AN ECONOMETRIC MODEL FOR BROILER CHICKEN MEAT PRICES IN MALAYSIA: STRUCTURAL TIME SERIES APPROACH

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ABSTRACT. Envisaging a stable trend of commodity price can control the hike in price of goods especially during the festive season. As the demand increases from the consumer, the supply is expected to increase until it achieves the equilibrium point to meet the demand. Hence, there is a mounting need to investigate the historical price to provide valuable insights about the livestock industry in Malaysia. This paper investigates the trend of the monthly chicken meat prices in Malaysia using structural time series model from January 2014 until December 2020 using quantitative approach. The models are developed in this study using stepwise method which started with local level model, local linear trend model and local linear trend with seasonal component model. The Akaike Info Criterion (AIC) values are referred as a tiebreaker to determine the best fit model. This study found that the data best fit local linear trend with seasonal component model to represent the chicken meat prices in Malaysia. This model can be a useful tool to predict the monthly price in the future.

Keywords: structural time series model, chicken meat, local level, local linear trend, seasonal

INTRODUCTION

Chicken has been the most preferred white meat and the source of protein for Malaysians (Jayaraman *et al*., 2013). The production of poultry meat for chicken has maintained around 1.5 – 1.6 tonne metric since 2014 until 2020 as published in Statista (https://www.statista.com). It is important to maintain the same amount of production to meet the demand because the per capita consumption of chicken for the past six years has been around 50 - 60 kg (Bahri *et al*., 2019). Any shortage in supply will cause the price per kilogram spike especially during festive seasons such as Eidul Fitri and Chinese New Year.

However, the issue of unstable chicken meat price has been debated over the years. This study concerns about the issue of unstable chicken meat price. The Domestic Trade and Consumer Affairs Ministry in Malaysia has been actively involved in controlling the price of poultry meat. Even though the self-sufficiency level for chicken production has achieved over 100 %, the shortage in supply still occurs. The short-term solution is to import the chicken meat from China and Thailand to meet the demand in Malaysia. But, to date there has yet to be any successful long-term solution that has been implemented to stabilise the chicken price in Malaysia especially during the festive seasons when the market faces excess demand (Hamzah *et al*., 2021).

Having greater insight into the poultry price would yield useful information about the behaviour and trend of its price in Malaysia. Previous studies such as Dostain *et al*. (2018), Hamzah *et al*. (2021), and Purbasari *et al*. (2021) employed Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) to investigate the trend of commodity price.

However, this study takes a new look to investigate the behaviour and predict the trend of chicken broiler price in Malaysia using structural time series approach. The model determined in this study may become a valuable tool to predict the future price of chicken broiler in Malaysia. This study aims to close the knowledge gap by investigating the trend of chicken price in Malaysia using structural time series approach. The structural time series approach has been widely used in many research areas. For instance, Murthy and Kishore Kumar (2021) employed this technique to study the seasonal surface air temperature in India, Viswanath *et al*. (2020) used this approach to model and predict the patterns of seasonal rainfall in Tamil Nadu, and Junus and Ismail (2014) modelled the road accidents in several states in Malaysia. As for this study, the structural time series approach is chosen instead of ARIMA model for several reasons. First, the structural time series model is able to handle the missing values and outliers (Harvey & Koopman, 2000). Second, the structural time series model is able to model the seasonal and trend components presence in the series compared to ARIMA which eliminates the seasonal and trend components after differencing the series (Jalles, 2009). Third, the structural time series approach consists of Markovian nature which allows the computational occur in recursive form (Koopman *et al*., 1999).

DATA

The weekly prices of chicken meat were extracted from Department of Veterinary Services portal (http://www.dvs.gov.my). The data went through data cleaning process to remove any outlier or missing data as part the analysis. Then, the data were transformed into monthly price by taking the average of four weekly prices from January 2014 until December 2020. Hence, this study consists of 84 observations of monthly time series data for structural time series modelling. As shown in Table 1, the mean is slightly lower than the median by 0.15 unit indicating that the distribution of the data set is slightly skew to the left. This research found that there are few potential sudden shifts presence in the time series plot illustrated in Figure 1. The trend of time series plot in Figure 1 suggests that the data are additive model.

Table 1. Descriptive statistics of poultry retail price in Ringgit Malaysia.

Descriptive statistics	Min.	Mean	Median	Max.	Q1	Q3
Price (RM)/kg	5.05	7.16	7.30	8.85	6.60	7.65

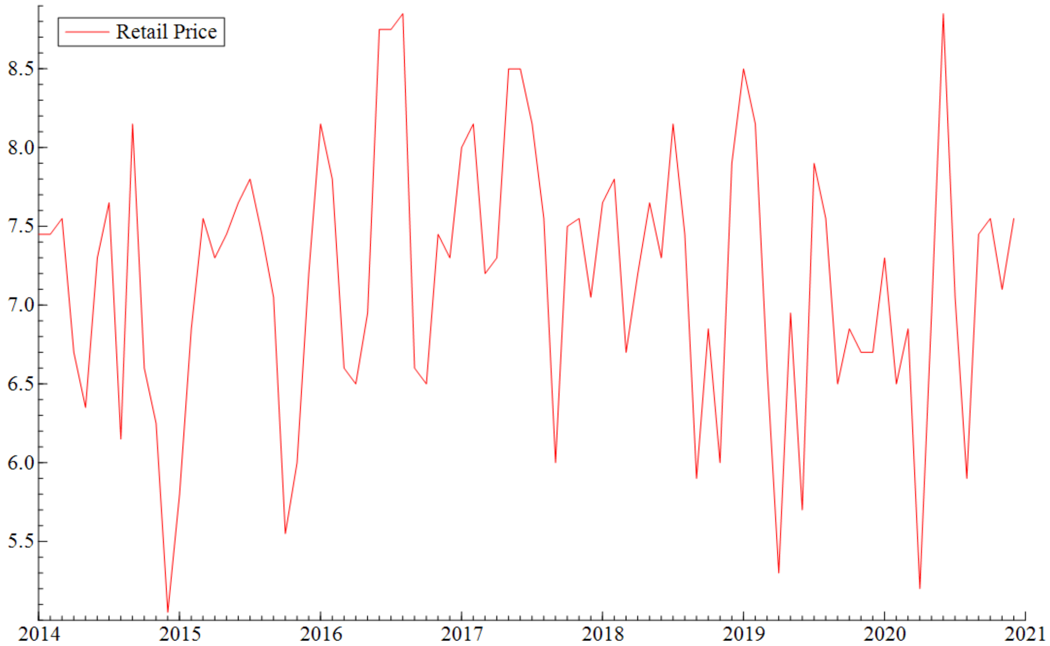

Figure 1. The time series plot of monthly retail price of poultry.

METHODOLOGY

Structural time series model (SSTM) is a model representing the unobserved components in the time series data such as level, trend, and seasonal component. The simplest model in structural time series is the local level model since it consists only a level component. Level component in this model can be treated as the intercept in linear regression equation. The main difference between the level component and intercept is the former is treated as stochastic process while the latter is treated as deterministic process. Stochastic process means that the level components is allowed to vary over the time. Hence, the general equation for local level model can be written as. For simplicity, let y_t be a univariate time series for a set of observations $y_1, y_2, \dots, y_t$ where $t = 1, 2, \dots, T$.

The series can be represented in an additive model:

$$y_t = \mu_t + \gamma_t + c_t + \varepsilon_{t,} \quad (1)$$

where μ_t denoted as time varying component called trend, γ_t is periodic component of fixed period or seasonal component, c_t is a cycle component of a longer period than seasonal and ε_t is an irregular component or error. The SSTM approach able to analyse the behaviour of each component in (1) by putting them in a single matrix model called state space model (SSM). The SSM can be expressed in unified formula as:

$$y_t = \mathbf{Z}_t^{'}\boldsymbol{\alpha}_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \quad (2)$$

$$\alpha_{t+1} = \mathbf{S}_t\boldsymbol{\alpha}_t + \mathbf{R}_t\xi_t \qquad \xi_t \sim N\left(0, \mathbf{Q}_t\right) \quad (3)$$

for where y_t and ε_t remained as scalar of order 1×1 and the other terms denote vectors and matrices. The term $\mathbf{Z}_t$ is a design vector of size $m \times 1$, S_t is a $m \times m$ transition matrix, $\boldsymbol{\alpha}_t$ is a state vector of $m \times 1$, $\mathbf{R}_t$ is an identity matrix of order $m \times m$ and m represents the number of elements in the state vector. The vector $\mathbf{Q}_t$ contains the m state disturbances with zero means and unknown variances.

The local level model (LLM) or also known as *random walk plus noise* model is the basic and simplest structure of the state space model. The model can be formulated as:

$$y_t = \mu_t + \varepsilon_{t,} \quad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right) \text{ (4)}$$

$$\mu_{t+1} = \mu_t + \eta_t, \quad \eta_t \sim N\left(0, \sigma_\eta^2\right) \text{ (5)}$$

for the whole observations $t = 1, 2, \ldots, T$ where ε_t and η_t are independent and identically distributed of μ_1. This model consists of level component, varies slowly over the time that serve to measure the stochastic trend.

The extension of LLM is local linear trend model where there is a trend component with a slope. In this model, both level and slope vary over the time. The LLTM can be formulated as:

$$y_t = \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right) \text{ (6)}$$

$$\mu_{t+1} = \mu_t + \nu_t + \omega_{t,} \qquad \omega_t \sim N\left(0, \sigma_\omega^2\right) \text{ (7)}$$

$$\nu_{t+1} = \nu_t + \psi_{t,} \qquad \psi_t \sim N\left(0, \sigma_\psi^2\right) \text{ (8)}$$

for the whole observations where ω_t and ψ_t are independent and identically distributed.

The recurring patterns in time series in a specified period is known as a seasonal effect. In SSM, the seasonal effect can be modelled by adding the seasonal component either in LLM or LLTM. For simplicity, this study adds the seasonal component, ϕ_t in LLM to become a basic structural model (BSM). The BSM can be formulated as follows:

$$y_t = \mu_t + \phi_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right) \text{ (9)}$$

$$\mu_{t+1} = \mu_t + \delta_t, \qquad \delta_t \sim N\left(0, \sigma_\delta^2\right) \text{ (10)}$$

$$\phi_{t+1} = \sum_{j=1}^{s-1} \phi_{t+1-j} + \omega_t, \qquad \omega_t \sim N\left(0, \sigma_\omega^2\right) \text{(11}$$

for the whole observations $t = 1, 2, \ldots, T$ where δ_t and ω_t are independent and identically distributed. There are three assumptions for residual of the state space model need to fulfill which are the residuals are independence on each other, homoscedasticity and following normal distributions (Harvey & Koopman, 1992). The diagnostic tests used in this study are Ljung Box (LB), heterocedasticity test (Goldfeld-Quandt), and Jarque Bera (JB) tests. These diagnostics tests were conducted to investigate whether the assumptions made can be fulfilled using the diagnostics test proposed. Specifically, the LB test, Goldfeld-Quandt test and JB test were conducted to check the assumptions made for residuals that are independence, constant variance (homoscedasticity) and following normal distributions respectively.

The test of serial correlation suggested by Ljung and Box (1978) as a standard portmanteau test statistic given by:

$$Q(q) = n(n+2) \sum_{j=1}^{k} \frac{c_j^2}{n-j} \text{ (12)}$$

where *n* is the number of observations, *j* and *k* is a preset positive integer, and is the *j*th correlogram value. The heterocedasticity test was formulated to compare the total of two exclusive subsets from the observations. Under the null hypothesis, the statistics of heterocedasticty test is:

$$H(h) = \sum_{t=n-h+1}^{n} (A_t - F_t) \text{ (13)}$$

where *n* is the number of observations, *h* is a preset positive integer under distribution, is the actual value at time *t*, is the forecast value at time *t*. The JB test statistics is formulated to check whether the residuals have skewness and kurtosis similar to normal distribution. The value given by JB test statistics if it deviates from zero, it indicates that the residuals do not match with normal distribution. Formulation of JB test statistics is as below:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \quad (14)$$

where n is the number of observations, S is the skewness and K is sample kurtosis.

The structural time series model for poultry (chicken) price is built using stepwise method. Initially, the model is built from the deterministic local level model, followed by stochastic local level model, then adding the trend component in local level model, and finally adding the seasonal component in the local linear trend model. In each model, the residuals are analyzed using the diagnostics tests mentioned to ensure that it has fulfilled the assumptions. In addition, this study uses the Akaike Info Criterion (AIC) to measure the goodness of model fitting. The AIC used is based on the formula given as follow:

$$AIC = \frac{1}{n}\left[-2n\log L_d + 2\left(q+w\right)\right] \quad (15)$$

where $\log L_d$ is the maximized diffuse log likelihood function in state space modelling, *q* is the number of diffuse initial values in state equation, and *w* is the total number of disturbance variances estimated in the model. The selection of AIC over another info criterion is still debatable especially Bayesian Info criterion (BIC) in model selection criteria. This study employs the AIC over BIC in model criteria selection for several reasons. First, the AIC attempts to measure the goodness of fit of the true model while the BIC selects the model among different number of parameters. This research puts the structural time series into the state space form making it to have high dimension through its vector. Hence, this research finds that it is suitable to use AIC since AIC finds the true model that has high dimensional reality (Harvey & Koopman, 1992).

To ensure the accuracy of prediction, this study proposes the mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean square error (MSE) as reference. The MAPE, MAE and RMSE are formulated as shown in equation (16), (17), and (18) below.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|A_t - F_t|}{A_t} \quad (16)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \quad (17)$$

$$RMSE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|^2 \quad (18)$$

where *n* is the total number of observations, is the actual value at time *t*, is the forecast value at time *t*. All computations were done using ***stsm*** package in R programming language.

RESULTS AND DISCUSSION

Table 2 reports the estimation for each structural time series model using the monthly chicken meat prices. The results demonstrate that local linear trend with seasonal has the lowest AIC value compared to the rest. In addition, the model has also passed the diagnostics test indicating that it did not violate the assumptions for residual. Finally, this study found that the local linear trend with seasonal appropriately describes the monthly chicken meat prices in Malaysia as well as the best fitted model. As expected, there is no doubt that the seasonal component exists in the data series as the real issue is the hike of price during the festive season.

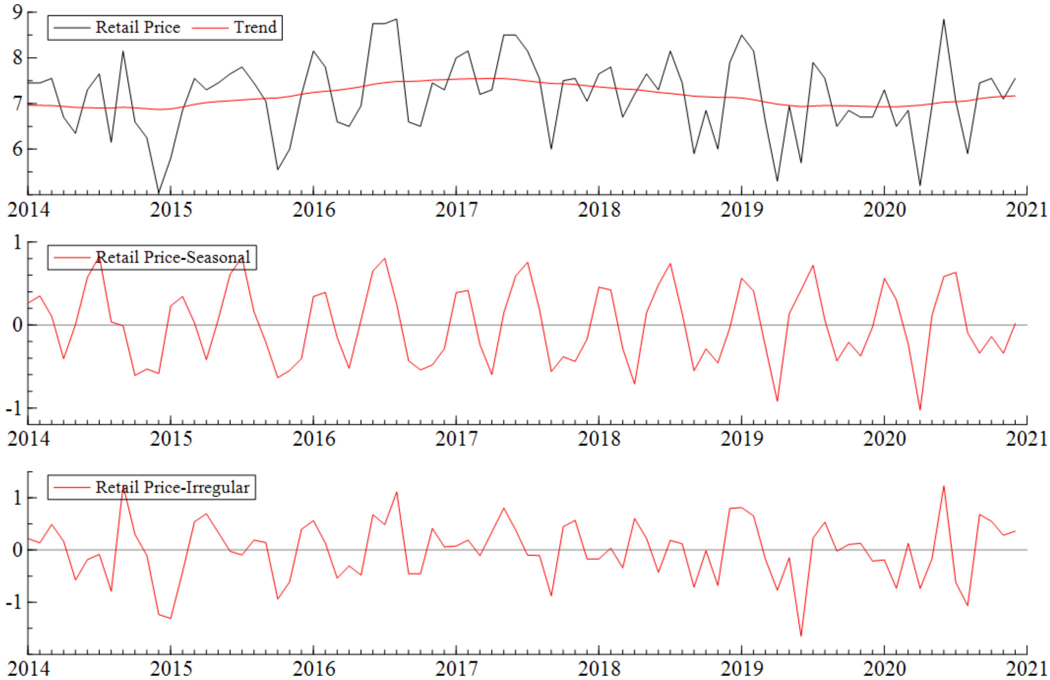

Figure 2. The time series plot for level, slope, and seasonal component.

Table 2. Estimation of chicken meat prices in structural time series model.

Structural Time Series Model	Diagnostic tests			AIC	BIC
	Ljung Box	Goldfeld-Quandt	Jarque-Bera		
Stochastic Local Level	0.2984	< 0.001*	< 0.0001*	21.23	32.37
Local Linear Trend	0.1312	< 0.001*	0.0014*	20.64	26.12
Local Linear Trend with Seasonal	0.8978	0.0035*	< 0.0001*	**18.56**	**19.38**

*denotes significant at 5% level

Table 3. Forecast accuracy measurement values.

RMSE	MAE	MAPE
0.09968	0.0755	0.0395

The time series plot of structural time series components is illustrated in Figure 2 below. The trend component plotted in the top panel shows a stable trend with a constant mean and variance. In addition, based on the plot, there are potential location shifts that may occurr from 2014 till 2020. Further investigations are needed to detect the true location shifts using structural break test that is excluded in this study. On the other hand, the seasonal component captured in the middle panel in Figure 2 shows that there is a seasonal occurrance.

As mentioned, the RMSE, MAE, and MAPE values tabulated in Table 3 indicate the prediction accuracy for local linear trend with seasonal model. This study employs the last 70 % of the dataset as the training data while the remaining as the testing data. The selection of proportion for splitting the data into training-test dataset was based on the recommendation in Vrigazova (2021). Based on the MAPE value recorded, the local linear trend model with seasonal yields a better prediction for monthly chicken meat price as it has the lowest error of prediction (about 4 %). In addition, the alternative indicator for forecast accuracy indicates that the forecast error is below than 10 %. The comparison of predicted and actual prices using test data set is illustrated in Figure 3 below. The red line indicates the actual monthly prices from 2019 until 2020. Meanwhile, the blue line indicates the predicted monthly prices. The green line acts as a 95 % confidence interval for the forecast values. Referring to Figure 4 below, the forecast of chicken price for 2021 is depicted using *h*-step ahead forecast technique.

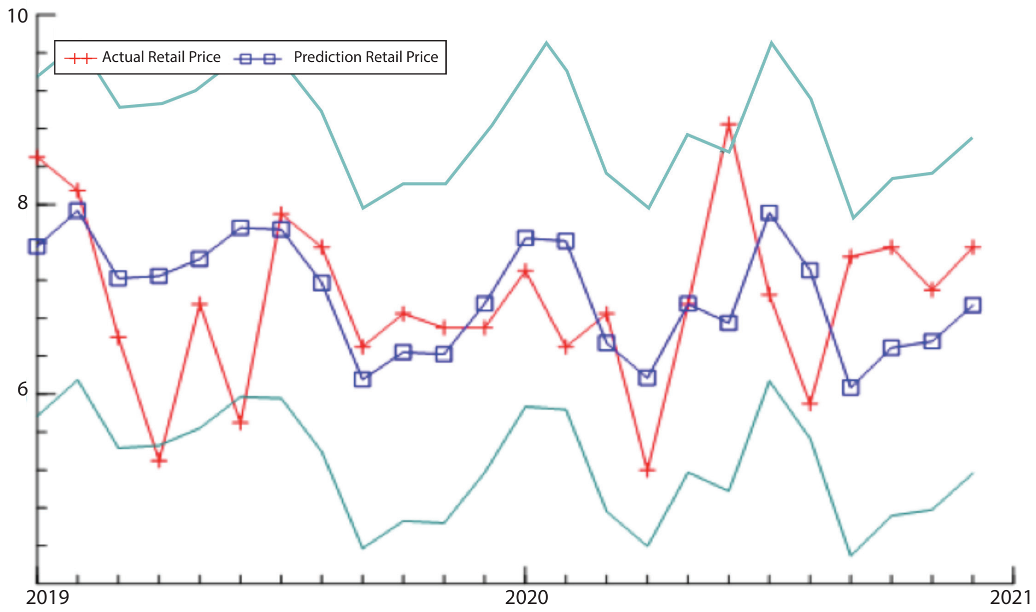

Figure 3. The time series plot of comparison between actual and predicted retail price.

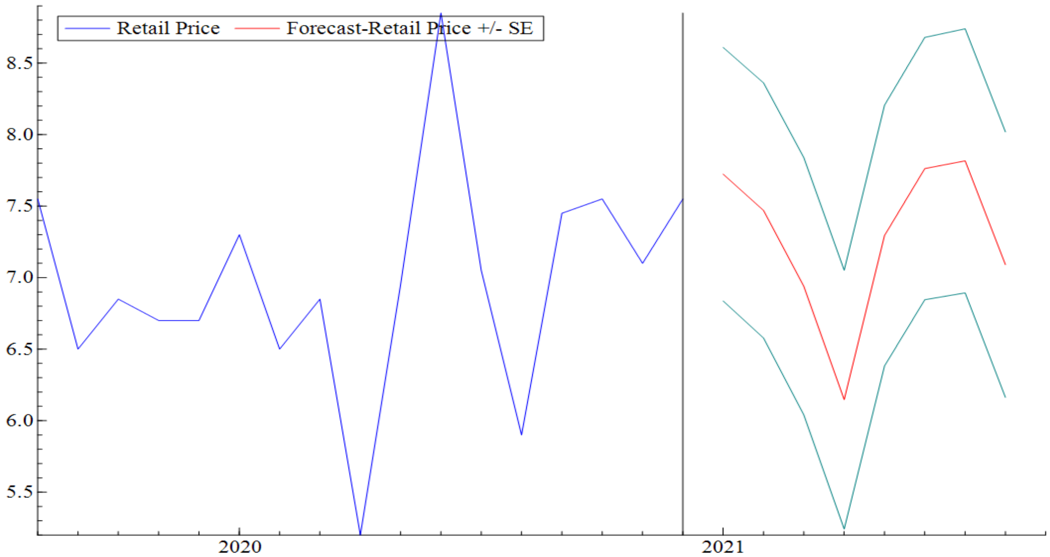

Figure 4. The time series plot of one-step forecast.

CONCLUSION

This study has applied the univariate structural time series analysis to model and predict the monthly chicken meat prices in Malaysia. This paper focused on three main components which are the level, trend, and seasonal components. For each model, the residual diagnostics tests have been made to ensure each model fulfil the assumptions. The main finding from this study is the local linear trend with seasonal component model is the best fitted model to describe the monthly chicken meat prices in Malaysia. This model can be a useful tool to predict the weekly price in the future. There is still a great deal of work to be done in this area. This study has potential for further direction to include the explanatory variables in the model for a better prediction.

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