Combined Model of Markov Switching and Asymmetry of Generalized Seasonal Autoregressive Moving Average Conditional Heteroscedasticity for Early Detection of Financial Crisis in Hong Kong

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***Abstract*—The financial crisis in Hong Kong occurred in 1997 and 2008. To prevent a crisis or reduce the impact of a crisis, action is needed through early detection of the crisis using export indicator. The combination of Markov Switching and Asymmetric Generalized Seasonal Autoregressive Moving Average Conditional Heteroscedasticity (MS-AGSARMACH) models explains the crisis well. The results show that the MS-AGSARMACH(2,1,1) model can explain past and future crises well.**

***Index Terms*—Financial Crisis, Early Detection, Export, MS-AGSARMACH**

I. Introduction

THE development of Hong Kong to become one of the major countries began when Hong Kong became the world's financial center, and is considered the most influential country in the world. In fact, according to the Global Financial Centers Index in 2014 [1], Hong Kong is the third most important financial center in the world after New York and London. In addition, the Hong Kong currency is the 8th most traded currency worldwide [2].

In addition to Hong Kong's prowess in its economic field, Hong Kong has also experienced financial crises several times. One of the causes of Hong Kong's economic downturn was the Asian financial crisis in 1997. At the height of the Asian crisis in 1998, Hong Kong's gross domestic product (GDP) shrank by around five percent, property prices fell by 50% [3]. Unemployment reached six percent [4]. In addition, Hong Kong also experienced a crisis in 2008 which resulted in real GDP to 2.5% from 6.4% in 2007 [5].

A way is needed to detect financial crises that occur based on historical data from financial indicators so that the government is able to prevent crises or prepare appropriate policies to minimize the impact of crises. One of the indicators that can be used to detect the crisis is the export indicator [6] in the International Monetary Fund (IMF) [7].

When a crisis occurs, the export indicator will fluctuate highly (volatile). Therefore the volatility model is very appropriate to be used to explain crises. Engle has used the autoregressive conditional heteroscedasticity (ARCH) model to explain inflation in England from 1958 to 1977 [8]. Bollerslev used the generalized autoregressive conditional heteroscedasticity (GARCH) model to improve the ARCH(8) model using gross national product (GNP) data from 1948 to 1983 [9]. If there is an element of asymmetry in the GARCH model, then Nelson uses the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model to overcome this [10].

An ARMA model that contains a seasonal element is known as SARMA. If the data contains seasonal elements, there are heteroscedasticity and asymmetry effects, then the AGSARMACH model is very appropriate to use. However, the AGSARMACH model has not considered shifts in volatility. The shift in volatility can be explained through the Markov switching model. Hamilton and Sumsel have combined the Markov switching model and autoregressive conditional heteroscedasticity (MS-ARCH) to explain the shift in volatility in New York stock prices from July 1962 to December 1987, the results are very good [11]. Sugiyanto et al. also combined the two models to explain the crisis in Indonesia using real output and domestic credit/GDP indicators but different crisis thresholds presented by Hamilton and South Sumatra, the results were also very good [12]. According to Ford et al., a smoothed probability value of more than 0.5 describes a condition of high volatility, and conversely, a smoothed probability value of less than 0.5 describes a condition of low volatility [13]. According to Hermo-sillo and Hesse, a smoothed probability value of less than 0.4 is said to be low volatility, between 0.4 and 0.6 is said to be moderate volatility, and more than 0.6 is said to be high volatility [14]. In conditions of high volatility, crises tend to occur. Something that has not been answered in other studies is determining the crisis threshold. In this study, the crisis threshold is determined by the lowest value of the smoothed probability in the MS-AGSARMACH model when past crises occur. Using this crisis threshold, we predict whether or not Hong Kong will be in financial crisis based on export indicator in 2021.

II. Method

The data used is monthly Hong Kong export data for the period January 1990 to December 2020 taken from the International Monetary Fund (IMF) website. The analysis used in this research was carried out with the help of R Studio software. The steps in this research begin with designing

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the data so that it is stationary to obtain the ARMA model. Detecting seasonal patterns to get the SARMA model, detecting heteroscedasticity to get the SARMACH model, and detecting asymmetry to build the AGSARMACH model. The use of the Markov Switching model begins with determining the conditions corresponding to the export indicator. Volatility shifts are described using a transition matrix. The transition matrix is used to determine the smoothed probabilities. The smallest value of the smoothed probability from the MS-AGSARMAC model, when a crisis occurs, is used as the threshold. A smoothed probability value greater than the threshold represents a crisis. The model used is a model that can explain past crises, and then this model is used to detect future crises.

III. Discussion

The export data indicator plot can be seen in Fig. 1.

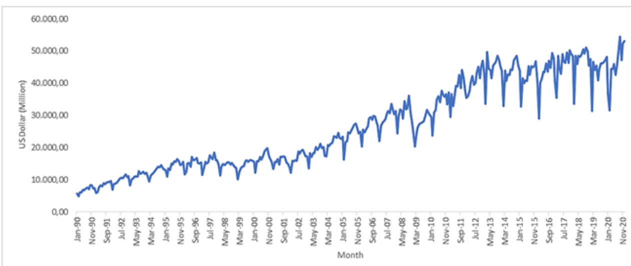

Fig. 1: Plot Export Indicator

Figure 1 shows that Hong Kong's export data tends to have an upward trend so that the data can be said to be non-stationary and contains seasonal elements. For this reason, the data must be stationary and seasonality removed. (see Fig. 2)

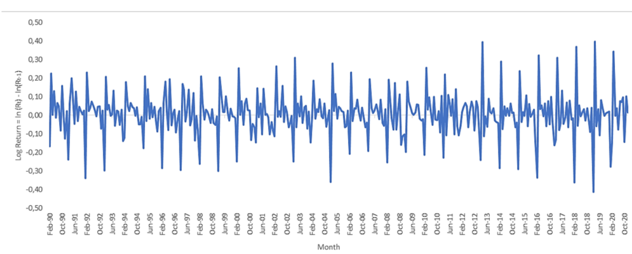

Fig. 2: Plot Stationary Export Indicator

After the data is stationary and does not load seasonally, the SARMA model is built. The SARMA model that has the smallest AIC is $SARMA\ (1,1)\times(0,2)_{12}$.

The normality test for model residues was carried out using the Kolmogorov-Smirnov test. The results of the test show that the residuals of the SARMA model are normally distributed.The non-autocorrelation test for the residues of the SARMA model uses the Ljung-Box test. The results of the test show that there is no residual correlation between lags. The Lagrange-Multiplier test is used to perform a non-heteroscedasticity test. The test results on the residues show that there is heteroscedasticity. Therefore, the GSARMACH model was formed. The best model is GSARMACH (1,1).

The non-heteroscedasticity test uses the Lagrange – Multiplier for the residues of the GSARMACH(1,1) model. The results show that the value of ξ is 0.757 which is smaller than $\chi^2_{0,05;3} = 7.815$ and the p-value is 0.384 which is greater than α so it can be concluded that there is no heteroscedasticity problem. The next step that needs to be done is to test the asymmetric effect on the model. Based on the hypothesis test shows that the model has an asymmetric effect. The best asymmetry model is the AGSARMACH(1,1) model because it has the smallest AIC value and is the only model where all parameters are significant. The model AGSARMACH(1,1) can be written as

$$\begin{aligned}\ln\left(\sigma_t^2\right) = &-4,651 + 0,062\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \\ &+ 0,070\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + 1,804\ln\left(\sigma_{t-1}^2\right) + e_t\end{aligned}$$

The test of asymmetric effect on the model is performed. The result gives p-value equal to 0.897 which is greater than the α value, so it can be concluded that there is no asymmetric effect in the model.

Changes in volatility in the export indicator can be explained by combining the Markov Switching model with the volatility model. To model the change in volatility, a transition probability matrix can be formed. Before forming the transition matrix, it is necessary to know the number of states that will be used in the model. In this study, the number of suitable states is two, as can be seen in Fig. 3. State 1 states low

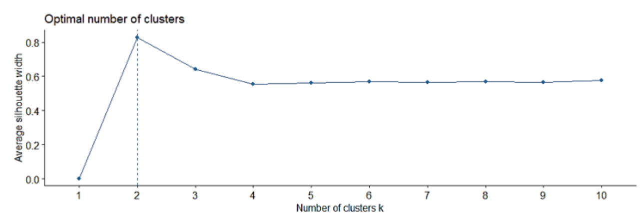

Fig. 3: The Number of States That Match

volatility and state 2 states high volatility. After obtaining the optimal state of 2, the model that will be used to detect a crisis is the MSAGSARMACH(2,1,1) model with the transition probability p_{ij} for $i, j = 1,2$. The transition probability matrix can be written as

$$P = \begin{pmatrix} 0.972 & 0.028 \\ 0.281 & 0.719 \end{pmatrix}$$

Based on the probability matrix P, information is obtained that the probability of surviving in state 1 from time t to $t+1$ is 0.972 while the probability of surviving in state 2 is 0.719. The probability of a shift from state 1 to state 2 is 0.028 and the probability of a shift from state 2 to state 1 is 0.281.

After constructing the MS-AGSARMACH(2,1,1) model, the next step is to construct a smoothed probability plot to see whether there is no crisis or crisis based on export indicator. The smoothed probability plot can be seen in Fig. 4.

Crisis detection can be performed using the smallest smoothed probability value from the MS-AGSARMACH(2,1,1) model during a crisis period. In

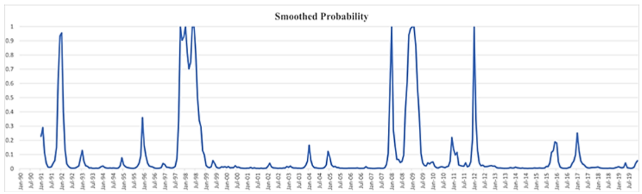

Fig. 4: Plot Smoothed Probability Model MS-EGSARIMACH(2,1,1)

this case we need to define the treshold first by observing the smoothed probability at the time when the crisis occurred. Therefore we calculate the smoothed probability for October 1997 to July 1998 and October 2009 to March 2009 and presented the results in Table I and Table II, respectively.

TABLE I: Smoothed Probability Value for October 1997 - July 1998

Periods	Smoothed Probability	Condition
October 1997	1	Crisis
November 1997	0.904621877	Crisis
December 1997	0.926915404	Crisis
January 1998	0.999912329	Crisis
February 1998	0.819500022	Crisis
March 1998	0.703018496	Crisis
April 1998	0.749705088	Crisis
May 1998	0.999999965	Crisis
June 1998	0.99999688	Crisis
July 1998	0.806485433	Crisis

TABLE II: Smoothed Probability Value for October 2008 - March 2009

Periods	Smoothed Probability	Condition
October 2008	0.608479256	No Crisis
November 2008	0.939707576	Crisis
December 2008	0.986052288	Crisis
January 2009	0.999473833	Crisis
February 2009	0.999999959	Crisis
March 2009	0.857731036	Crisis

Based on Table I and Table II, we can see that 0.703018496 is the smallest smoothed probability when the actual condition is crisis. Therefore this value can be considered as the threshold of crisis condition. Later, we predict crisis when the predicted smoothed probability is higher than the threshold.The next stage is to carry out early detection for test data, namely the period January 2020 to December 2020. Based on the calculation using MS-AGSARMACH(2,1,1) we obtain smoothed probability values for January to July 2020 and present the results in Table III. It shows the values are less than the threshold, so we can conclude that predicted conditions are stable, the same as the actual condition. Thus, MSAGSARMACH(2,1,1) is appropriate for predicting the financial crisis (testing data) in Hong Kong.

TABLE III: Comparison of Predicted Value and Actual Smoothed Probability in 2020

Periods	Prediction		Actual	
	Smoothed Probability	Condition	Smoothed Probability	Condition
Jan 2020	0.07299872	Stable	0.06753469	Stable
Feb 2020	0.04081590	Stable	0.07562632	Stable
March 2020	0.01437945	Stable	0.08123661	Stable
April 2020	0.00898845	Stable	0.08513457	Stable
May 2020	0.00617813	Stable	0.08785089	Stable
June 2020	0.00847926	Stable	0.08975179	Stable
July 2020	0.02914526	Stable	0.09108999	Stable
August 2020	0.05340193	Stable	0.09203991	Stable
September 2020	0.06183671	Stable	0.09272191	Stable
October 2020	0.03066240	Stable	0.09321903	Stable
November 2020	0.04612338	Stable	0.09358559	Stable
December 2020	0.06103007	Stable	0.09387015	Stable

Based on Table III, it can be concluded that the MS-AGSARMACH(2,1,1) model can predict Hong Kong crisis conditions using export indicator correctly because the actual conditions and the predicted values are the same.

Hong Kong's economic conditions in 2021 can also be predicted using the MSAGSARMACH(2,1,1) model by looking at the prediction of the smoothed probability value in 2021. The prediction results for 2021 can be seen in Table IV.

TABLE IV: Smoothed Probability Prediction for 2021

Periods	Prediction	Condition
January 2021	0.06101758	Stable
February 2021	0.07056027	Stable
March 2021	0.07710178	Stable
April 2021	0.08158599	Stable
May 2021	0.08465992	Stable
June 2021	0.08676709	Stable
July 2021	0.08821156	Stable
August 2021	0.08920174	Stable
September 2021	0.08988051	Stable

Table IV shows that throughout 2021 it is predicted that Hong Kong will not experience a financial crisis based on export indica

IV. CONCLUSION

Based on export indicator, the MS-AGSARMACH(2,1,1) model can accurately explain the financial crisis in Hong Kong in the 1997 – 1998 and 2008 – 2009 periods. The model can also predict that there will be no crisis based on export indicator in 2021. For future research, another macroeconomy indicators will be better to be considered in the model to improve forecast accuracy.

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