t$) that contains a seasonal pattern. Thus we can write the nonseasonal part as

$$\phi(B)\nabla^d Z_t = C^* + \theta(B)\, b_t \qquad (3.2)$$

where $C^* = \mu\left(1-\sum_{i=1}^{p}\varphi_i\right)$; if d=0, then $\mu=\mu_z$; if d>0, then $\mu=\mu_w$; w is the differenced series.

Now suppose the seasonal pattern in the series $b_t$ can be represented by AR and MA terms at the seasonal lags up to some maximum AR seasonal lags (Ps) and some maximum MA seasonal lag (Qs). Define the following operators:

$\nabla_s^D = (1-B^s)^D$ (the D-order seasonal differencing operator)

$\phi(B) = (1-\phi_s B^s-\phi_{2s} B^{2s}-\phi_{3s} B^{3s} - \ldots\ldots\ldots\ldots\ldots - \phi_{ps} B^{ps})$ (the P-order seasonal AR operator)

$\theta(B)= (1-\theta_s B^s-\theta_{2s} B^{2s}-\theta_{3s} B^{3s}- \ldots\ldots\ldots\ldots\ldots - \theta_{qs} B^{qs})$ (the Q-order seasonal MA operator)

Now suppose that the seasonal behavior of $b_t$ can be described as

$$\phi(B^s)\nabla_s^D b_t = \theta(B^s)\, a_t \qquad (3.3)$$

Solving (3.13) for $b_t$ gives $b_t = [\theta(B^s)/\ \phi(B^s)\nabla_s^D]a_t$; substitute this expression for $b_t$ into (3.3) and rearrange to get the combined multiplicative seasonal and nonseasonal ARIMA (p, d, q)(P, D, Q)$_s$ process

$$\phi(B^s)\ \phi(B)\nabla_s^D\, \nabla^d Z_t = C+ \theta(B^s)\theta(B)\, a_t$$

where $C = \phi(B^s)\, C^* = \mu\left(1-\sum_{i=1}^{p}\varphi_i\right)\left(1-\sum_{i=1}^{P}\varphi_{is}\right)$

If d=D=0 then $\mu=\mu_z$; otherwise $\mu=\mu_w$, the mean of the differenced series $w_t=\nabla_s^D\ \nabla^d Z_t$. In practice all the orders (p, d, q, P, D, Q) tend to be small, often no more than 1 or 2. The nonseasonal and seasonal AR operators multiply each other, and the nonseaonal and seasonal MA operators multiply each other. These elements may also be treated as additive.

# 4. Time Series Properties of the Variable and Model building

Time series can be characterized in many ways. In checking the time series properties, we focus on the presence or absence of unit roots or stochastic trends in the variable used in this article. In order to form a statistically adequate model, like ARIMA(p,d,q), the variable should first be checked as to whether they could be considered as stationary or non-stationary.

## 4.1. Tests for the orders of integration of the data

Identification of the orders of integration of nominal wheat price is an important issue before modelling an ARIMA(p,d,q). Unfortunately, it is well known that unit-root tests have low power and that results can vary with the types of test used and on the number of lags included in the test equations. For this reason, it becomes a strategy among the researchers to examine the results of several test procedures in order to draw conclusions regarding variable integration. With this in mind, three unit root tests procedures are performed: (i) most widely used Augmented Dicky-Fuller (ADF) test of Dicky and Fuller (1979, 1981) (ii) the asymptotically most powerful DF-GLS test of Elliott *et al*. (1996) and (iii) the Kwiatkowski *et al*. (1992) LM test (KPSS). The null hypothesis of ADF and DF-GLS tests is that a time series variable has a unit root while that of KPSS test is that a variable is stationary. A common strategy is to present results of both ADF/DF-GLS and KPSS tests, and show that the results are consistent (e.g., that the former reject the null while the later fail to do so and vice-versa). The lag length is selected by using the Akaike Information Criteria (AIC).

Before beginning the formal tests for unit roots, the variables should be plotted against time to visually determine if a trend exists in the time series. The necessity of this step is simply due to the fact that the critical values of the tests depend on the sample size and the inclusion of deterministic components, i.e., the inclusion of a constant and a time trend. Logarithm of price variable in level has been graphed against time in Figure 1(a) over the period 1984q3-2008q4. By referring Figure 1(a), it is visually evident that price series presents upward trend. This upward trend indicates that the series is non-stationary, but it is difficult to guess whether the trend is deterministic or stochastic. Sample

**Figure 1(a):** Logarithm of wheat price in level over the period 1946q3-2008q4

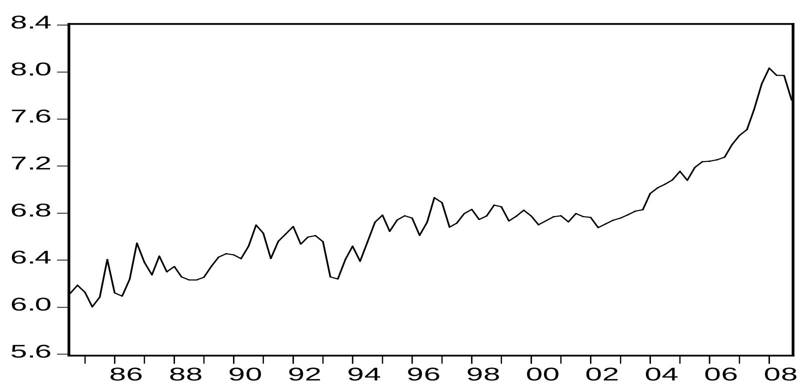


**Figure 2(a):** SACF for wheat price in level over the period 1984q3-2008q4

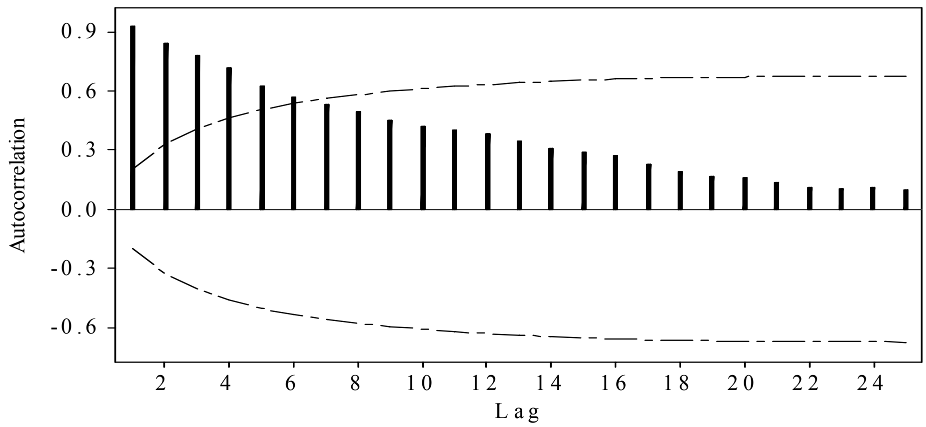
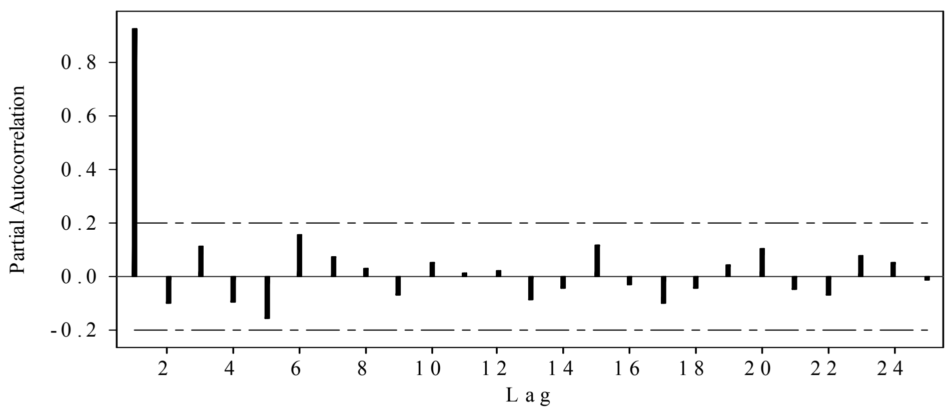



**Figure 2(b):** SPACF for wheat price in level over the period 1984q3-2008q4




correlograms of wheat price in level (d=D=0) for sample autocorrelations (SAC) and sample partial autocorrelations (SPAC) are depicted in figures 2(a) and 2(b). The key feature of this SAC is that the spikes decay very slowly to zero. That is, the feature of this sample correlogram is that many autocorrelation functions lie outside the 95-percent confidence interval. This type of pattern is generally an indication that the time series is non-stationary. Since wheat price shows upward trend, both constant, and constant and trend are used in the models to test for unit roots. Table 1 contains the results for three test procedures mentioned above. For the level series, both ADF and DF-GLS tests cannot reject the null hypothesis of unit root, while KPSS test reject the null hypothesis of stationarity. For first difference series both ADF and DF-GLS tests reject the null hypothesis of unit root, while KPSS test cannot reject the null hypothesis of stationarity. These results conclude that wheat price is integrated of order one, that is, I (1).

**Table 1:** Unit-root tests for the order of integration

| ADF | | DF-GLS | | KPSS | |
|---|---|---|---|---|---|
| **constant** | **constant & trend** | **constant** | **constant & trend** | **constant** | **constant & trend** |
| **Level** | | | | | |
| 0.3026(6) | -2.3249(4) | 1.3839 | -2.4277(4) | 1.1220(7)*** | 0.1741(6)** |
| **First difference** | | | | | |
| -4.7770(5)*** | -4.7972(5)*** | -3.4693(3)*** | -3.1353(3)*** | 0.2764(46) | 0.0678(3) |

**Note:** Constant, and constant and linear trend terms are included in ADF, DF-GLS and KPSS tests. **, and *** indicate statistical significance at the 5 and 1 percent levels respectively. The lag length was determined using the AIC, with a maximum of 12 lags considered. First bracket contains number of lag for ADF and DF-GLS tests and number of bandwidth for KPSS test

### 4.2. Seasonality

The non-seasonal first differences (d=1) of wheat price plotted in Figure 1(b) moves through a constant value, which indicate that the first difference of wheat price is stationary or integrated of order one, I(0). This implies indicate that the first difference of wheat price is non-stationary or integrated of order one, I(1). But the data in Figure 1(b) shows a strong seasonal variation. SACF and SPACF for the first difference of wheat price series are shown in Figures 3(a) and 3(b) respectively. Significant seasonal pattern is obviously seen in SACF in Figure 3(a) for differenced series. To remove this seasonal pattern, seasonal first difference is made on non-seasonal. SACF and SPACF are displayed in Figure 4(a) and Figure 4(b) respectively. These figures shows that non-seasonal and seasonal differencing series returns quickly to a constant overall mean, and the seasonal strong pattern is gone.

**Figure 1(a):** Logarithm of wheat price in level over the period 1984q3-2008q4

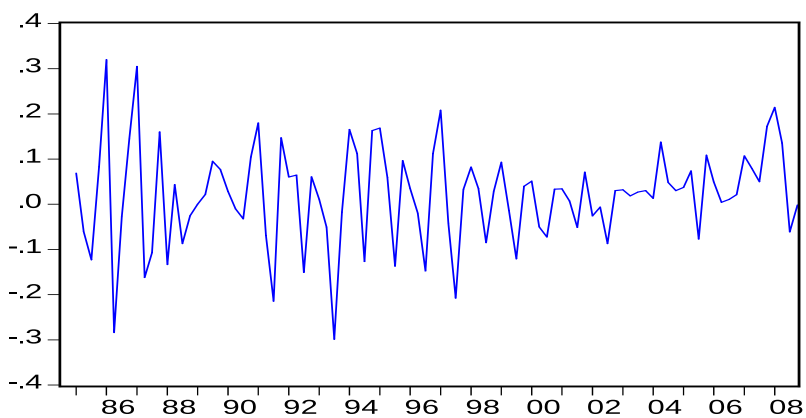


**Figure 3(a):** SACF for first difference wheat price over the period 1984q3-2008q4

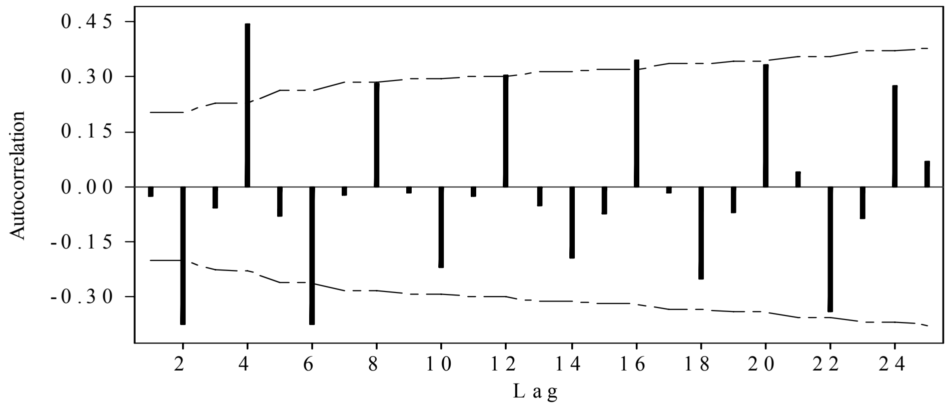



**Figure 3(b):** SPACF for first difference wheat price over the period 1984q3-2008q4

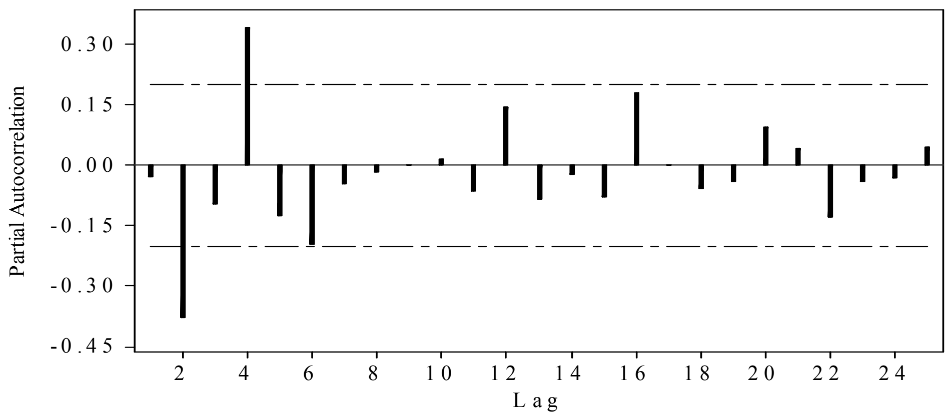



**Figure 4(a):** SACF for both non-seasonal and seasonal first difference wheat price over the period 1984q3-2008q4

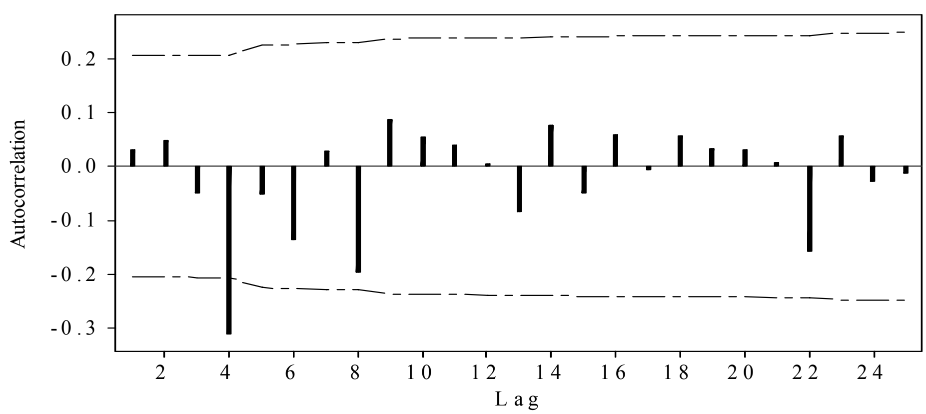
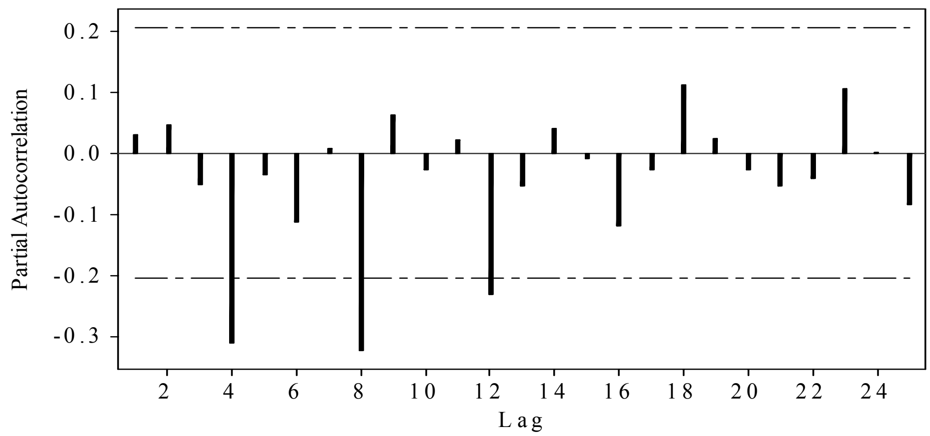


**Figure 4(b):** SPACF for both non-seasonal and seasonal first difference wheat price over the period 1984q3-2008q4




As a formal test for seasonality, we used the auxiliary regression in equation (4.1) proposed by Miron (1994).

$$(1-L)y_t = \gamma_1 s_{1t} + \gamma_2 s_{2t} + \gamma_3 s_{3t} + \gamma_4 s_{4t} + \varepsilon_t \quad (4.1)$$

where $s_{st}$ (=1 in season $s$, 0 elsewhere, for $s$ = 1, 2, 3, 4) is a seasonal dummy variable and $\varepsilon_t$ is assumed to be a stationary and invertible ARMA process. If any logarithmic variable $y_t$ is taken as the dependent variable, the equation involves the regression of the growth rate of the variable on a set of seasonal dummy variables. Estimates of the $\gamma_s$ ($s$ = 1, 2, 3, 4) coefficients can be used to observe the pattern of seasonality which are shown in Table 2. As can be seen from the table, except last one all coefficients are highly significant. Thus it can be concluded that wheat price exhibit seasonal patterns.

**Table 2:** Estimates of auxiliary regression

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| S1 | -0.082543 | 0.018036 | -4.576514 | 0.0000 |
| S2 | 0.070952 | 0.018036 | 3.933879 | 0.0002 |
| S3 | 0.087737 | 0.018036 | 4.864492 | 0.0000 |
| S4 | 0.001024 | 0.018036 | 0.056797 | 0.9548 |

## 4.3. Model Building

There is no formal procedure to choose the best model for modeling a time series in ARIMA framework. Although SACF and SPACF are helpful in choosing an ARIMA model, we rely on the criteria of root mean squared forecast error (RMSFE). That is, we choose a variety of ARIMA model for forecasting. The model which has minimum RMSFE would be selected as the best model for modeling wheat price under study.

There is one defensible way to account for the remaining nonseasonal pattern: We can include an AR(1) component. The AR(1) seems justified since the SPACF in Figure 2(b) has a large spike at lag 1, followed by an irregular pattern that could be interpreted as a cut-off to zero values. Further, the SPACF in Figure 2(b) could be loosely interpreted as decaying on the positive side. The SACF and SPACF look somewhat like the theoretical AR(1). The AR(1) option is attractive since it is quite parsimonious: it calls just one estimated coefficient after differencing. Further, choosing an AR(1) gives us an ARIMA(1,1,0) for the nonseasonal part of the model. Also, there is one defensible way to account for the remaining seasonal pattern: We can include an SMA(1) component. The SMA(1) seems justified since the SACF in Figure 4(a) has a large spike at lag 4, followed by an irregular pattern that could be interpreted as a cut-off to zero values. Further, the SPACF in Figure 4(b) shows two significant seasonal spike and then loosely interpreted as decaying on the negative side. That is, SPACF look somewhat like the theoretical SAR(2). The SAR(2) option is attractive since it is quite parsimonious: it calls just two estimated coefficient after differencing. Further, choosing SAR(2) and SMA(1) gives us an ARIMA$(2,1,1)_4$ for the seasonal part of the model. So, finally we may fit the model ARIMA(1,1,0)(2,1,1)4.

## 5. Estimation and diagnostic checking

Using our data the estimated ARIMA $(1, 1, 0)(2,1,1)_4$ model is

$$(1- 0.031B)(1+0.223B^2)\nabla_4 (1\text{-}0.026B)\nabla Z_t = 0.001 + (1\text{-}0.721B^4)a_t \tag{5.1}$$

t = (0.200) (-1.624) (0.252) (2.503) (5.423)

$\hat{\sigma}_a^2 = 128.413$

If (5.1) is an adequate ARIMA model, then the residuals $a_t$, taken from this equation should from a stationary series. Figures 5(a) and 5(b) shows the sample ACF and PACF of residuals. We have shown the ACF and PACF upto 25 lags. One feature of this ACF and PACFs, there is no ACF and PACF is lie outside the interval. So we may say that the residuals series is stationary.

**Figure 5(a):** SACF for residuals of the fitted model

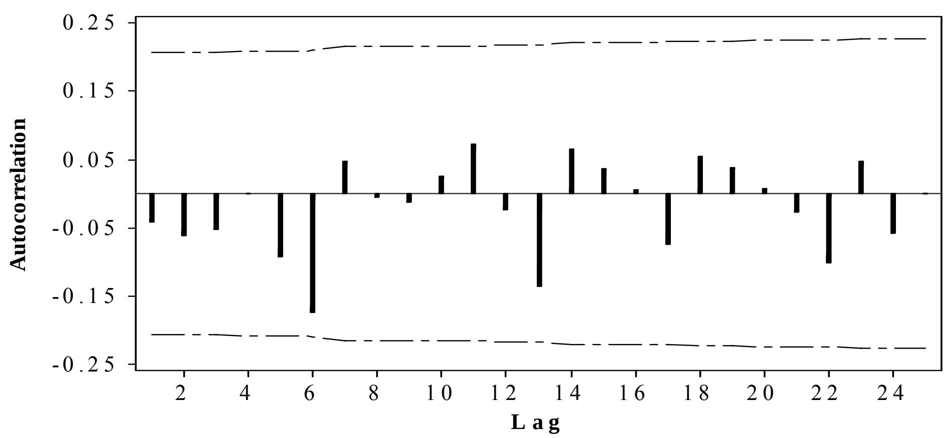
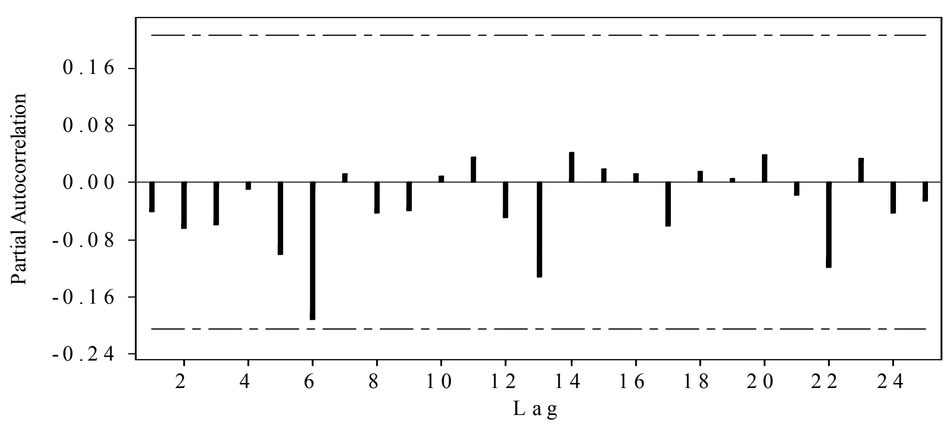



**Figure 5(b):** SPACF for residuals of the fitted model



### 5.1. Forecast

Forecast from model (5.1) are shown in Table 3. In Table 3 also shown 95-percent confidence interval around each forecast. The root mean squared forecast error (RMSFE) can be used as an overall measure of accuracy for these 12 forecasts.

The resulting RMSFE is interpreted as an average of the *m* forecast errors. The RMSFE of the 12 forecasts in the Table 3 shown below the table is 11.332, which is small.

**Table 3:** Forecast value of wheat price.

| Time | 95% Lower value | Forecast Value | 95% Upper value | Observed value | Error |
|---|---|---|---|---|---|
| 2006q1 | 1430.41 | 1178.08 | 1721.05 | 1391.33 | -0.02 |
| 2006q2 | 1314.28 | 1082.44 | 1581.33 | 1397.67 | 0.08 |
| 2006q3 | 1523.26 | 1254.55 | 1832.77 | 1413.00 | -0.05 |
| 2006q4 | 1513.16 | 1246.24 | 1820.63 | 1444.00 | 0.06 |
| 2007q1 | 1668.14 | 1373.87 | 2007.09 | 1607.00 | 0 .05 |
| 2007q2 | 1727.30 | 1422.60 | 2078.27 | 1738.67 | 0.06 |
| 2007q3 | 1907.94 | 1571.38 | 2295.62 | 1828.33 | 0.13 |
| 2007q4 | 2329.09 | 1918.23 | 2802.34 | 2172.67 | 0.15 |
| 2008q1 | 2893.09 | 2382.74 | 3480.94 | 2692.33 | 0.07 |
| 2008q2 | 3064.60 | 2524.00 | 3687.30 | 3082.00 | -0.05 |
| 2008q3 | 3214.02 | 2647.06 | 3867.08 | 2899.67 | -0.10 |
| 2008q4 | 3192.48 | 2629.32 | 3841.16 | 2895.33 | -0.30 |
| | | | **RMSFE=** | 11.332 | |

## 6. Conclusion

After first differencing the data series becomes stationary but the weavy pattern suggests the presence of seasonality. So we have developed ARIMA model for the quarterly wholesale price of wheat in Bangladesh including the seasonal terms. From the constructed model we made forecasts 12 future points (quarter). The RMSFE of the 12 forecasts is 11.332 indicates that the forecast is better. The developed model can be used as a policy instrument of the producers, importers and sellers.

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