Analysis of Markov switching seemingly unrelated regression model with skewed distributions, and its application to Thai cassava market

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Abstract. This study conducts a Markov switching seemingly unrelated regression with skewed distribution. We analyse MS-SUR model under skewed distributions. In other words, the multivariate skew-normal and skew-t with unknown skewness parameter are adopted to be the likelihood for the MS-SUR model. The simulation results show that parameters of MS-SUR model appear to be quite reasonable. In addition, we apply our model to study Thai cassava market and the results provide evidence that given skewed student-t distribution for both demand and supply equations in the MS-SUR models present the lowest AIC and BIC. Moreover, the empirical results show that exchange rate and export price are two main factors that affect, respectively, demand for and supply of Thai cassava in market downturn regime.

1. Introduction
The regime switching multivariate regression model with normal error term is widely used in causal analysis, and in various other areas of study. The model is normally based on the assumption of normality which is easy to implement in the statistical inference for the analysis of the model. However, in practice, many studies often become painfully aware that the normality assumption is not quite reasonable and accurate, and heavy tails and asymmetric distribution are required for capturing the characteristics of high fluctuation market data. One of the most recent approaches in the regime switching multivariate regression analysis is the Markov switching seemingly unrelated regression (MS-SUR) model which has become a popular nonlinear model as it can clarify the heterogeneous behaviors in different time periods and can detect the change in the data structure (see [1, 2, 3]). [1] and [2] assumed a symmetric normal distribution on the structure of likelihood function while [3] extended the work of [1] and [2] by allowing the model to have either normal or student-t distribution. The study of [2] proposed a Copula based MSSUR model, which seems to be more flexible to use since it can capture the different behavior of the time series data as well as relax the assumption of the normal distribution in the structural disturbances of the multiple equations. However, these studies might not be accurate to fit the real data and may be counterfactual in many real applications nowadays. In addition, modeling the likelihood structure of the MS-SUR model through normal and student-t distributions is limited to the symmetric nature. Although, the model of [2] is likely to have a great performance to deal with the asymmetric nature through the copula function, but the distribution
assumption of each equation is still restricted to be symmetric distributions, namely normal and student-\( t \).

To overcome these problems, we proposed a skew parameter to the likelihood of the MS-SUR model in order to gain more efficiency of the system equations with regime switching. Thus, the model will become more flexible and capture the asymmetric behavior of the datasets as well as relax the assumption of the symmetric normal and student-\( t \) distribution. To do this, we analyze MS-SUR model under skewed distribution. In other words, the multivariate skew-normal and skew-\( t \) with unknown skew parameter are adopted to be the likelihood for the MS-SUR model. This model will become more useful for data sets having skewed distributions from both analytical and practical points of view. In the estimation procedure, we use the maximum likelihood (ML) method based on the maximization of the likelihood function with respect to parameters of interest.

In short, this study proposes to use a skewed likelihood distribution to relax the symmetric error assumption in the conventional MS-SUR model. To examine the accuracy of the model using a simulated data and the usefulness of the model, we use a real data analysis. We apply our model to study and derive the demand and supply configurations in Thai cassava market. The data set related to Thai cassava is used as an application since cassava has created a large economic value for the Thai economy as it is one of the important agricultural exports of Thailand and Thailand is a major exporter of cassava in the world market.

In this study, we intend to estimate the demand and supply equations to determine a market equilibrium and elasticities of any products. In the conventional methods, for example seemingly unrelated regression (SUR), Two-stage least squares (2SLS), Three-stage least squares (3SLS) are proposed to deal with the simultaneous equation (see [4]). These methods have been widely adopted to derive demand and supply equations of several markets e.g. [5], [6], [7] and [8]. Nevertheless, these studies were likely to obtain the efficient results as the strong assumption of normal distribution is not always true in the real data analysis. To use the normality assumption for statistical inference of any highly dynamic scenarios is not quite reasonable and accurate, and heavy tails and asymmetric distribution are required for capturing the characteristics of high fluctuation market data. Therefore, it is reasonable to apply the MS-SUR model under skewed distribution for deriving demand for and supply of Thai cassava in market.

The remainder of this study is organized as follows: Section 2 presents a methodology used in this study and elaborates the estimation procedures, Section 3 presents Monte Carlo simulation study, and the application study is provided in Section 4 and Section 5 is conclusion.

2. Methodology

An MS-SUR with skewed distribution model is described in this section to provide a general framework to analyze non-linearity and structural breaks in the movement of agricultural market across regimes. Section 2.1 sets out the details of two families of skewed distribution, namely, the multivariate skew-normal distribution and the multivariate skew student-\( t \) distribution that underlies the MS-SUR model. The skew-normal and skew student-\( t \) likelihood with regime switching allows the correlation and skewness parameters to become regime dependent. In comparison to conventional MS-SUR model, there is also an allowance for structural breaks in the skewness.

2.1. Overview of the MS-SUR model

Mathematically, the MS-SUR model is given by:

\[
y_j = \beta_j(s_j)X'_j + u_j(s_j), \quad j = 1, ..., M, \quad \text{with} \]

\[
E[u_i(s_i)u'_j(s_j)] = \begin{cases} 
\sigma_{ij}(s_i)I, & (i \neq j) \\
\sigma^2_i(s_i)I, & (i = j), 
\end{cases}
\]

(2.1)

where \( y_j \) is \( T \times 1 \) vector of dependent variables of equation \( j \) and \( X_j \) is \( T \times K_j \) matrix of \( K_j \) independent variables of equation \( j \) and \( \beta_j(s_j) \) is \( 1 \times K_j \)-dimensional regime dependent coefficient.
vector of equation $j$. $u_j(s_j)$ is a $T \times 1$ vector of regime dependent error of equation $j$. In the conventional method, the error term here is assumed to have normal distribution with mean zero and covariance matrix $\Sigma(s_j)$, and thereby having $u_j \sim N(0, \Sigma(s_j))$, where

$$
\Sigma(s_j) = \begin{bmatrix}
\omega_1(s_j) & \omega_2(s_j) & \cdots & \omega_{n_j}(s_j) \\
\omega_2(s_j) & \cdots & \cdots & \cdots \\
\vdots & \ddots & \ddots & \ddots \\
\omega_{n_j}(s_j) & \cdots & \cdots & \omega_{n_j}(s_j)
\end{bmatrix}
$$

The regime $\{s_j\} = \{1, \ldots, H\}$ at time $t$ is an unobserved state variable in regime $h$. Hence, there are $H$ sets of regime-dependent parameters, $\Sigma(s_j = h)$, $\beta_j(s_j = h)$ which are governed by first order Markov process and the transition probabilities matrix $Q$. To estimate the MS-SUR model, the maximum likelihood is used. If the values of $(s_j)$ are known, let’s say $H = 2$ regimes, the normal likelihood can be written as

$$
L(\Theta|y_j, X_j) = \sum_{h=1}^{2} \prod_{t=1}^{T} f(y_j|s_j = h|\Theta_{t-1}) \Pr(s_j = h|\Theta(s_j = h))
$$

log $L(\Theta|y_j, X_j) = \sum_{h=1}^{2} \left[ \frac{M}{2} \log(2\pi) - \frac{M}{2} + \log(\Sigma|s_j = h|) - \frac{1}{2} \left( \frac{y_j - \beta_j(s_j = h)X_j}{\Sigma|s_j = h|} \right)^2 \right] \Pr(s_j = h|\Theta)$,

where $\Theta = \beta_j(s_j), \Sigma(s_j)$ are all available information sets of the model, and $Pr(s_j = h|\Theta(s_j)$ is state’s probabilities which are obtained from the Hamilton’s filter algorithm (see[9]). The probability of each state is to be updated by the following formula

$$
Pr(s_j = h|\Theta(s_j = h)) = \frac{f(y_j|s_j = h|\Theta_{t-1}) \Pr(s_j = h|\Theta(s_j = h))}{\sum_{h=1}^{2} f(y_j|s_j = h|\Theta_{t-1}) \Pr(s_j = h|\Theta(s_j = h))}, \ h = 1, 2
$$

By the Bayes’ theorem, and the filtered probability at time $t+1$ is updated by

$$
Pr(s_{t+1} = h|\Theta(s_t = h)) = p_{11}Pr(s_t = 1|\Theta(s_t = 1)) + p_{22}Pr(s_t = 2|\Theta(s_t = 2)),
$$

where $p_{11}$ and $p_{22}$ are transition probability of switching in their own regime, thus we can have a transition matrix $Q$ as

$$
Q = \begin{bmatrix}
p_{11} & 1 - p_{11} \\
1 - p_{11} & p_{22}
\end{bmatrix}
$$

2.2. Regime switching with the skewed distributions

The model extends the MS-SUR of [1] and [2] by assuming that the likelihood has a multivariate skewed distribution, like skew-normal or skew-$t$. This extension is useful as it has the ability to capture the stylized behavior of data as well as the asymmetric and the heavy tail. Therefore, in this study, we consider exploring into the four distributions consisting of normal, student-$t$, skew-normal, and skew-$t$.

- Normal likelihood function

$$
L_N(\Theta|y_j, X_j) = f_N(\cdot) = \sum_{h=1}^{2} \prod_{t=1}^{T} \exp\left( -\frac{1}{2} (u_j(s_j = h))^T \Sigma(s_j = h)^{-1} (u_j(s_j = h)) \right)
$$

where $u_j(s_j = h)$ is regime dependent error term.

- Skewed normal likelihood
\[
L_{SN}(\Theta | y_j, X_j) = f_{SN}(\cdot) = \sum_{h=1}^{H} \prod_{t=1}^{T} \left( \frac{2}{\xi(s_i = h) + (\xi(s_i = h))^{-1}} \cdot f_n(z_j/ Y(s_i = h)) \right) \tag{2.9}
\]

\[
z_j|(s_i = h) = \frac{u_j(s_i = h)}{\Sigma(s_i = h)} \sqrt{((1-m_t^2)\left(\xi^2(s_i = h) + (\xi^2(s_i = h))^{-1}\right) + 2m_t^2 - 1)} + mu(s_i = h) \tag{2.10}
\]

\[
m_i = 2/\sqrt{2\pi},
\]

\[
Y(s_i = h) = \xi^{sign(z)}(s_i = h)
\]

\[
mu(s_i = h) = m_i \left( \xi(s_i = h) - (\xi(s_i = h))^{-1} \right),
\]

where \( \xi \) is skewness parameter of return \( i \). \( f_n(\cdot) \) is density of normal distribution in equation (2.8) and \( sign(\cdot) \) is a function returning a vector with the signs of the corresponding elements of \( z_i \) (the sign of a real number is 1, 0, or -1 if the number is positive, zero, or negative, respectively).

- Student- \( t \) likelihood

\[
L_t(\Theta | y_j, X_j) = f_{t}(\cdot) = \sum_{h=1}^{H} \prod_{t=1}^{T} \left( \frac{\Gamma(\nu(s_i = h) + 1)}{\sqrt{(\nu(s_i = h)-2)\nu(s_i = h)}} \left( \frac{\nu(s_i = h) - 1}{\nu(s_i = h)-2} \right)^{-\nu(s_i = h)/2} \cdot \frac{1}{\Sigma(s_i = h)} \right), \tag{2.14}
\]

where \( \nu \) is degree of freedom and \( \Gamma \) is gamma distribution.

- Skewed student- \( t \) likelihood

\[
L_{ST}(\Theta | y_j, X_j) = f_{ST}(\cdot) = \sum_{h=1}^{H} \prod_{t=1}^{T} \left( \xi(s_i = h) + 1 \right) / \xi(s_i = h) \cdot f_r(z_j/ \xi(s_i = h), \nu(s_i = h)) F(s_i = h), \tag{2.15}
\]

\[
z_j|(s_i = h) = \frac{u_j(s_i = h)}{\Sigma(s_i = h)} F(s_i = h) + \left[ \frac{2\nu(s_i = h) - 2}{\nu(s_i = h) - 1} \left( beta(0.5, \frac{\nu(s_i = h)}{2}) \right)^{-1} \right]^{-1} \left( \xi(s_i = h) - 1 \right) \left( \xi(s_i = h) \right), \tag{2.16}
\]

\[
F(s_i = h) = \left[ 1 - \left( \frac{2\nu(s_i = h) - 2}{\nu(s_i = h) - 1} \right) \left( beta(0.5, \frac{\nu(s_i = h)}{2}) \right)^{-1} \right]^{-1} \left( \xi(s_i = h) \right)^{-1}, \tag{2.17}
\]

where \( f_r(\cdot) \) is the density of student- \( t \) distribution. \( beta(\cdot) \) is beta distribution.

To estimate the MS-SUR model, we use the maximum likelihood estimation (MLE) to estimate the parameter sets including \( \Theta \) and \( Q \) by maximizing equation (2.4) and the last step is to find an appropriate MS-SUR likelihood by identifying the best fitted skew distribution using lowest Akaikiki information criterion (AIC) and Bayesian information criterion (BIC).

3. Simulation

This section deals with the simulation study of two-regime MS-SUR with two equations. Thus, we generate random data from the following model specifications (table 1):

Remind that, two equations with two-regimes, \( s_i =1,2 \) consisting of the high regime \( s_i = 1 \) and low regime \( s_i = 2 \), is considered in this application study. The filtered probabilities is generated from \( U[0,1] \), transition probability is \( p_{1} = 0.95 \) , \( p_{2} = 0.95 \) and the independent variables \( X \) are generate form \( N(0,1) \). Then, our simulated model is
\[ \begin{align*}
\gamma_1(s_i=1) & = \beta_1(s_i=1) + \beta_2(s_i=1) X_1 + u_1(s_i=1) \\
\gamma_1(s_i=2) & = \beta_1(s_i=2) + \beta_2(s_i=2) X_1 + u_2(s_i=2) \\
\gamma_2(s_i=1) & = \alpha_1(s_i=1) + \alpha_2(s_i=1) X_2 + u_1(s_i=1) \\
\gamma_2(s_i=2) & = \alpha_1(s_i=2) + \alpha_2(s_i=2) X_2 + u_2(s_i=2)
\end{align*} \] (3.1)

| Case | $T=100$ | $T=200$ |
|------|----------|----------|
|      | TV       | SSTD     | SNORM       | SSTD     |
| $\beta_1(s_i=1)$ | 1  | 1.1597 (0.1461) | 0.3062 (0.0832) | 0.6597 (0.0770) | 1.2425 (0.0769) |
| $\beta_2(s_i=1)$ | 2  | 1.6601 (0.1179) | 1.7561 (0.0705) | 1.6488 (0.0691) | 2.1769 (0.0569) |
| $\beta_1(s_i=2)$ | 1.5 | 1.2857 (0.1001) | 2.5451 (0.0968) | 1.2449 (0.0892) | 1.7503 (0.0572) |
| $\beta_2(s_i=2)$ | 3   | 2.8889 (0.0722) | 2.7901 (0.0689) | 2.9210 (0.0511) | 2.8659 (0.0586) |
| $\alpha_1(s_i=1)$ | -2 | -1.1368 (0.093) | -1.7789 (0.100) | -1.5218 (0.096) | -1.7645 (0.053) |
| $\alpha_2(s_i=1)$ | 2  | 1.9012 (0.0816) | 2.0556 (0.0850) | 1.8721 (0.0378) | 2.6045 (0.0834) |
| $\alpha_1(s_i=2)$ | 1   | 1.5747 (0.1088) | 1.3459 (0.1191) | 1.2857 (0.0786) | 1.2425 (0.0769) |
| $\alpha_2(s_i=2)$ | 2   | 2.1475 (0.0601) | 2.0112 (0.0112) | 1.9256 (0.0292) | 1.8598 (0.0586) |
| $\xi_1(s_i=1)$ | -0.5 | -0.9763 (0.071) | -0.9192 (0.419) | -0.4409 (0.003) | -0.2052 (0.066) |
| $\xi_2(s_i=1)$ | 1  | 1.9516 (0.1565) | 1.5034 (0.1169) | 1.1545 (0.0958) | 1.0038 (0.0012) |
| $\xi_1(s_i=2)$ | -1 | -0.5275 (0.275) | -1.6591 (0.616) | -1.6589 (0.531) | -0.9469 (0.281) |
| $\xi_2(s_i=2)$ | 3   | 3.0741 (0.3199) | 9.1732 (2.4080) | 4.5223 (0.4273) | 3.6454 (0.1045) |
| $v(s_i=1)$ | 6   | 12.1205 (5.551) | 10.1245 (4.225) | 10.1245 (4.225) | 10.1245 (4.225) |
| $v(s_i=2)$ | 3   | 4.8541 (1.5584) | 3.8458 (0.8555) | 3.8458 (0.8555) | 3.8458 (0.8555) |
| $p_{11}$ | 0.95 | 0.9592 (0.0121) | 0.9448 (0.0169) | 0.9433 (0.0111) | 0.9465 (0.0107) |
| $p_{22}$ | 0.95 | 0.9355 (0.0181) | 0.9660 (0.0105) | 0.9537 (0.0096) | 0.9541 (0.0093) |

The error terms are assumed to follow a skewed normal and skewed student-t distributions with mean zero and variance $\Sigma(s_i)$ being set to be

\[
\Sigma(s_i=1) = \begin{bmatrix} 0.8 & -0.5 \\ -0.5 & 1 \end{bmatrix}, \Sigma(s_i=2) = \begin{bmatrix} 1 & -0.8 \\ -0.7 & 1.2 \end{bmatrix}
\] (3.2)

while the skewness parameters are set to be $\xi(s_i=1)=[-0.5, 1], \xi(s_i=2)=[-1.3]$. In the case of skew student-t distribution, the degree of freedom parameters are set as $v(s_i=1)=6$ and $v(s_i=2)=3$. In this study, we consider sample size $T=100,200$. The results of this simulation study are shown in tables 1. We can observe the estimated means from 2 cases of skew-normal and skew student-t distributions. We observe an unbiased parameter estimates when compared with their true values. It can be seen that the estimated parameters appear to be quite reasonable as their values are close to the true values with reasonable standard error. In addition, when the sample size increases, the estimated parameters get closer to the true values and the estimated standard errors decrease. The results confirm the validity of the asymptotic properties of our model.

4. Application to Thai cassava market
Cassava is one of staple food crops that are critical to food security. For Asia, demand for cassava is continuing in various industries such as the alcohol, ethanol, food and feed industries. The cultivation of cassava is not complicated as it is easily grown and resistant to variability of climate. The main
market of Thai cassava is China. Thailand’s cassava exports to China account for about 99.76 percent. Competitors of Thai cassava are Indonesia and Vietnam. There is still high demand for cassava from the world market. In practice, the cassava market consists of two main components, i.e. demand for and supply of the cassava. They are used to determine the equilibrium price and quantity for the market. Moreover, the study of [2], [3], [10] and [11] confirmed the structural change in the agricultural and economic data. Thus, it is reasonable to have a MS-SUR in Thai cassava market.

4.1. Overview of the MS-SUR model
The data sets include monthly data from January 2007 to September 2016 for demand for cassava sum of quantity of export and domestic consumption ($Q^d_t$), output of cassava ($Q^i_t$), average export price of Thai cassava ($P^\text{export}_t$), export price of Indonesian cassava ($P^\text{indo}_t$), water storage ($W_t$), quantity of rainfall ($R_t$), price of oil ($P^\text{oil}_t$), exchange rates ($E_t$) which were obtained from Thomson Reuter data stream, and Office of Agricultural Economics of Thailand. The descriptive statistics are shown in table 2. It is found that export price of Indonesia’s cassava has standard deviation the highest. The Jarque-Bera (JB) statistic indicates that virtually all series, except the exchange rates are not normally distributed because it rejects the null hypothesis. The data were converted into $(x_t - x_{t-1})/x_{t-1}$ form. To avoid the spurious regression problem, an Augmented Dickey Fuller unit root test is used before estimating the MS-SUR model. The results show that all variables are stationary. In this study, two equations, namely demand and supply, are investigated in Thai cassava market. Thus, we can model the equations as:

$$Q^d_t = f (P^\text{export}_t, P^\text{indo}_t, O_i, E_t), \quad Q^i_t = f (P^\text{export}_t, R_t, W_t)$$

(4.1)

| Variable | Mean | Maximum | Minimum | Skewness | Kurtosis | JB | ADF-Test | Note |
|----------|------|---------|---------|----------|----------|----|----------|------|
| $Q^d_t$  | 0.1470 | 0.1819  | 0.0062  | 0.4898   | -0.0001  | 0.0053 | 494.0534*** | *** |
| $Q^i_t$  | 3.9043 | 4.4656  | 0.1581  | 9.4937   | 0.0420   | 0.3167 | 98.3143***   | **  |
| $P^\text{export}_t$ | -0.8203 | -0.8087 | -0.2461 | -0.9400  | -0.0332  | -0.4479 | 24.9392***    | -     |
| $P^\text{indo}_t$ | 2.4961 | 2.1409  | -0.8468 | 3.0849   | 0.4746   | -0.4093 | 98.3143***    | **  |
| $E_t$    | 11.7419 | 11.2357 | 7.1591  | 13.8682  | 2.8482   | 5.1084 | 98.3143***    | **  |
| $O_i$    | 7.1591 | 11.2357 | 7.1591  | 13.8682  | 2.8482   | 5.1084 | 98.3143***    | **  |
| $R_t$    | 0.0062 | 0.0040  | 0.0062  | 0.0040   | 0.0040   | 0.0040 | 52.441***     | *    |
| $W_t$    | 0.0062 | 0.0040  | 0.0062  | 0.0040   | 0.0062   | 0.0040 | 52.441***     | *    |

4.2. Model selection

| Model | Distribution | AIC | BIC |
|-------|--------------|-----|-----|
| Regime 1 | normal | 551.625 | 576.484 |
| 1 | Student-t | 545.201 | 572.823 |
| 2 | Skewed student-t | 509.712 | 542.858 |
| 3 | Skewed normal | 488.871 | 519.255 |
| 4 | Student-t | 495.064 | 550.307 |
| 5 | Skewed student-t | 403.056 | 474.11 |
| 6 | Skewed normal | 407.817 | 474.87 |

Table 3. Information criteria values.
In this section, one-regime and two-regime MS-SUR models with four different likelihood distributions are chosen, where the selection of the best fit model is based on (AIC) and (BIC). We consider normal, student-\( t \), skewed student-\( t \) and skewed normal as the distribution assumption for MS-SUR model. According to table 3, the result shows that two-regime MS-SUR model with skewed student-\( t \) distribution shows the better fit than other specifications as it has the lowest AIC (403.056), and BIC (474.11). The results provide evidence that the given skewed student-\( t \) distribution appropriate for both demand and supply equations in two-regime MS-SUR model.

4.3. Estimation results

Estimated demand and supply equations from MS-SUR model (Conventional MLE)

\[
Q^d = -0.313 P_{exp}^d - 0.355 P_{supp}^d + 0.0024 P_{exp}^d + 0.241 P_{supp}^d + 1.28 E_X, (S_i = 1)
\]

\[
(0.056) (0.994) (0.0193) (0.376) (1.41)
\]

\[
Q^d = 0.119 - 0.968 P_{exp}^d + 0.0045 P_{supp}^d - 0.721 P_{exp}^d + 2.99 E_X, (S_i = 2)
\]

\[
(0.084) (1.36) (0.036) (0.531) (1.39)
\]

\[
Q^s = -0.179 + 0.803 P_{exp}^s + 0.012 W_T + 0.0047 R_T, (S_i = 1)
\]

\[
(0.178) (1.13) (0.922) (0.019)
\]

\[
Q^s = -0.278 + 1.24 P_{exp}^s - 0.692 W_T - 0.002 R_T, (S_i = 2)
\]

\[
(2.94) (0.635) (0.687) (0.009)
\]

Note: *** Significant at 1% level, ** Significant at 5% level, and * Significant at 1% level, ( ) is Std.error

\[Q = \begin{bmatrix} 0.65 \\ 0.35 \\ 0.59 \\ 0.41 \end{bmatrix}. \quad (4.2)\]

Figure 1. The filtered probabilities of regime 1

The filtered probabilities obtained from Hamilton's filter are plotted in figure 1. We can observe that cassava market is more likely to stay in regime 1 (65% probability) than in regime 2 (41%), see equation 4.3. This indicates that regime 1 is more persistent than regime 2.

Equation (4.2) shows the estimation results of two-regime MS-SUR model. In this study we interpret regime 1 as market upturn regime, while regime 2 as market downturn regime. We find that Thai cassava export prices shows a significant effect to supply of cassava in regime 2, its coefficient indicates a positive effect of export price to supply of Thai cassava, which is corresponding to the theory of supply. The increase in Thai cassava export prices by 1% will lead to a decrease in the demand for Thai cassava by 1.24%. Next, Indonesian cassava export prices, which is viewed as the competing price of Thai cassava, seems not to be the factor affecting the demand for Thai cassava since it does not show a significant result. In the case of exchange rate, we can obtain a significant effect of this variable to demand for Thai cassava only in market upturn regime where the positive sign of coefficient indicates a positive effect of exchange rate on the demand for Thai cassava. This means if exchange rate increases (depreciate) by 1%, it will increase the demand for Thai cassava by 2.99%. In addition, for the cases of water storage and quantity of rainfall, we cannot obtain the significant effect of these variables on Thai cassava supply in both two-regimes.
5. Conclusions
The errors in a MS-SUR model are normally assumed to have elliptical distributions, namely normal and student-t. However, these assumptions are rarely satisfied in practice. In the other words, when real data are used, we often become painfully aware that the symmetric assumption is not quite tenable, and heavy tails and skewness are required to adequately capture the behavior of the data, especially in finance studies. In this study, therefore, consider MS-SUR error terms that are distributed as multivariate skewed normal and student-t. To do this, we generalize the parametric distribution on the structure of the error term in the system equations of the Markov switching seemingly unrelated regression by modelling the likelihood function from the multivariate skewed normal and skewed student-t distribution. These skewed distributions can be viewed as a generalization of the normal and student-t distribution in which there is some skewness present a particularly valuable property is the continuity of the passage from the symmetric case to asymmetric distributions. In the simulation study, we assess the performance of our proposed model and obtained satisfactory results (the estimated values are close to the true values) regardless of the number or observations. Then, we apply our model to study Thai cassava market. The application study demonstrated the superiority of the proposed model to the existing model in term of the AIC and BIC. From these results, it is encouraging that the use of skewed likelihood distribution offers a better alternative in the analysis of MS-SUR models. Finally, the proposed model can be extended to copula-based approach. The MS-SUR model for non-normal multivariate distributions can be modeled and captured by various copula functions. General speaking, we can further extend the work of [3] by introducing several skewed distributions for each equation.

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