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Seasonality and Forecasting of Monthly Broiler Price in Iran

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Abstract

The objective of this study was to model seasonal behavior of broiler price in Iran that can be used to forecast the monthly broiler prices. In this context, the periodic autoregressive (PAR), the seasonal integrated models, and the Box-Jenkins (SARIMA) models were used as the primary nominates for the forecasting model. It was shown that the PAR (q) model could not be considered as an appropriate method for modeling seasonal behavior of the broiler price. Results of seasonal unit root test indicated that the monthly prices of broiler follow a non-stationary stochastic seasonal process. Accordingly, the regression-based model is an appropriate modeling framework. While SARIMA is an alternative modeling approach, the RMSE of forecasting error suggested the superiority of the regression-based model over the SARIMA model. Therefore, the estimated parameters of the regression-based model can be used to predict the monthly prices of broiler in Iran.

Keywords:
Seasonality, Broiler price, Periodic autoregressive (PAR), Seasonal unit root, Seasonal integrated

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INTRODUCTION

Broiler industry is one of the main sub-sectors of agricultural sector and is a growing industry in Iran. The production of broilers has increased from 632000 tons in 1998 to about 1967 000 tons in 2013 with an annual growth rate of 13.2 percent on average (Ministry of Agriculture Jihad, 2014). This industry plays a major role in providing food security in Iran by producing more than one million tons of chicken.

In Iran, the production and distribution of the broiler has been under the direct control of government since the 1979 Revolution until 1998. Government sets the prices of the product and the subsidized prices of inputs. In 1998, following the economic adjustment in Iran, the government lifted its control over the broiler industry and allowed market to determine the prices of inputs and output. Consequently, price fluctuation was added to the production variability in the broiler industry. This liberalization in the boiler industry has led to higher broiler price and its seasonal fluctuations whereas it was relatively stable over the past years. This situation amazes the producers and consumers of broiler and they are not stratified. To overcome this problem and stabilize the produces incomes and to support the consumers, Iranian government implemented the policy of chicken market regulation in 2002 [1]. However, Ghahremanzadeh (2008) and Hosseini *et al.* (2008) pointed out that this policy could not give satisfying consequents whilst if the prediction of the broiler prices is available, it can provide a guide for government to develop and design efficient plan for the storage and redistribution of chicken. Since the Iranian boiler markets exhibit characteristics of significant seasonality in both the prices and quantities, the study of the seasonal behavior in the broiler price series is important for model evaluation and forecasting. As Franses (1991) points out, it is extremely important to determine the nature of the seasonality since this bears heavily on forecasting accuracy. The seasonal movements in the broiler price are direct reflection of seasonality in the boiler's marketing and demand. Seasonality in demand is related to religion ceremonies, the New Year's celebration, consumer's seasonal product preferences and change in calendar. On the other hand, seasonality in the boiler supply is related to seasonal demand of consumers, change of weather and calendar, some biological factors and management practices.

Many economic time series contain important seasonal components and it is a common belief that modeler need to pay specific attention to the nature of seasonality. Seasonality has been a major research area in economics. For example, Gustavsson and Nordstrom (2001), Kim and Moosa (2001 and 2005), Koc and Altinay (2007), Kulendran and King (1997), Kulendran and Wong (2005) and Lim and McAleer (2000 and 2002) analyzed the seasonality in international tourism flow. Seasonality was evaluated by Silvapulle (2004) for the financial market, Franses and Van Dijk (2005) for the industrial productions and Arnade and Pick (1998) and Tiffin and Dawson (2000) for the agricultural market. In spite of the importance of seasonality, there are a few studies on analyzing seasonal behavior in economic variables in Iran and this study is a pioneering work in this field. The main objective of present study was to model seasonal behavior of the broiler price in Iran. The seasonality characteristic of the broiler price was evaluated to develop a forecasting model which can be used to predict the broiler price in Iran. This paper was organized as following: section two presents methodology of models and forecasting of seasonal economic time series and section three describes the data and empirical analysis. The final section contains conclusion and implications.

MATERIALS AND METHODS

One of the most popular techniques for forecasting future outcomes of economic variables is time series models. The selection of the proper time series technique to model the behavior of the series depends on the characteristics of the time series. One of the major characteristics of many economic time series is the presence of

[1] *In this policy, a price rang of broiler is determined. If the broiler price is below this range, the government buys the excess broiler and if the actual price is over the price range, the stocked chicken is resupply.*

seasonal movement (Darne and Diebolt, 2002). The main types of movements are the trend, cycle and irregularity. Hence, the proper time series model must be selected based on type and nature of these components.

Since the Iranian broiler price exhibits characteristics of seasonality, the seasonal time series models should be applied. We resorted to time series technique and utilized the periodic autoregressive (PAR), the seasonal integrating and regression-based time series, and the Seasonal Box-Jenkins (SARIMA) models as the primary nominates for forecasting model.

Seasonal integration

If the seasonality is deterministic, the time series should be modeled with seasonal dummy variables (Arnade and Pick, 1998; Brendstrup *et al.* 2004 and Kim and Moosa, 2001). The application of seasonal dummies may be justified in some cases, whereas many economic time series seem to be characterized by seasonal patterns that evolve over time (Franses and Van Dijk, 2005). A very popular approach is to model the seasonality as a non-stationary stochastic process, i.e. seasonality evolves over time by allowing for seasonal unit roots. In this case, the time series should be differentiate distinguished by appropriate filter to account for the presence of seasonal unit roots and the differenced data are modeled by proper approach.

To determine the presence of unit roots, a seasonal unit roots test should be used. The most widely used seasonal unit roots test is the Hylleberg *et al.* (1990) test for quarterly data that extended to monthly data by Franses (1991) and Beaulieu and Miron (1993). The most popular test in practice is the Beaulieu and Miron (1993) [BM], which is based on the following auxiliary regression:

$$(1-L^{12})P_t = \alpha + \sum_{s=1}^{11}\delta_s D_{s,t} + \beta t + \sum_{i=1}^{12}\pi_i y_{i,t-1} + \sum_{j=1}^{p}\phi_j (1-L^{12})P_{t-j} + \xi_t \quad (1)$$

where, P_t represents the broiler price series; $D_{s,r}$ are monthly seasonal dummy variables equal to 1 if time t corresponds to season s and $D_{s,r}= 0$ otherwise; $_t$ is trend; $y_{i,t-1}$'s are non-singular linear transformations of lagged values of P_t whose details are given by Beaulieu and Miron (1993), and ξ_t is white noise process. In equation (1), the value of p should be determined so that the residuals from the above regression mimic a white noise process.

In order to test for the presence of unit roots at zero and π frequencies, the null hypotheses of H_{k0}:π_k=0 for k=1, 2 against the alternative hypotheses H_{k1}:π_k<0 are tested using the conventional *t-statistics*, denoted by t_k. To test the complex unit roots, the joint null hypotheses H_{k0}:$\pi_{k}=\pi_{k+1}=0$ for k = 3, 5, 7, 9, 11 against the alternative hypotheses H_{k1}: at least one of π_k and π_{k+1} is not equal to zero are tested using the conventional *F-statistic*, denoted by $F_{k,k+1}$. Alternatively, the null hypotheses of H_{k0}:π_k=0 for k=3, 4… 12 are tested against the alternative hypotheses H_{k1}:π_k<0 using the t-statistic. The asymptotic distributions of the above statistics are non-standard and the critical values are tabulated in BM (1993). To prove that no unit root exists at any seasonal frequency, π_k must be different from zero for k=2 and for at least one member of each of the sets {3, 4}, {5, 6}, {7, 8}, {9, 10}, {11, 12}.

When the BM test is carried out, the proper differencing filter is determined to obtain stationary data and they are molded by a proper approach. A popular approach to allow for time varying seasonality is the autoregressive model, so-called regression-based model, for seasonally differenced data. For the broiler prices, it can be written as:

$$\phi_p(L)\,\Delta_s P_t=\mu+\varepsilon_t \quad (2)$$

where ϕ_p is a polynomial of order p in the lag operator L, Δ_s is the appropriate differencing filter operator, P_t represents the broiler monthly prices, μ is intercept and ε_t is white noise process.

Seasonal ARIMA model

The traditional multiplicative seasonal ARIMA model [ARIMA (p, d, q)(P, D, Q)$_s$] proposed by Box and Jenkins (1976) was used as alternative forecasting model to forecast the seasonal price variables. Fitting a seasonal ARIMA model for monthly price of the broiler requires the data to be stationary. The number of seasonal differences *(1-L*^{12}*), D*, and the number of regular differences

$(1-L)$, d, are used to reduce the series to stationary so that a seasonal ARIMA model can be fitted. For monthly price of broiler, a multiplicative seasonal ARIMA model can be written as:

$$\phi(L)\phi_{12}(L^{12})(1-L^{12})^{D}(1-L)^{d}P_t=\theta(L)\theta_{12}(L^{12})\varepsilon_t \quad (3)$$

where, $\phi(L)$ and $\theta(L)$ are invertible lag polynomials in L of nonseasonal orders p,q, while $\phi_{12}(L)$ and $\theta_{12}(L)$ are invertible lag polynomials in L of seasonal orders P,Q, and ε_t is the white noise term. Notice that the SARIMA model assumes seasonal unit roots at all frequencies.

Periodic autoregressive model

An entirely different approach to allow for flexible seasonal patterns is offered by periodic autoregressive (PAR) models, which suppose that not only is the intercept (and trend if present) seasonal, but also the autoregressive parameters vary across seasons (Franses and van Dijk, 2005). The PAR model assumes that the broiler prices in each month can be described using different autoregressive models, and the same goes for the periodic extensions to the MA and ARMA models. Fallowing Brendstrup *et al.* (2004), the PAR (p) model for the broiler monthly price that is observed for N years (N=10) can be represented as:

$$P_t = \sum_{s=1}^{12}\mu_s D_{s,t} + \sum_{s=1}^{12}\varphi_s D_{s,t}t + \sum_{s=1}^{12}\phi_{1,s} D_{s,t}P_{t-1} + \ldots + \sum_{s=1}^{12}\phi_{p,s} D_{s,t}P_{t-p} + \xi_t \quad (4)$$

where, $t=1,2,...,n$ and $n=12N(12\times 10)$, μ_s, φ_s and $\phi_{i,s}$ are periodically varying parameters, $D_{s,t}$ is seasonal dummy equal to 1 when t falling in s and zero otherwise and $\xi_t \sim NID(0, \sigma^2)$.

However, to apply the PAR (p) model, the data generating process of broiler price must have periodic variation. In practice, we must test whether the periodic variation in some or all of the parameters is significant. Boswijk and Franses (1996) showed that testing for periodicity in (4) amounts to testing the hypothesis H_0: $\phi_{is} = \phi$ for $s = 1,2,...12$ and $i=1, 2,...,p$. This hypothesis can be tested by likelihood ratio test that is asymptotically $X^2(11p)$ under the null, irrespective of unit root in P_t. An important implication of this result is that equation (4) can be estimated directly by P_t series and no need to consider priori differenced P_t series. We determine the order of PAR (q) using a general-to-specific approach based on diagnostic check tests following Franses and Paap (2004). Also, *F-test* version for this hypothesis, denoted here by F_{per}, has the standard F $(11p, n-(12+12p))$ distribution in the case of a PAR (q) series with S seasonal intercept (Boswijk and Franses, 1996). If the null hypothesis is not rejected, we may proceed with BM analysis of seasonal unit roots; if significant periodicity is found, we may test for periodic unit root tests (Boswijk and Franses, 1996).

Brendstrup *et al.* (2004) and Franses and Paap (2004) pointed out that fitting a PAR (q) model does not prevent the finding of a non-periodic AR process if the latter is, in fact, the DGP. Thus, we will start by selecting a PAR (q) model, and then it will be tested whether the autoregressive parameters are periodically varying using the method described above.

Forecast evolution criteria

In this paper, the regression-based model, SARIMA and PAR (q) and their comparative performances are considered. The accuracy of these forecasting models needs to be evaluated so that the model that generally works the best and which produces the smallest error could be identified. The selection of the most accurate forecasting model should be based on the out-of-sample forecasting performance. In this context, we use the root mean square forecast error (RMSE), mean absolute forecast error (MAE) and mean absolute percentage forecast error (MAPE) criterion and final model selected based on minimizing these criterion.

RESULTS AND DISCUSSION

Our application is to Iran's broiler monthly prices from 1998:2 to 2013:2. The monthly prices of broiler were collected from Ministry of Agriculture Jihad (MAJ). Statistical properties of the broiler monthly prices are reported in Table 1.

Figure 1 illustrates the variations of broiler price over 1998-2013. By visual inspection of Figure 1, it is clear that the monthly prices of

Table 1: Statistical properties of the monthly prices of broiler

Mean	SD	CV[a]	Min	Max	Skewness	Kurtosis
13068	8082	0.618	3874	42673	1.619	5.516

a: Coefficient of variation= SD/Mean.

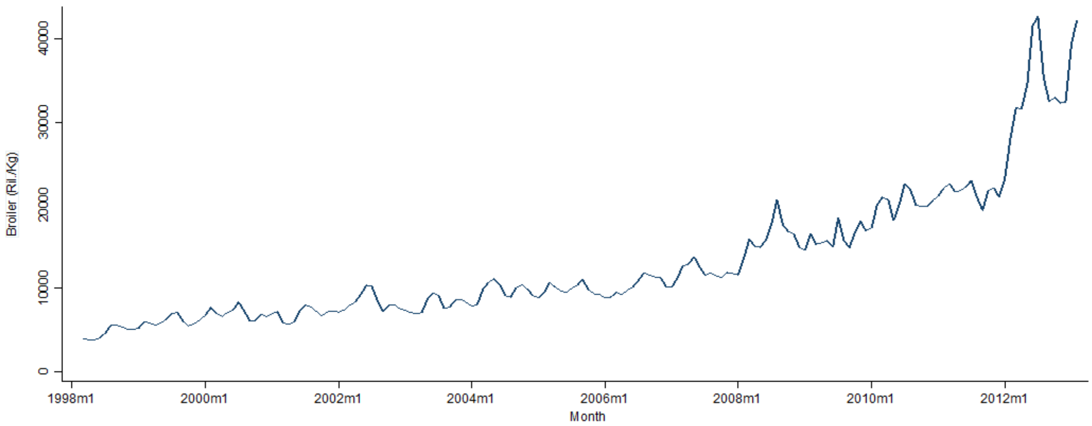

Figure 1: Broiler monthly prices in Iran (1998-2013)

broiler potentially have seasonality and exhibit an upward trend during whole period.

The periodicity test

In this section, the tests for periodic integration were applied to the logarithmically transformed of broiler price series. The pursued model selection strategy amounts to estimating periodic autoregressive models as in (4) of order *p*, where p is the initially set equal to 12, and *p* is decreased when diagnostic tests indicate no obvious signs of misspecification. The diagnostic checks that were used included LM tests for first-order (F_{ser}) and first to twelfth order (F_{12}) residual autocorrelation, LM tests for first- and twelfth -order ARCH effects (ARCH(1) and ARCH(12)) and a LM test for first-order periodic autocorrelation, F_{pser}. The specification search yields that the lags in the PAR model are 1 and 12 (PAR (1, 12). Results of the diagnostic check test for PAR (1, 12) are presented in Table 2.

As can be observed, the diagnostic test values of F_{pser}, F_{ser}, F_{12}, ARCH (1) and ARCH (12) are statistically significant at the 5 percent level. It is important to note that the F_{per} test resulted in the value of 1.46 with the *p-value* of 0.112. Consequently, we cannot reject the null hypothesis of non-periodicity. That is, there is not significantly periodic variation in the parameters suggesting that the PAR model is not suitable to model and generate future outcomes of the broiler price. Therefore, we must consider the regression-based and SARIAM models.

The seasonal unit root test

The BM test was applied to the broiler monthly pieces. The appropriate lag length in the auxiliary regression was selected in the same way as for the PAR (q) models. Results from the BM test are shown in Table 3. As can be observed, the

Table 2: Results of the periodicity test

F_{PER}	Diagnostic check tests				
	ARCH(12)	ARCH(1)	F12	F_{PSER}	F_{SER}
1.46 (0.112)	14.43 (0.298)	0.043 (0.871)	1.87 (0.185)	1.65 (0.175)	3.45 (0.098)

Notes: values in parentheses are p-values

Table 3: Results from seasonal unit root test

Series	Lags	0	π	π/2	2π/3	π/3	5π/6	π/6
		t1	t2	F3.4	F5.6	F7.8	F9.10	F11.12
Data in level	1,12	-2.98	-2.45	3.23	2.65	3.65	4.32	4.87
Differenced data	1,12	-4.32	-3.02	11.32	7.98	9.34	8.54	11.45

Note: the critical value at 1% level are: t_1=-3.37, t_2=-3.21 and $F_{k,k+1}$=7.86. ; at 5% level are: t_1=-3.19, t_2=-2.65 and $F_{k,k+1}$=5.77; and at 10% this level are: t_1=-2.91, t_2=-2.36 and $F_{k,k+1}$=4.86 (Franses and Hobijn, 1997)

results indicate that the null hypothesis of unit root is not rejected at the 5 percent significance level at all frequencies. In conclusion, the test shows strong evidence for unit root at long run and seasonal frequencies; hence, seasonal differencing, , is an appropriate filter for removing the unit roots from the monthly prices of broiler. However, to see whether the price series become stationary after imposing the identified filter, the differenced series were tested for unit roots again. The results revealed that this filters leads to a stationary series.

Estimation of the forecasting model

The regression-based model, defined in Equation 2, and seasonal ARIMA models in Equation 3 were estimated as competitive models to select the best forecasting model for the broiler price. Appropriate lag length of regression-based model, p, is determined based on the same rule for the BM auxiliary regression model. As the appropriate lags in the regression-based model are 1 and 12, therefore the AR (1, 12) is the most preferred model. The seasonal ARIMA models were estimated based on the Box – Jenkins technique (Enders, 2004). The residuals were subjected to diagnostic tests, including visual inspection of residual sample autocorrelation function and the use of the Liung-Box statistics (1978). The SARIMA models were estimated and evaluated at the multiplicative and additive functional forms. According the minimization of the AIC and SBC criteria and the procedure explained above, the ARIMA (2, 1, 1) (0, 1, 1)12 was selected as a most preferred model. Table 4 presents outcomes of the estimated regression-based model and ARIMA (2, 1, 1) (0, 1, 1) 12 models. As can be observed, the estimated parameters are statistically significant and there is no serial correlation at the 5% level.

Evaluation of forecasting performance

In order to select the best forecasting model for the broiler price, the root mean square forecast error (RMSE), mean absolute forecast error (MAE) and mean absolute percentage forecast error (MAPE) were calculated. We considered short forecast horizons of up to four

Table 4. Estimates of regression-based and ARIMA(2,1,1)(0,1,1)12 models for the broiler price

Regression-Based model

$(1 - L^{12})LnP_t = 0.5510+0.726(1 - L^{12})LnP_{t-1} - 0.312\,(1 - L^{12})LnP_{t-12}$

(4.13[a]) (10.32) (-6.21)

F_{ser}=0.1662 (0.69) ARCH(1)[b]=0.512 (0.43)

F_{12}=1.54 (0.146) ARCH(12)=13.42 (0.54)

ARIMA(2,1,1)(0,1,1)12 model:

$(1-0.675L+0.432L^2)(1-L)(1-L^{12})LnP_t=-0.032+(1+0.674\varepsilon_{t-1})(1+0.745\varepsilon_{t-12})$

(4.65) (-6.54) (-1.66) (6.34) (4.65)

Q(6)[c] =7.54(0.28) Q(12)=9.61(0.38) Q(24)=22.82(0.12) AIC=-6.61 SBC=-5.92

(a): values in parentheses are t-test statistic. (b): ARCH(1) and ARCH(12) denote to LM tests for first- and twelfth-order ARCH effects, respectively, and the associated p-values are in the parenthesis. (c): Q(p) indicates the Ljung-Box statistic for the joint significance of the residual autocorrelations of up to lag 6, 12 and 24 and the associated p-values 4

Table 5: Out of sample forecasting performance of broiler price

Model	Measure	1 month	2 month	Horizon 4 month	6 month	8 month
Regression-Based	RMSE	53	77	85	81	92
	MAE	47	69	71	68	81
	MAPE	6.7	7.1	7.4	6.1	4.3
	RMSE	78	113	131	81	121
ARIMA(2,1,1)(0,1,1)12	MAE	64	96	108	67	102
	MAPE	7.4	11.1	12.3	7.3	11.2

years and the identified models were estimated on data up to 2009:12. Then, 2009:12 was taken as the forecast origin for forecasting 1,2,4,6, and 8 steps ahead. The model was, then, re-estimated on data up to 2010:1, with the unchanged form of the model. 2010:1 was taken as the forecast origin, and, so on, subject to constrain that we have data on the period being forecasted (the sample ends in 2013:12). The forecasts were, then, transformed from the differentiated form to forecasts in levels. By comparing the forecasts in level, we do not need to calculate the Generalized Forecast Error Second Moment (GFESM) measure developed by Clements and Hendry (2004).

Table 5 illustrates the RMSE, MAE and MAPE measures for the regression-based and ARIMA (2, 1, 1) $(0, 1, 1)_{12}$ models according to the forecasting horizon for the broiler prices. The results indicate that the RMSE, MAE and MAPE measures for the regression-based model are smaller than the ARIMA (2, 1, 1) $(0, 1, 1)_{12}$ model in the forecasting horizon. It can be concluded that the regression-based model is selected as the best model to model and forecast future value of the boiler prices.

CONCLUSION

This study was aimed to analyze the seasonal behavior of broiler prices in Iran using monthly data during the 1998-2013. The BM test shows strong evidence for unit root at long run and seasonal frequencies and forecasting model were established based on this result. Although forecasting is vital to the planning of all activities, it is particularly crucial in the broiler industry due the perishable nature of the broiler product. Choosing the right model to forecast price series requires not only sufficient knowledge about the nature and characteristic of the time series but also a good understanding of the theory behind the models.

There are a number of factors used to evaluate the effectiveness of a forecasting method, such as forecasting accuracy, costs associated with the application of a forecasting procedure such as installation and operating costs, and ease of application and interpretation of the output from a forecasting method. In this context, we found that the regression-based model is most proper method to forecast and model the broiler price. This model is relatively easy to apply and install in the public and private sectors. The government can use this model to predict broiler price and consequently, make better plans to regulate the broiler market. Furthermore, the broilers producers can simply apply this model to generate future outcomes of the broiler prices and therefore, increase own income through organizing the production plans.

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