Modeling of Big Chili Supply Response Using Bayesian Method

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10 December 2020

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Abstract— This study aims to estimate the response model of Big Chili offerings with the Bayesian method so that information elasticity of price (production) derived from posterior hyperparameter can be obtained. The method used in this study is a supply response model that adopts the Nerlove model and it is estimated with the Bayesian method. The data used in this study are Big Chili production (kg), harvested area (hectares), and Big Chili prices of producer level (IDR/kg) with the period 2008 - 2018 monthly sourced from Statistics Indonesia. The Bayesian method can be applied in the estimation of the Nerlove Model of The Big Chili supply. However, the resulting coefficient of determination is low by 21.05%. The reason is thought to be the use of prior that have a bias effect on posterior distribution and/or there is a nonlinear relationship to the variables in the model. However, only two variables were not significant from the five predictor variables, namely the price of producer level of Big Chili at time t-1 and the production of Big Chili at time t-2. The estimation results of price elasticity in the short and long-term were 8.49% and 2.50%, respectively, which are the inelastic category. It shows that farmers are not responsive to prices. Because the costs of cultivation are high, so it causes the profits obtained by farmers not so much, even though the farm-level prices increase. It becomes insignificant for income farmers.

Keywords: Big Chili, Supply, Nerlove Model, Price Elasticity, Bayesian, Prior

I. INTRODUCTION

Big Chili is one of the horticulture strategic that contributed to inflation. This is the second dominant commodity to inflation during 2019, that is 0.15 percent. This contribution is influenced by Big Chili prices of consumer-level that volatile because of price increasing significantly on Eid holidays. Then, the price is normal again in other months. The Big Chili price is caused by the interaction between demand and supply. On-demand, demand for Big Chili is increasing, as the increase in consumption. This demand must be balanced with supply, that is production of Big Chili. The trend of domestic production of Big Chili from 2008 to 2018 shows an increase although there is seasonal volatility (Figure 1).

Based on economic theory, the supply of commodities is the function of commodities price variables and other related endogen variables. In the supply function, information on price elasticity can be obtained. The price elasticity is a measure of goods quantity changing which supply from a commodity caused by price changing. It is important to know how much income is obtained by the farmer. The reference [5] shows that the elasticity of the Big Chili price of producer level in short-term and long-term are 5.22% and 9.39%. That result is obtained by Nerlove Model, a frequentist approach.

This research uses the Bayesian approach to estimate the Nerlove Model of supply response of Big Chili commodities. It is used to get price elasticity estimation based on Bayesian regression coefficients. In statistics, there are two different points of views on parameters, there are frequentist and Bayesian approach [11], [12], [13]. According to the frequentist view, the parameter is constant. While, in the Bayesian view, there is the information of parameter that is prior. In this method, prior information is applied and the parameters are random variables. The Bayesian analysis uses two pieces of informations to estimate the parameter of the statistical model. The first information is from sample data and the second information is from expert opinion, which is called prior information. Information from sample data comes from the likelihood function, while prior information is from expert subjective opinion or previous research. Experts can give different prior information. Uncertainty of expert opinion is explained in a prior distribution. The combination of those two pieces of informations makes a posterior distribution.

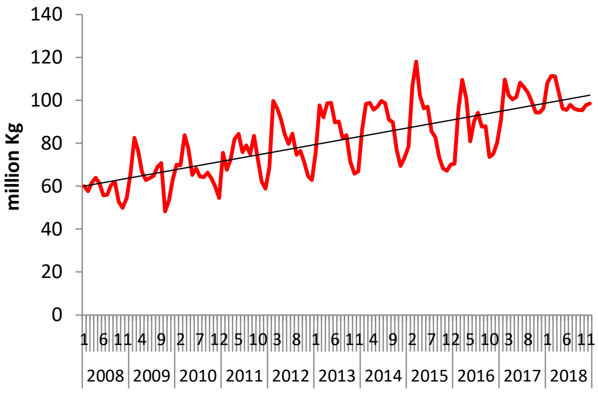

Figure 1. Trend of Big Chili Production in Indonesia, 2008 – 2018

II. RELATED WORK

Some research of measuring the supply response function using the Nerlove Model [1], [9], [10] has been carried out, such as measuring the supply response function of tobacco in Zimbabwe [6], a note on the Nerlove Model of agricultural supply response [3], and dynamic supply response: implications for Indonesia Soybean crop [4].

According to reference [6], estimation of the price elasticity of supply for tobacco output in Zimbabwe using an adapted Nerlov Model. This research shows that elasticity in short-term is 0.34 and elasticity in long-term is 0.81. Both of them are inelastic. It indicated that tobacco farmers are highly unresponsive to price changes. Reference [3] about the model of agricultural supply response show that reduced form of the Nerlove Model is likely to be accompanied by a demand function type relationship between the explanatory variables of the area under cultivation at time t-1 and price at time t-1. The result shows that the reliability of the long-run supply elasticity estimate may suffer.

On the other hand, reference [4] explains that the supply response model of the Soybean crop in terms of alternative specifications also implications economics. The model considers the availability of production lags concept, the existence of expected price, and gross revenue. The results showed that the existing lags were due mostly to the problems also quick adjustment expenditure rather than correcting expected time.

III. METHODOLOGY

Data Source

Data used in this research is Big Chili production (kg), harvested area (hectares), and Big Chili prices of producer level (IDR/kg) from the period 2008 to 2018 monthly. Data is from Statistics Indonesia-BPS. On the estimation process, data is transformed into natural logarithms first.

Nerlove Model

Formation of the model of Big Chili supply responses is obtained directly, that is by production responses. The model used to estimate the supply model is the Nerlove Model [6]. The simple form of the Nerlove model consists of three equations [1,6], they are:

$$Q_t^* = a_0 + a_1 P_t^* + a_2 Z_t + u_t \quad (1)$$

$$P_t^* = P_{t-1}^* + \theta(P_{t-1} - P_{t-1}^*) \quad (2)$$

$$Q_t = Q_{t-1} + \gamma(Q_t^* - Q_{t-1}) \quad (3)$$

Where:

Q_t^* : potential production of Big Chili at time t (kg)

P_t^* : expected price of big chille of producer level at time t (IDR/kg)

Z_t : other related explanatory variables, that is harvested area of Big Chili (hectares)

P_{t-1}^* : expected price of Big Chili of producer level at time t-1 (IDR/kg)

P_{t-1} : actual price of Big Chili of producer level (farm-level) at time *t* – 1 (IDR/Kg)

Q_t : actual production at time *t* (Kg)

Q_{t-1} : actual production at time *t* - 1 (Kg)

To estimate equations (1), (2), and (3), the unobservable variable must be eliminated first. Reformulation equation (3) become:

$$Q_t = \gamma Q_t^* + (1-\gamma)Q_{t-1} \quad (4)$$

Put equation (1) to equation (4), become:

$$Q_t = \gamma a_0 + \gamma a_1 P_t^* + \gamma a_2 Z_t + (1-\gamma)Q_{t-1} + \gamma u_t \quad (5)$$

Rearrange equation (2) to be:

$$P_t^* = \theta P_t + (1-\theta)P_{t-1}^* \quad (6)$$

Put equation (6) to equation (5), become:

$$Q_t = \gamma a_0 + \gamma a_1 \theta P_t + \gamma a_1(1-\theta)P_{t-1}^* + \gamma a_2 Z_t + (1-\gamma)Q_{t-1} + \gamma u_t \quad (7)$$

From equation (5) with index $t-1$, equation change to be:

$$Q_{t-1} = \gamma a_0 + \gamma a_1 P_{t-1}^* + \gamma a_2 Z_{t-1} + (1-\gamma)Q_{t-2} + \gamma u_{t-1} \quad (8)$$

The equation (8) is multiplied with $(1-\theta)$, so it can be obtained:

$$Q_{t-1}(1-\theta) = \gamma a_0(1-\theta) + \gamma a_1(1-\theta)P_{t-1}^* + \gamma a_2(1-\theta)Z_{t-1} + (1-\gamma)(1-\theta)Q_{t-2} + \gamma(1-\theta)u_{t-1} \quad (9)$$

Equation (7) minus equation (9) and the result is simplified become:

$$Q_t = \alpha + \beta_1 P_{t-1} + \beta_2 Q_{t-1} + \beta_3 Q_{t-2} + \beta_4 Z_t + \beta_5 Z_{t-1} + \varepsilon_t \quad (10)$$

where:

$\alpha = \gamma a_0 \theta$, $\beta_1 = \gamma a_1 \theta$, $\beta_{2_2} = (1-\theta) + (1-\gamma)$, $\beta_3 = -(1-\gamma)(1-\theta)$, $\beta_4 = \gamma a_2$, $\beta_5 = \gamma a_2(1-\theta)$, and $\varepsilon_t = \gamma(u_t - (1-\theta)u_{t-1})$.

Equation (10) is the supply responses model of red Big Chili with the Nerlove Model approach. Equation 10 can be estimated with ordinary least square, so get regression coefficient estimations, they are , $\hat{\beta}_1, \dots, \hat{\beta}_5$. Used equation (11) and equation (12) to get elasticity, [5],[10];

- Elasticity of price in short-term:

$$e_S = \hat{\beta}_1 \quad (11)$$

- Elasticity of price in long-term:

$$e_L = \left(\frac{\hat{\beta}_1}{1 - \hat{\beta}_2 - \hat{\beta}_3}\right) \quad (12)$$

with: $\bar{P}$ is arithmetic mean price of Big Chili of producer level during observation period and $\bar{Q}$ is arithmetic mean production of Big Chili.

Bayesian Regression

Generally, equation (10) can be formatted in matrix, as follows:

$$\boldsymbol{y} = \alpha \boldsymbol{1}_n + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad (13)$$

where:
$\boldsymbol{y}$**:** responses variable $(y_1, \dots, y_n)$ in this case Q_t, α**:** constant (intercept), $\boldsymbol{\beta}$**:** vector regression coefficients p x 1, $\boldsymbol{X} = [\boldsymbol{x}_1 \dots \boldsymbol{x}_p]$, design matrix n x p, with p is predictor variable (in this case p are P_{t-1}, Q_{t-1}, Q_{t-2}, Z_t, and Z_{t-1}), and $\boldsymbol{\varepsilon}$**:** vector of random error (v_t) with i.i.d distribution $N(\boldsymbol{0}_n, \sigma^2\boldsymbol{I}_n)$**.** Equation (13) is estimated by the least square method or maximum likelihood method. So, the estimators of the regression coefficients are obtained as follows:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y}$$

Zellner propose Gaussian prior to $\boldsymbol{\beta}$ [12],[13]:

$$\boldsymbol{\beta}|\alpha, \sigma^2 \sim N_p(\widetilde{\boldsymbol{\beta}}, g\sigma^2(\boldsymbol{X}^T\boldsymbol{X})^{-1})$$

And noninformative prior to α, σ^2:

$$\pi(\alpha, \sigma^2) \propto \sigma^{-2}$$

with assumption that $\boldsymbol{X}$ is full rank matrix, and g can be interpreted as constant and inverse proportional to available information. According to Ref. [8], the value of g is same with sample size ($g = n$). It means that prior give same share as one observation of samples. Prior $\pi(\alpha, \beta, \sigma^2)$ can be decomposed to be [5]:

$$\pi(\alpha, \boldsymbol{\beta}, \sigma^2) \propto (\sigma^2)^{-\frac{p}{2}} \exp\left[-\frac{1}{2g\sigma^2}\{\boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{X}\boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{P}\boldsymbol{X}\widetilde{\boldsymbol{\beta}}\}\right] \times \sigma^{-2}\exp\left[-\frac{1}{2g\sigma^2}\widetilde{\boldsymbol{\beta}}^T\boldsymbol{X}^T\boldsymbol{P}\boldsymbol{X}\widetilde{\boldsymbol{\beta}}\right]$$

with $\boldsymbol{P} = \boldsymbol{X}(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T$, so:

$$\pi(\alpha, \boldsymbol{\beta}, \sigma^2|\boldsymbol{y}) \propto (\sigma^2)^{-\frac{n}{2}-\frac{p}{2}-1} \exp\left[-\frac{1}{2\sigma^2}(\boldsymbol{y} - \bar{\boldsymbol{y}}\boldsymbol{1}_n - \boldsymbol{X}\boldsymbol{\beta})^T(\boldsymbol{y} - \bar{\boldsymbol{y}}\boldsymbol{1}_n - \boldsymbol{X}\boldsymbol{\beta})\right] \times \exp\left[-\frac{n}{2\sigma^2}(\bar{\boldsymbol{y}} - \alpha\right] \text{x} \exp\left[-\frac{1}{2g\sigma^2}\widetilde{\boldsymbol{\beta}}^T\boldsymbol{X}^T\boldsymbol{P}\boldsymbol{X}\widetilde{\boldsymbol{\beta}}\right] \times \exp\left[-\frac{1}{2g\sigma^2}\{\boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{X}\boldsymbol{\beta} - 2\boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{P}\boldsymbol{X}\widetilde{\boldsymbol{\beta}}\}\right] \quad (14)$$

Due to $\boldsymbol{1}_n{}^T\boldsymbol{X} = \boldsymbol{0}$, **so**

$$\pi(\alpha, \boldsymbol{\beta}, \sigma^2|\boldsymbol{y}) \propto (\sigma^2)^{-\frac{n}{2}-\frac{p}{2}-1} \exp\left[-\frac{1}{2\sigma^2}(\boldsymbol{y} - \bar{\boldsymbol{y}}\boldsymbol{1}_n - \boldsymbol{X}\boldsymbol{\beta})^T(\boldsymbol{y} - \bar{\boldsymbol{y}}\boldsymbol{1}_n - \boldsymbol{X}\boldsymbol{\beta})\right] \times \exp\left[-\frac{n}{2\sigma^2}(\bar{\boldsymbol{y}} - \alpha\right] \text{x} \exp\left[-\frac{1}{2g\sigma^2}\widetilde{\boldsymbol{\beta}}^T\boldsymbol{X}^T\boldsymbol{P}\boldsymbol{X}\widetilde{\boldsymbol{\beta}}\right] \times \exp\left[-\frac{1}{2g\sigma^2}\{\boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{X}\boldsymbol{\beta} - 2\boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{P}\boldsymbol{X}\widetilde{\boldsymbol{\beta}}\}\right]$$

Due to $\boldsymbol{P}\boldsymbol{X} = \boldsymbol{P}$**,** so equation (14) is conditional to $\boldsymbol{y}, \boldsymbol{X}$ and σ^2, so α dan $\boldsymbol{\beta}$ are independent. Posterior distribution of α dan $\boldsymbol{\beta}$ as follows:

$$\alpha|\sigma^2, \boldsymbol{y} \sim N_1\left(\bar{\boldsymbol{y}}, \frac{\sigma^2}{n}\right) \quad (15)$$

$$\beta|\boldsymbol{y}, \sigma^2 \sim N_p\left(\frac{g}{g+1}\left(\widehat{\boldsymbol{\beta}} + \frac{\boldsymbol{X}\widetilde{\boldsymbol{\beta}}}{g}\right), \frac{\sigma^2 g}{g+1}(\boldsymbol{X}^T\boldsymbol{X})^{-1}\right) \quad (16)$$

$$\sigma^2|\boldsymbol{y} \sim IG\left[\frac{(n-1)}{2}, s^2 + \frac{(\widetilde{\boldsymbol{\beta}} - \widehat{\boldsymbol{\beta}})^T\boldsymbol{X}^T\boldsymbol{X}(\widetilde{\boldsymbol{\beta}} - \widehat{\boldsymbol{\beta}})}{g+1}\right] \quad (17)$$

where $\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y}$. Posterior distribution is independent between $\boldsymbol{\alpha}$ dan $\boldsymbol{\beta}$. It is caused by a condition, that the matrix of $\boldsymbol{X}$ is centered. $IG(a, b)$ is distribution of inverse Gamma with mean is $b/(a-1)$ and variance is $b^2/((a-1)^2(a-2))$. $s^2 = (\boldsymbol{y} - \bar{\boldsymbol{y}}\boldsymbol{1}_n - \boldsymbol{X}\widehat{\boldsymbol{\beta}})^T(\boldsymbol{y} - \bar{\boldsymbol{y}}\boldsymbol{1}_n - \boldsymbol{X}\widehat{\boldsymbol{\beta}})$. Mean and variance of marginal posterior distribution as follows [5]:

- α
  Mean of Posterior:
  $E^\pi(\alpha|\boldsymbol{y}) = \bar{\boldsymbol{y}}$
  Variance of Posterior:
  $V^\pi(\alpha|\boldsymbol{y}) = \kappa/n(n-3)$
  with: $\kappa = s^2 + (\widetilde{\boldsymbol{\beta}} - \widehat{\boldsymbol{\beta}})^T\boldsymbol{X}^T\boldsymbol{X}(\widetilde{\boldsymbol{\beta}} - \widehat{\boldsymbol{\beta}})/(g+1)$

- β
  Mean of Posterior:
  $$E^\pi(\boldsymbol{\beta}|\boldsymbol{y}) = \frac{g}{g+1}\left(\widehat{\boldsymbol{\beta}} + \frac{\widetilde{\boldsymbol{\beta}}}{g}\right) \quad (18)$$
  Variance of Posterior:
  $$V^\pi(\boldsymbol{\beta}|\boldsymbol{y}) = \frac{\kappa g}{(g+1)(n-3)}(\boldsymbol{X}^T\boldsymbol{X})^{-1}$$

- σ^2
  Mean of Posterior:
  $$E^\pi(\sigma^2|\boldsymbol{y}) = \frac{\kappa}{(n-3)}$$
  Variance of Posterior:
  $$V^\pi(\sigma^2|\boldsymbol{y}) = \frac{\left(\frac{(\widetilde{\boldsymbol{\beta}} - \widehat{\boldsymbol{\beta}})^T\boldsymbol{X}^T\boldsymbol{X}(\widetilde{\boldsymbol{\beta}} - \widehat{\boldsymbol{\beta}})}{g+1}\right)^2}{\left(\frac{(n-1)}{2} - 1\right)^2\left(\frac{(n-1)}{2} - 2\right)}$$

In this research, value of $g = 130$ (it is equal to observation size) and $\widetilde{\boldsymbol{\beta}} = \boldsymbol{0}_p$. Predictor variables are centered, so they affect intercept on Bayesian regression is the average of the response variable. The research used $\boldsymbol{1}_n{}^T\boldsymbol{X} = \boldsymbol{0}$ and $\boldsymbol{1}_n{}^T\boldsymbol{y} = \boldsymbol{0}$ transformation because those transformation are suitable with flat prior specification [2]. Besides that, this research focus on regression coefficient (except intercept). Thus, elasticity is measured based on Bayesian regression, which is equation (18) refers to equation (11) and (12).

IV. RESULTS AND DISCUSSION

Model Estimation

Estimation of equation (10) with Bayesian Method as follows:

Table 1. Estimation of equation (10) with Bayesian Method

Coefficient of Regression	Posterior Means	Posterior standard deviation of Coefficient of Regression	Log_{10} of Bayes Factor
α	18.1966	0.0057	**-**
$\hat{\beta}_1$	0.0227	0.0089	0.3394
$\hat{\beta}_2$	**0.0849**	**0.0185**	**3.2497**
$\hat{\beta}_3$	0.0061	0.0127	-1.0074
$\hat{\beta}_4$	**0.1500**	**0.0129**	**19.3220**
$\hat{\beta}_5$	**-0.0540**	**0.0192**	**0.6265**
Posterior mean of σ^2	0.0043	Posterior standard deviation of σ^2	0.0061
R^2	0.2105		

Table 1 gives information that based on the value of Log_{10} of Bayes Factor [7] can be known that variable of production at time t-1, harvested area at time t, and harvested area at time t-1 have strong effect and significant to production of Big Chili at time t. The signs of coefficient $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3$, and $\hat{\beta}_4$ are positive. It suitable with economic theory that price of producer level at time t-1, harvested area at time t, production at time t-1, and production at time t-2 have same relation with supply (production). Overall, Bayesian regression model can explain 21.05% of variance on the response variable (production), and 78.95% of variance on the response variable is explained by other factors.

The Bayesian method can be applied in the estimation of the Nerlove Model of the Big Chili supply. This is indicated from the five predictor variables in the model, only two variables are not significant and three variables are significant. The coefficient of determination generated by the model is low, due to the use of priors which have a bias effect on the posterior distribution and there is a nonlinear relationship between the response variables and/or the predictor variables, which is not included in the model.

Estimation of Price Elasticity

Table 2 Estimation of Elasticity of Producer Price

Price Elasticity	Value
Price elasticity in short-term	0.0849
Price elasticity in long-term	0.0250

Table 2 gives information that the value of price elasticity in the short-term and long-term between 0 and 1. It means inelastic. The value of price elasticity in the short-term and long-term are 8.49% and 2.50%. In the short-term, if the price of the producer level (farm-level price) increase by 1%, Big Chili supply increase by 8.49%. Then, in the long-term, if the price of producer level (farm-level price) increase by 1%, Big Chili supply increase by 2.50%.

V. CONCLUSION AND FUTURE SCOPE

The Bayesian method can be applied in the estimation of the Nerlove Model of the Big Chili supply. However, the resulting coefficient of determination is low by 21.05%. The reason is thought to be the use of prior that have a bias effect on posterior distribution and/or there is a nonlinear relationship to the variables in the model. However, only two variables were not significant from the five predictor variables, namely the level of producer price of big chili at time t-1 and the production of Big Chili at time t-2.

Based on the estimation of the Nerlove Model, it is known that the production variables at time t-1, harvested area at time t, and harvested area at time t-1 have a strong and significant effect on the production (supply) of Big Chili at time t is based on Bayes Factor. The signs of the coefficients model are positive. This is consistent with the economic theory that producer prices at time t-1, harvested area at time t, production at time t-1, and production at time t-2 have a unidirectional relationship with supply (production).

The estimation results of price elasticity in the short and long-term were 8.49% and 2.50%, respectively, which is the inelastic category. It shows that big chili farmers are not responsive to prices. Because the costs of cultivation are high, so it causes the profits obtained by farmers not so much, even though the farm-level prices increase. It becomes insignificant for income farmer.

For further research, the Nerlove Model needs to include seasonal elements, because several variables such as price and production are influenced by significant seasonal elements. Using the Bayesian approach in estimastion of nonlinear model, it is also necessary to investigate the effects of using noninformative priors on the accuracy of the Nerlove Model and the significance of the predictor variables.

ACKNOWLEDGMENT

Give thanks to Allah, and for our institutions, Statistics-Indonesia (Badan Pusat Statistik).

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