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Study on Import and Export Indicators in Indonesia Using Volatility and Markov Switching Model Combination

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Abstrak

Krisis ekonomi tahun 1997 merupakan masalah yang terjadi di hampir semua negara berkembang termasuk Indonesia. Berdasarkan krisis ekonomi, diperlukan indikator performance knowledge. Impor dan ekspor merupakan indikator penting yang harus dilihat kinerjanya. Data bulanan impor dan ekspor merupakan data deret waktu karena dikumpulkan, dicatat, dan diamati dalam urutan waktu. Data impor dan ekspor mengandung masalah heteroskedastisitas pada model residual dan conditional change pada volatilitas. Kombinasi model volatilitas dan Markov switching dapat mengatasi permasalahan dalam penelitian ini. Penelitian ini dikembangkan dengan menggunakan data volatilitas dan smoothed probability, selanjutnya penelitian ini memperoleh tingkat akurasi dengan membandingkan probabilitas prediksi dengan probabilitas smoothed dari data aktual. Hasil dari penelitian ini diperoleh model SWARCH(4,1) dengan ARIMA(1,0,0) untuk rata-rata dan ARCH(1) untuk varians yaitu untuk total data impor dan model SWARCH(2,1) dengan ARIMA(1, 0,0) untuk rata-rata dan ARCH(1) untuk varian yang merupakan total data ekspor. Probabilitas prediksi perbandingan dan probabilitas pemulusan dari data aktual diperoleh akurasi 40,91% untuk indikator impor dan 100% untuk indikator ekspor, artinya untuk indikator impor harus mengubah nilai awal model SWARCH agar lebih akurat.

Abstract

The economic crisis in 1997 is a problem that occurs in almost all developing countries including Indonesia. Based on the economic crisis, indicators perfomance knowledge is needed. Imports and exports are important indicators that must be seen for their performance. Monthly data on import and export is time series data because it is collected, recorded, and observed in a time sequence. The data on import and export contain heteroskedasticity problem on the model residual and conditional change on the volatility. The combined model of volatility and Markov switching can solve the problem in this study. This study developed to use volatility data and the smoothed probability, furthermore this study obtained the level of accuracy by comparing the prediction probability with smoothed probability from actual data. Result of this study obtain SWARCH(4,1) model with ARIMA(1,0,0) for mean and ARCH(1) for variance thats for the total data of import and SWARCH(2,1) model with ARIMA(1,0,0) for mean and ARCH(1) for variance thats for the total data of export. Comparism prediction probability and smoothed probability from the actual data obtained an accuracy 40,91% for impor indicator and 100% for ekspor indicator, that's mean for impor indicator must changed the initial value SWARCH model for more accuracy.

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INTRODUCTION

Economic crisis is a problem that occurs in almost all developing countries including Indonesia. The economic crisis occurs in Indonesia 1997 was part of the Asian Financial Crisis, and that crisis was a severe combination of financial market behavior that was beyond the limits and weak government policies (Margana and Fitrianingsih, [6]).

Learning from the crisis that occurred in the mid-July 1997, it was necessary to know anout performance on each indicators. Sugiyanto et al. [7], said some crisis indicators like a banking conditions, bank deposits, Real exchange rates, trade terms ondicators real output, domestic credit per GDP, import and export. Sugiyanto et al. [8], said that imports and exports are an important indicator in the economy in Indonesia. Import is process of entering goods or commodities from one country to another country. Export is process to sell goods or commodities that we have to other country.

Hermawan [5], said that import and export data is time series data because they are collected, recorded, and observed in a time sequence. Import and export data have significant. fluctuations, cause of that the data is not stationary. Import and export data also have heteroscedasticity effect on the stationary model residual. Engle [2], first introduced a model to solve the problem of heteroscedasticity effect, that model is Autoregressive Conditional Heteroscedastity (ARCH) used in the study of inflation data in the UK in 1958 to 1977.

Hermawan [5], said that the import and export data have condition changes in the volatility data. Hamilton [3], modeling time series data that have condition changes in the volatility data, that model is Markov switching (MS), but this model cannot describe heteroscedasticity effect. Hamilton and Susmel [4], introduce a model that can explain heteroscedasticity effect and condition changes in the volatility data, by combining the ARCH model and Markov switching model is known by Markov switching ARCH (SWARCH) model.

Previous studies by Hermawan (2015) based on import and export indicators using SWARCH (2.1), and SWARCH (3,1) models with ARMA (1.0) as a conditional average model and ARCH (1) as a conditional variance model. This study it has been obtained that the models combination can be used to solved heteroscedasticityeffect on the stationary model residual and condition changes on the volatility data. Sugiyanto et al. [8], has developed previous research to get forecasting based on filtered probability based on the three state SWARCH model and Sugiyanto et al. [7], redeveloping previous research by adding several indicators and changing filtered probability to smoothed probability, but that's study still have a weaknesses such as the volatility data obtained is not used to determine the state of the combined model and smoothed probability value is not based on the combined model. Previous studies also no accuracy of smoothed probability is used to see the performance of model combination, and this study was developed how the use of data volatility and the search the smoothed probability value with initial value appropriate. After obtaining the smoothed probability value, the accuracy level is also obtained by comparing the value of prediction probability by smoothing the probability on the actual data. Based on that developing, needed something study to see the performance model combination with export and import indicators. The perfomance can be see froom prediction probability, and that prediction probability is smoothed probability in the coming period

METHODOLOGY

A. Create a plot of import and export data.
B. Perform stationary data test using ADF (Augmented Dickey Fuller) test. If the data is not stationary, then the data must be transformed by using log return.
C. Analyze ARMA and ARIMA models by:
   1. ACF and PACF plot from data that has been transformed to form the ARMA, ARIMA, or seasonal ARIMA models,

2. form the ARMA, ARIMA, or seasonal ARIMA models based on the smallest akaike information criterion (AIC),
3. parameters estimation ARMA, ARIMA, or seasonal ARIMA models.

D. Perform a diagnostic test in the models to determine the best model for mean models.

E. Test the heteroscedasticity effect on the best residual ARMA, ARIMA, and seasonal ARIMA models. If there is a heteroscedasticity effect on the residual ARMA, ARIMA, or seasonal ARIMA models, then used ARCH model.

F. Form and analyze the ARCH model by:
1. the appropriate ARCH model can be form from ARIMA model square residual and choose the best ARCH model the smallest AIC,
2. parameters estimation ARCH model,
3. test the heteroscedasticity effect and white noise on the best ARCH model residual.

G. Forming a volatility and Markov switching models combination, cause of heteroscedasticity effect on the residual mean model and condition changes on the volatility data. Forming can be done by:
1. Clustering the volatility data to determine the state in the volatility model and Markov switching model combination,
2. looking for transition probability matrices between states, conditional mean and conditional variance,
3. looking for smoothed probability on each states,

H. Test the performance of volatility and Markov switching model combination based on import and export indicators by looking at the value of smoothed probability:
1. forming a plot of smoothed probability on each states in the transformation data based on the appropriate Markov Switching model and looking at the performance of import and export indicators from January 1990 to December 2016,
2. determine prediction probability for the performance of a combined model based on import and export indicators in the next period,
3. enter the actual value of the data to get the value of smoothed probability in the same period as prediction probability,
4. comparing the results of the smoothed probability and prediction probability value to get the level of accuration model by using classification tables and evaluation criteria.
5. based on accuracy seen the prediction probability value to assess the performance of the model combination.

DATA ANALYSIS

This study used data on the amount of import value and the total value of exports of Indonesian countries from January 19090 to with December 2016 totaling 324 observations. The data will then be divided into training data and testing data.

A. Establishment of Combined Volatility and Markov Switching Models

1. Data Plot

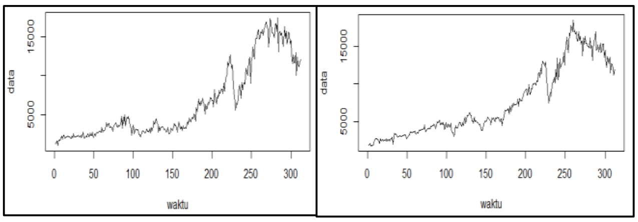

Figure 1. Data Plot for Impor and Ekspor

Figure 1 shows the plot data for import and export indicators is not stationary.

2. ADF Test

Data plots for import and export indicators indicate that the data is not stationary. To ensure the stability of the data the number of import values and the amount of export value is carried out by the ADF test.

H_0 : $\phi \geq 1$ (time series data not stasioner)

H_1 : $\phi < 1$ (time series stasioner)

based on test statistic from ADF test got probability value equal to 0,4763 bigger than α = 0,05. Then H_0 is not rejected which means that the data amount of import value is not stationary. After use the transformasi data log return then must cek again that uji ADF and got probability value equal to 0,0000 smaller than α = 0,05. Then H_0 is rejected which means that the data amount of import value is stationary.

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3. ARIMA Model Building

The autoregressive integrated moving average (ARIMA) model is a model used for stationary data. Because the data of the value of import value and the amount of export value of the transformation is stationary, it can be modeled using ARIMA model.

a. *ARIMA Model Identification*

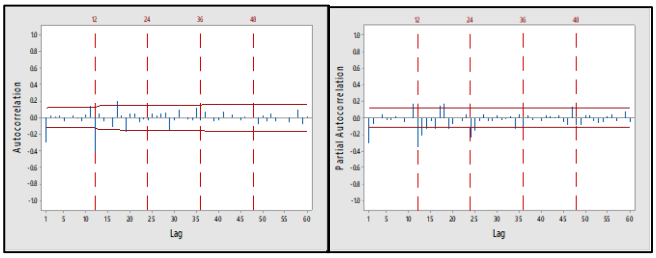

Figure 2. ACF and PACF Plot for Impor Indicator

Figure 2 shows shows that the model choices that can be used are ARIMA (1,0,0), and ARIMA (2,0,0). While Figure 2 shows the same for the data of the export value amount ie on the PACF plot out of the confidence limit in the first and second lag then disconnects afterwards which means the plot drops exponentially toward zero. This means that the choice of models that can be used also there are two namely ARIMA (1.0.0), and ARIMA (2.0.0).

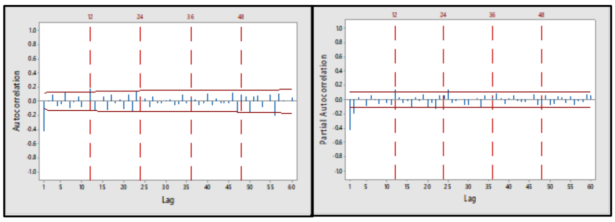

Figure 3. ACF and PACF Plot for Export Indicator

Figure 3 shows that the choice of models that can be use are ARIMA (1,0,0) (1,0,0), ARIMA (1,0,0) (0,0,1), ARIMA (2,0,0) (1,0,0), ARIMA (2,0,0) (0,0,1), ARIMA (0,0,1) (1,0,0) and ARIMA (0,0,1) (0 , 0.1). Figure 3 show for the transformation data of the amount of export value that is on the plot of ACF and PACF many lag out of confidence limit so it needs to be done differencing 12.

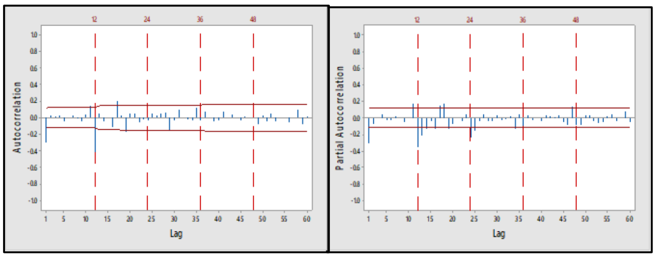

Figure 4. ACF and PACF after differencing 12 for Export Indicator

The result from differencing 12 can be seen in Figure 4 that ACF and PACF plot have a seasonal pattern in the MA model. So that the model that can be formed is ARIMA (1,0,0) $(0,1,1)^{12}$, and ARIMA (0,0,1) $(0,1,1)^{12}$.

a. Estimation Parameter for ARIMA Model

Based on Table 2 the ARIMA probability value in each parameter shows that all parameters are significant. ARIMA(2,0,0) model has an AIC value smaller than ARIMA(1,0,0) model, then can be written the average model for import indicator

$$r_t = -0{,}51262 r_{t-1} - 0{,}19425 r_{t-2} + a_t$$

with r_t is the log return at time t, and a_t is the residual generated by the model at time t.

Tabel 2. Parameter Estimation ARIMA and Seasonal ARIMA Model with Impor Data

Model	Parameter	Coefficient	Probability	*AIC*
ARIMA(1,0,0)	$\hat{\phi}_1$	-0,42538	0,0000	-439,81
ARIMA(2,0,0)	$\hat{\phi}_1$	-0,51262	0,0000	-451,95
	$\hat{\phi}_2$	-0,19425	0,0005	
$ARIMA(1,0,0)(1,0,0)^{12}$	$\hat{\phi}_1$	-0,4281	0,000	-446,58
	$\hat{\Phi}_1$	0,2143	0,000	
$ARIMA(1,0,0)(0,0,1)^{12}$	$\hat{\phi}_1$	-0,4214	0,000	-444,96
	$\hat{\Theta}_1$	-0,1873	0,000	
$ARIMA(2,0,0)(1,0,0)^{12}$	$\hat{\phi}_1$	-0,5038	0,000	-454,13
	$\hat{\phi}_2$	-0,1757	0,002	
	$\hat{\Phi}_1$	0,1914	0,001	
$ARIMA(2,0,0)(0,0,1)^{12}$	$\hat{\phi}_1$	-0,4989	0,000	-452,97
	$\hat{\phi}_2$	-0,1796	0,002	
	$\hat{\Theta}_1$	-0,1702	0,003	
$ARIMA(0,0,1)(1,0,0)^{12}$	$\hat{\theta}_1$	0,4477	0,000	-450,82
	$\hat{\Phi}_1$	0,1897	0,001	
$ARIMA(0,0,1)(0,0,1)^{12}$	$\hat{\theta}_1$	0,4460	0,000	-449,92
	$\hat{\Theta}_1$	-0,1757	0,002	

Based on table 3 the probability value of ARIMA in each parameter shows that all parameters are significant. ARIMA(2,0,0) has an AIC smaller than ARIMA(1,0,0), then the average model for export indicator can be wrtitten

$$r_t = -0{,}34686 r_{t-1} - 0{,}11135 r_{t-2} + a_t$$

with r_t is the log return at time t, and a_t is the residual generated by the model at time t.

Tabel 3. Parameter Estimation ARIMA and Seasonal ARIMA Model with Export Data

Model	Parameter	Coefficient	Probability	*AIC*

$ARMA(1,0)$	$\hat{\phi}_1$	-0,3135	0,000	-650,69
$ARMA(2,0)$	$\hat{\phi}_1$	-0,3468	0,000	-653,31
	$\hat{\phi}_2$	-0,1113	0,048	
$ARIMA(1,0,0)(0,1,1)^{12}$	$\hat{\phi}_1$	-0,290	0,000	-650,15
	$\hat{\Theta}_1$	-0,952	0,000	
$ARIMA(0,0,1)(0,1,1)^{12}$	$\hat{\theta}_1$	0,315	0,000	-652,14
	$\hat{\Theta}_1$	0,911	0,000	

Based on table 2 the probability value of seasonal ARIMA in each parameter shows that all parameters are significant. After that, based on Table 2, a model with the smallest AIC value is selected. ARIMA $ARIMA(2,0,0)(1,0,0)^{12}$ model has the smallest AIC value.

The average seasonal model is for impor indicator can be written

$$r_t = -0{,}5038r_{t-1} - 0{,}1757r_{t-2} + 0{,}1914r_{t-12} + a_t$$

with r_t is the log return at time t, and a_t is the residual generated by the model at time t.

Based on table 3 the probability value of seasonal ARIMA in each parameter shows that all parameters are significant. After that, based on table 3, the model with the smallest AIC. value is selected. $ARIMA(0,0,1)(0,1,1)^{12}$ model has AIC value smaller than the other seasonal models. The average seasonal model for export can be written

$$r_t = r_{t-12} + a_t - 0{,}3159a_{t-1} - 0{,}9112a_{t-12} + 0{,}2879a_{t-13}$$

with r_t is the log return at time t, and a_t is the residual generated by the model at time t.

b. Diagnostic Test for ARIMA Model

Normalitas

Based on the Kolmogorov-Smirnov test p-value of the import model.The model with p-value greater than α is ARIMA(1,0,0) model, but the model is not the model with the smallest AIC, the model with the smallest AIC value is ARIMA (2,0,0). Therefore the model that should be ARIMA (2,0,0), but the best model reduced to the ARIMA model (1.0), because the ARIMA model (1.0.0) meets the assumption of normality test.

Kolmogorov-Smirnov test p-value export model, the value is all below the significance level α. That means the export model does not meet the assumption of the normality diagnostic test. Armstrong [1], the assumption of normality can be ignored if the model is only used for forecasting. For this reason, the assumption of normality in export transformation data is ignored because the goal is to get the forecasting value of smoothed probability or prediction probability.

The p-value of the transformation data of the total export value is 0.072 which is greater than the significance level α which means that H_0 is not rejected or the model residual is normally distributed.

Autocorrelation

Based on Ljung-Box test on models that meet the assumption of white noise is all models, cause of the p-value for all models is above α = 0.05. Thats p-value means all models import and export indicators have met the requirements of white noise. To get the best model needs to be matched by testing the assumption of normality.

Heteroscedasticity

Based on p-value from all models obtained for import and export indicator have a smaller p-value than the significance level of α. That means H_0 is rejected, all residues in the model obtained contain heteroscedasticity effects.

4. Volatility Model Building *Import*

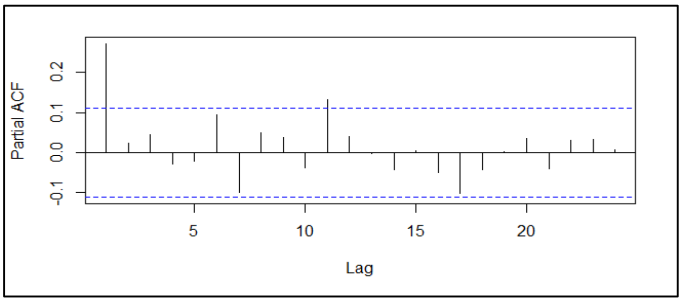

Figure 5. *PACF* Residual Square Plot from Mean Model from Import Data

Figure 5 shows that the PACF squared residual is interrupted in the 1st lag so that an indication of the volatility model that can be formed is the ARCH(1) model. To prove the best model is ARCH(1) parameter estimation needs to be done. The estimation results of parameter estimation ARCH(1) model has probability value is more than $\alpha = 0.05$, that means parameters is significant and white noise assumptions are met. So that the volatility model used is ARCH(1) can be written

$\sigma_t^2 = 0{,}00035 + 0{,}7888\alpha_{t-1}^2$.

Export

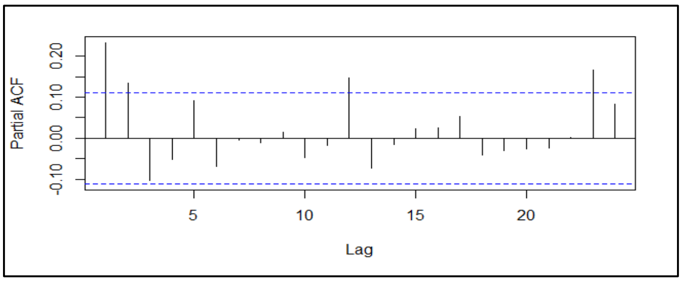

Figure 6. *PACF* Residual Square Plot from Mean Model from Export Data

Figure 6 shows that the PACF squared residual is interrupted in the 2nd lag so that an indication of the volatility model that can be formed is the ARCH(2) model. To prove the best model is ARCH(2) parameter estimation needs to be done. The estimation results of parameter estimation ARCH(2) model has probability value is more than $\alpha = 0.05$, that means parameters is significant and white noise assumptions are met. So that the volatility model used is ARCH(2) can be written

$\sigma_t^2 = 0{,}00012 + 0{,}2525\alpha_{t-1}^2 + 0{,}2386\alpha_{t-2}^2$.

5. Cluster Analysis

Based on the results of cluster analysis from each stage for data transformation of the number of import values and data on the total value of exports. From the result, it can be seen that the first drastic surge occurred at 890 which occurred in the 309th stage towards 310, ie from 2.963 to 3.853, this occurred when the agglomeration process produced four clusters. Whereas from table 4.7 can be seen from the initial stage to the 309th stage the increase in the coefficient is not drastic, but the first drastic surge occurred at 1,080 which occurred in the 310th stage to the 311st stage, from 2.126 to 3.046 this occurred when the agglomeration process produced two cluster.

6. SWARCH Model Building

SWARCH(4,1) model with ARIMA(1,0,0) model is conditional average for transformation data of import value amount is as follows

$$\mu_{S_t} = \begin{cases} -0{,}00001074\text{ , untuk } state\ 1 \\ -0{,}00000821\text{ , untuk } state\ 2 \\ -0{,}00004617,\text{ untuk } state\ 3 \\ -0{,}00001060,\text{ untuk } state\ 4, \end{cases}$$

where is variance conditional model is ARCH(1)

$$\sigma^2_{t,S_t} = \begin{cases} 0{,}00002243, \text{untuk } \mathit{state}\ 1 \\ 0{,}00000783, \text{untuk } \mathit{state}\ 2 \\ 0{,}00008642, \text{untuk } \mathit{state}\ 3 \\ 0{,}00000824, \text{untuk } \mathit{state}\ 4, \end{cases}$$

and transition probability

$$P = \begin{pmatrix} 0{,}756225731 & 0.3110144 & 0{,}08562957 & 0{,}003514847 \\ 0{,}191923955 & 0{,}2088461 & 0{,}00000000 & 0{,}147009103 \\ 0{,}04308328 & 0{,}0000000 & 0{,}7836639 & 0{,}01353810 \\ 0{,}008767033 & 0{,}4801395 & 0{,}1307066 & 0{,}835937944 \end{pmatrix}$$

SWARCH(3,1) model with ARIMA(2,0,0) model is conditional average for transformation data of import value amount is as follows

$$\mu_{S_t} = \begin{cases} -0{,}00001659, \text{untuk } \mathit{state}\ 1, \\ 0{,}000009196, \text{untuk } \mathit{state}\ 2, \\ -0{,}00001622, \text{untuk } \mathit{state}\ 3, \end{cases}$$

where is variance conditional model is ARCH(1)

$$\sigma^2_{t,S_t} = \begin{cases} 0{,}00001964, \text{untuk } \mathit{state}\ 1 \\ 0{,}00005774, \text{untuk } \mathit{state}\ 2 \\ 0{,}00000419, \text{untuk } \mathit{state}\ 3 \end{cases}$$

and transition probability

$$P = \begin{pmatrix} 0{,}976970964 & 0{,}01733403 & 0{,}010399551 \\ 0{,}009763178 & 0{,}95774667 & 0{,}009323711 \\ 0{,}013265858 & 0{,}02491930 & 0{,}980276737 \end{pmatrix}$$

B. Model Accuracy Based on Prediction Probability and Smoothed Probability

1. Smoothed Probability

Judging from the results of forecasting the value of smoothed probability it can be said that for data transformation the number of import values is less probability 0 , 4 is in a very good import state, the probability value between 0.4 to 0.6 is in a good import state, the probability value between 0.6 to 0.8 is in a pretty bad import state, and the probability is more from 0.8 enter in severe condition. Whereas for the transformation data the number of exports is a probability value of less than 0.6 which enters into a situation where exports are good, probability values are between 0.6 and 0.8 in a state where exports are quite good and the probability value is more than 0, 6 means export conditions are in bad condition.

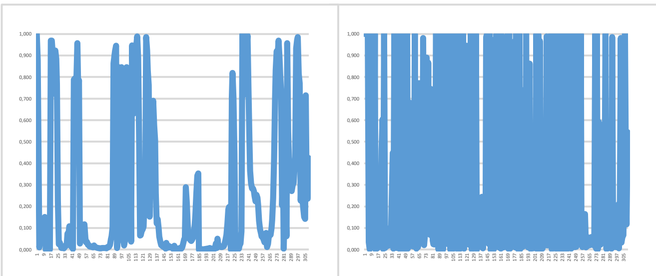

Figure 7. Four State and Two State Data Smoothed Probability

2. Smoothed Probability Forecast

The result of comparison between prediction probability with smoothed probability based on table 4 is classification table known that prediction probability with SWARCH(4,1) model is quite accurate in describing smoothed probability from actual data. Based on table 4 class that formed there are only two classes that is very good and good which means the condition experienced is imbalance, so it can be calculated for its accuracy is as follows.

Table 4. Forecast of Smoothed Probability with Ekspor Indicator

Periode 2016	Forecasting	Indication	Periode 2016	Aktual	Indication
January	0.440224	Good	January	0.12411	Very Good

February	0.383221	Very Good	February	0.06750	Very Good
March	0.338872	Very Good	March	0.03979	Very Good
April	0.304303	Very Good	April	0.57821	Good
May	0.277334	Very Good	May	0.06620	Very Good
June	0.256278	Very Good	June	0.22324	Very Good
July	0.239826	Very Good	July	0.11437	Very Good
August	0.226962	Very Good	August	0.55133	Good
September	0.216895	Very Good	September	0.13483	Very Good
October	0.209013	Very Good	October	0.11834	Very Good
November	0.202836	Very Good	November	0.34897	Very Good
December	0.197992	Very Good	December	0.12859	Very Good

$$Recall \rightarrow very\ good\ class = \frac{9}{9+2} \times 100\% = 81{,}82\%$$

$$Recall \rightarrow good\ class = \frac{0}{1+0} \times 100\% = 0\%$$

$$AUC = \frac{1}{2}(very\ good\ class + good\ class) = 40{,}91\%$$

The conclusion that can be taken based on the indication on prediction probability and smoothed probability has an accuracy of 40.91%.

Tabel 5. Forecast of Smoothed Probability with Ekspor Indicator

Periode 2016	Forecast	Indication	Periode 2016	Aktual	Indication
January	0.3408131	Good	January	0.124119	Good
February	0.3406884	Good	February	0.067504	Good
March	0.3405907	Good	March	0.039797	Good
April	0.3405179	Good	April	0.078216	Good
May	0.3404679	Good	May	0.066207	Good
June	0.3404391	Good	June	0.123241	Good
July	0.3404297	Good	July	0.114379	Good
August	0.3404381	Good	August	0.151335	Good
September	0.3404627	Good	September	0.134832	Good
October	0.3405023	Good	October	0.118349	Good
November	0.3405555	Good	November	0.148971	Good
December	0.3406210	Good	December	0.128593	Good

The result of comparison between prediction probability with smoothed probability based on table 5 that is classification table known that prediction probability SWARCH(3,1) model accurate in describing smoothed probability from actual data. The inaccurate conclusion is taken based on the indication on prediction probability and smoothed probability has the same indication so the accuracy is 100%

CONCLUSION

Volatility and Markov switching model combination can absorb the heteroscedasticity effect and condition changes in the volatility data based on cluster analysis. Thats model is SWARCH(4.1) model for import indicator and SWARCH(3.1) model for export indicator.

Forecasting value based on smoothed probability from the SWARCH(4.1) and SWARCH(3.1) models have an accuracy of 40.91% for import indicators and 100% for export indicators. Based on the indicator information, it can be concluded that the performance of the combined model can be used properly..

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