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Financial Crisis Forecasting in Indonesia Based on Bank deposits, Real Exchange Rates and Trade Terms Indicators

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Abstract. Indonesia has experienced a financial crisis several times, but the crisis that occurred in 1997 had a bad impact on the economy and national stability. Therefore, it needs a model that can be used to predict the condition ahead. This paper proposes forecasting the financial crisis in Indonesia. Bank deposits, real exchange rates and exchange rates of trade indicators are used in this paper. Data from January 1990 to December 2015 are used to form the models, while data from January to December 2016 are used to accurate the models. Combination of volatility and Markov switching models are used to model the data. The result suggests that the appropriate model for bank deposit and real exchange trade is SWARCH (3.1), and for real exchange rates is SWARCH (3.2). SWARCH (3.1) model has the accuracy 100%, while SWARCH (3.2) has the accuracy 75%. Based on these models, it can be forecasted that there is no financial crisis in Indonesia on 2017.

1. Introduction

The problem of financial system stability can lead to financial crisis. In order to overcome this problem, it needs to monitor the indicators that contribute to the occurrence of the crisis. The crisis that hit in Indonesia on the middle of 1997 has seriously effect on the economic stability. To detect crisis in a country, it could be seen through many indicators. Kaminsky et al. [1] said that there are 15 indicators that can be used to detect the crisis, three of them are bank deposits, real exchange rates, and terms of trade.

Monthly data of bank deposits, real exchange rates, and terms of trade are a time series data. These data are usually indicated heteroschedasticity and condition changes. In this paper we used a combination of volatility and Markov switching models to overcome this problem. SWARCH (switching autoregressive conditional heteroscedasticity), MS-GARCH (Markov switching generalized autoregressive conditional heteroscedasticity), and MS-EGARCH (Markov switching exponential generalized autoregressive conditional heteroscedasticity) are the models that can be used to solve the problem of heteroschedasticity and condition changes. Hamilton and Susmel [2] introduced SWARCH model. Some researchers have done a research on the detection of financial crisis using combination of volatility and Markov switching models. Chang et al. [3] used SWARCH model to identify the stock volatility foreign and global financial crisis in Korea based on real exchange rate on the period of January 4th 2000 to March 31st 2010. Gray [4] introduced the MS-GARCH model to model the rate data of the United States from January 1970 to April 1994. Mwamba and Majadibodu [5] used MS-GARCH (1.1) model to identify a currency crisis on South Africa based on indicators of foreign currency. Henry [6] used MS-EGARCH model to model short-term rates data in the UK on period of



January 2nd1980 until August 29th. The result shows that the MS-EGARCH model able to capture the volatility asymmetries and changing conditions on the data. Shojaei [7] used MS-EGARCH (1.1) to investigate the influence of oil price crisis in Tehran Stock Exchange.

In this study, it was conducted the combination of volatility and Markov switching models to model the movement of bank deposits, the real exchange rate and terms of trade indicators. The model can be used to predict the financial crisis in Indonesia on 2017.

2. Volatility Model

Some models of volatility that ever introduced by experts are ARCH, GARCH and EGARCH.

2.1. ARCH Model

Residue of ARMA model that contain heteroscedasticity can be modelled using a volatility model that can be written as

$$a_t = \sigma_t \epsilon_t \text{ for } \epsilon_t \sim N(0,1) \text{ and } a_t | F_{t-1} \sim N(0, \sigma_t^2)$$

where ϵ_t is a standardized residual of an ARMA model, and F_{t-1} is set of all the information in period t-1. Model ARCH (m) can be written as

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \dots + \alpha_m a_{t-m}^2 = \alpha_0 + \sum_{i=1}^m \alpha_i a_{t-i}^2$$

where α_0 is a constant, $\alpha_1, \alpha_2, \dots, \alpha_m$ is a parameter of the ARCH model, m is the order of ARCH model and σ_t^2 is the residual variance to the period-t (Tsay [8]).

2.2. GARCH Model

ARCH model that have high order can be solve using a GARCH (m, s) which can be written as

$$\begin{aligned} \sigma_t^2 &= \alpha_0 + \alpha_1 a_{t-1}^2 + \dots + \alpha_m a_{t-m}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_s \sigma_{t-s}^2 \\ &= \alpha_0 + \sum_{i=1}^m \alpha_i a_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 \end{aligned}$$

where $\beta_1, \beta_2, \dots, \beta_s$ are a parameters of GARCH model (Tsay [8]).

2.3. EGARCH Model

Nelson [9] introduced EGARCH(m,s) model to overcome leverage effect on GARCH model which can be written as

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^m \alpha_i \left(\left| \frac{a_{t-i}}{\sqrt{\sigma_{t-i}^2}} \right| - \sqrt{\frac{2}{\pi}} \right) + \sum_{i=1}^s \beta_i \frac{a_{t-i}}{\sqrt{\sigma_{t-i}^2}} + \sum_{j=1}^m \gamma_j \ln \sigma_{t-j}^2$$

where γ is a parameter Leverage effect .

3. Combined of Volatility and Markov Switching Model

3.1. SWARCH Model

Hamilton and Susmel [3] introduced SWARCH model that can be written as

$$\begin{aligned} r_t &= \mu_{s_t} + a_t, a_t = \sigma_t \epsilon_t, \\ \sigma_{t,s_t}^2 &= \alpha_{0,s_t} + \sum_{i=1}^m \alpha_{i,s_t} a_{t-i}^2, \end{aligned}$$

where $\epsilon_t \sim N(0,1)$, , and $s_t = \{1,2, \dots, k\}$. The equation is said to be a SWARCH process with k state and m order, and can be denoted as $a_t \sim \text{SWARCH}(k, m)$.

4. Smoothed Probability

Kuan [10] introduced smoothed probability value that defined as

$$P(s_t = i | Z^T; \theta) = \sum_{s_t=1}^3 P(s_{t+1} = i | Z^T; \theta) P(s_t = i | s_{t+1} = i, Z^T; \theta)$$

According to Sopipan et al. [11], forecasting of smoothed probability generally can be determined through forecasting at time $t + 1$ based on a smoothed probability at time t , and defined as

$$\Pr(S_{t+1} = i | F_t) = p_{1i} \Pr(S_t = 1 | F_t) + p_{2i} \Pr(S_t = 2 | F_t) + p_{3i} \Pr(S_t = 3 | F_t)$$

where p_{ij} is a transition probability of state.

5. Research Methods

This article used data of bank deposits and the real exchange rate from January 1990 to December 2015 were obtained from Bank Indonesia, while the data of terms of trade from January 1990 to December 2015 were obtained from the International Monetary Fund. These data are used to build the model, while the data in the year of 2016 are used to measure the accuracy of the model. The research steps are as follows.

- 1) Plot the data and then test the stationary of data. Transform the data using log return, when the data are not stationary.
- 2) Plot the partial autocorrelation function (PACF) of log return data, then determine the AR model.
- 3) Test the heteroscedasticity on the residue of AR model using Lagrange multiplier test.
- 4) Estimate the parameter of ARCH model.
- 5) Form the combination of volatility and Markov switching models with the assumption of a three-state.
- 6) Determine the financial crisis based on the smoothed probability.
- 7) Compare the value of smoothed probability and forecasting smoothed probability to see the accuracy of the model.
- 8) Forecast the crisis condition in 2017 based on the value of forecasting smoothed probability.

6. Result and Discussion

Plot the data of bank deposits, real exchange rate, and exchange rate of trade can be seen in Figure 1.

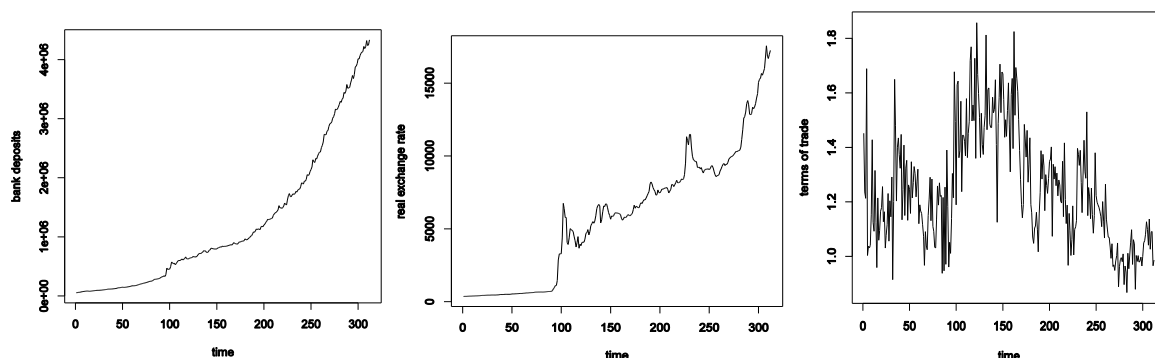


Figure 1. Plot of bank deposits, real exchange rate and terms of trade data.

Figure 1 showed that the data has fluctuated over time. It indicated that the data are not stationary in mean and variance. Then, we transformed the data using log return and these data have been stationary. Furthermore, it form an ARMA model based on PACF plot of log return data. For bank deposits indicator, it was obtained an AR(1) model ie $r_{t1} = -0.278500r_{t-1} + \varepsilon_t$, where r_{t1} is the return value of a bank deposit indicator at time t . Meanwhile for the real exchange rate indicator, it was obtained an AR(3) model ie $r_{t2} = 0.417500r_{t-1} - 0.179010r_{t-2} + 0.144000r_{t-3} + \varepsilon_t$, where r_{t2} is the return value of the real exchange rate at time t and for the terms of trade obtained an AR(2) model ie $r_{t3} = -0.620760r_{t-1} - 0.321390r_{t-2} + \varepsilon_t$, where r_{t3} is the return value of terms of trade at time t .

The next step is to test the effect of heteroscedasticity on the residue of each model using Lagrange multiplier test. It were obtained the probability values of bank deposits, real exchange rate and terms of trade as 3.893×10^{-7} , 3.575×10^{-12} and 0.000567 respectively. All of probability values are less than 0.05, it can be concluded that there are effect of heteroscedasticity on the residue. To solve this problem, it was used ARCH model. For bank deposits indicator, the best model is ARCH(1) which can be written as

$$\sigma_t^2 = 0.007855 + 0.251736 \varepsilon_{t-1}^2.$$

For real exchange rate indicator, the best model is ARCH(2) which can be written as

$$\sigma_t^2 = 0.000147 + 1.951000 \varepsilon_{t-1}^2 + 0.318900 \varepsilon_{t-2}^2,$$

Meanwhile for terms of trade indicator, the best model is ARCH(1) which can be written as

$$\sigma_t^2 = 0.007855 + 0.251736 \varepsilon_{t-1}^2.$$

Probability value of the residue of each model using Lagrange multiplier test is 0.114, 0.7449 and 0.2304 respectively. These values are more than 0.05, it means that there isn't the effect of heteroscedasticity on the residue of ARCH models. Furthermore, it tests the normality of residue using Kolmogorov Smirnov and the results are 0.5097, 0.7166 and 0.9709 respectively. These values are more than 0.05, it means that the residue of ARCH models are normally distributed. Probability values of bank deposits, real exchange rate, and terms of trade using Ljung-Box test are 0.1109, 0.2573 and 0.8540 respectively. These values are more than 0.05, it means that the residue of ARCH models do not contain autocorrelation. Based on these tests, the appropriate model for these data is ARCH model. Furthermore, Markov switching model is used to model the changes of condition.

In a Markov switching model, the condition changes is an unobserved random variable commonly called the state (Tsay [8]). State volatility used is low, medium and high. The third state has a probability to survive in the same state or move to another state. The third state probabilities are arranged in the form of the transition probability matrix. Transition probability matrix bank deposit data can be written as

$$P_1 = \begin{pmatrix} 0.000421 & 0.577365 & 0.583232 \\ 0.942167 & 0.416728 & 0.055915 \\ 0.057412 & 0.005907 & 0.360853 \end{pmatrix}$$

Based on the transition probability matrix P_1 it is found that the probability of surviving in the low volatility state in the next period is 0.000421. The probability of changing state from low volatility to moderate volatility in the next period is 0.942167. Probability of changing state from low volatility to high volatility in the next period is 0.057412. Probability of changing state from medium volatility to low volatility in the next period is 0.577365. The probability of surviving in the medium volatility state in the next period is 0.416728. Probability of changing state from medium volatility to high volatility in the next period is 0.005907. Probability of changing state from high volatility to low volatility in the next period is 0.583232. Probability of changing state from high volatility to medium volatility in the next period is 0.055915. Probability of surviving in the high volatility state in the next period is 0.360853. Transition probability matrix for the real exchange rate is symbolized by P_2 and for terms of trade symbolized by P_3 as follows

$$P_2 = \begin{pmatrix} 0.288781 & 0.135413 & 0.535178 \\ 0.399679 & 0.836838 & 0.116637 \\ 0.311540 & 0.027749 & 0.348185 \end{pmatrix} \text{ and}$$

$$P_3 = \begin{pmatrix} 0.462519 & 0.143799 & 0.022235 \\ 0.457236 & 0.217726 & 0.472469 \\ 0.080245 & 0.638475 & 0.505296 \end{pmatrix}$$

The interpretation of transition probability matrix P_2 and P_3 are similar to P_1 . The next step is to find smoothed probability value that can be used to determine the crisis condition. Smoothed probability value of bank deposits, the real exchange rate, and terms of trade from January 1990 to December 2015 is shown in Figure 2a, Figure 2b, and Figure 2c respectively.

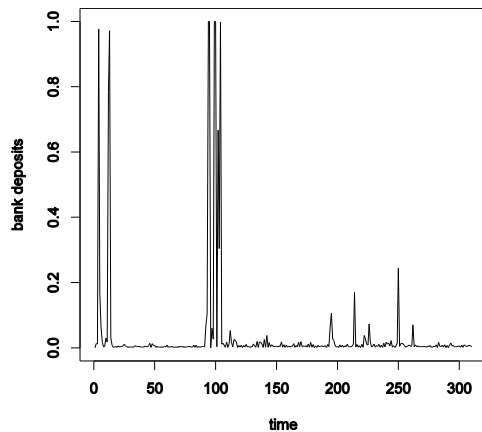


Figure 2a. Smoothed probability of bank deposits

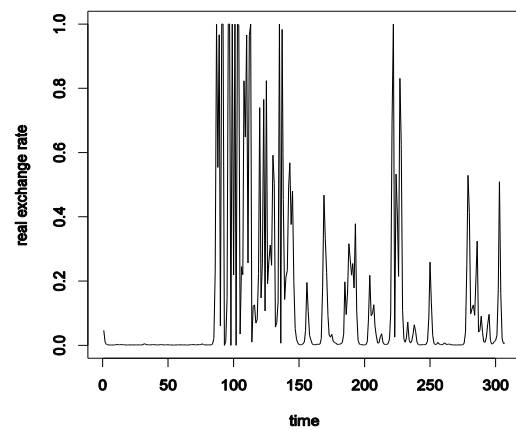


Figure 2b. Smoothed probability of real exchange rate

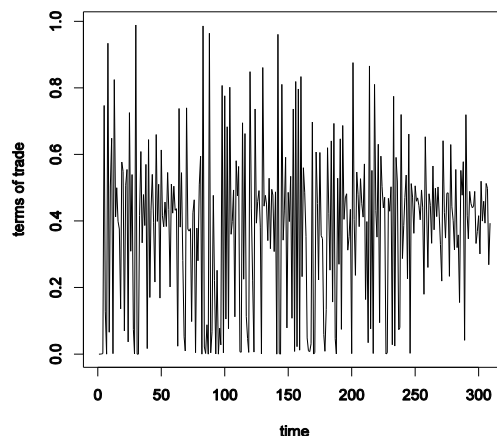


Figure 2c. Smoothed probability of terms of trade

Figure 2a and Figure 2b show that there are 9 data bank deposits and 24 data real exchange rate that have smoothed probability value more than 0.6. This condition showed that there were crisis. Figure 2c shows that there are 16 data term of trade that have smoothed probability value more than 0.8. It means that there are crisis.

To determine the accuracy of the model, it is compared the value of forecasting and actual smoothed probability of bank deposits, real exchange rate and terms of trade that can be seen in Table 1, Table 2, and Table 3 respectively.

Table 1. Comparison of Actual and Forecast Smoothed Probability Values of Bank Deposits Indicator

Period	Forecast	actual
January 2016	0.005494	0.028029
February 2016	0.008085	0.033348
March 2016	0.001369	0.037397
April 2016	0.007307	0.037589
May 2016	0.001820	0.038377
June 2016	0.005179	0.038241
July 2016	0.002429	0.038433
August 2016	0.007037	0.038362
September 2016	0.003863	0.038417
October 2016	0.004247	0.038391
November 2016	0.001544	0.038408
December 2016	0.005051	0.038399

Tabel 2. Comparison of Actual and Forecast Smoothed Probability Values of The Real Exchange Rate Indicator

Period	Forecast	actual
January 2016	0.003029	0.049086
February 2016	0.015014	0.085651
March 2016	0.006493	0.10566
April 2016	0.002473	0.117492
May 2016	0.001092	0.124385
June 2016	0.000505	0.128411
July 2016	0.000407	0.130763
August 2016	0.000394	0.132135
September 2016	0.000681	0.132937
October 2016	0.001370	0.133405
November 2016	0.004319	0.133679
December 2016	0.005878	0.133838

Tabel 3. Comparison of Actual and Forecast Smoothed Probability Values of Term of Trade Indicator

Period	Forecast	actual
January 2016	0.372156	0.629658
February 2016	0.376586	0.082709
March 2016	0.375033	0.610066
April 2016	0.375234	0.455844
May 2016	0.375100	0.465333
June 2016	0.375097	0.479329
July 2016	0.375082	0.462603
August 2016	0.375079	0.492814
September 2016	0.375077	0.380770
October 2016	0.375076	0.432720
November 2016	0.375075	0.493465
December 2016	0.375075	0.520857

Table 1, Table 2, and Table 3 show that the actual and forecasting of smoothed probability for bank deposits, real exchange rate, and terms of trade explain no crisis, except on January, March, and December periods for terms of trade. In that period, the actual value of smoothed probability gives a hint of crisis fragile while the value of forecasting is not a crisis. It means that SWARCH model for the bank deposits and the real exchange rate has 100% accuracy, while for the terms of trade has 75% accuracy.

Forecasting of smoothed probability of bank deposits, real exchange rate and terms of trade in 2017 is presented in Table 4 . Tabel 4 shows that all of the value of smoothed probability forecasting are less than 0,4. It can be predicted that there is no financial crisis in Indonesia in year 2017.

Tabel 4.The Value of Smoothed Probability Forecasting

Period	Smoothed Probability Forecasting					
	Bank deposits		Real exchange rate		Terms of trade	
	Forecasting	Condition	Forecasting	Condition	Forecasting	Condition
January 2017	0.015604	no crisis	0.026864	no crisis	0.356952	no crisis
February 2017	0.035557	no crisis	0.048302	no crisis	0.390445	no crisis
March 2017	0.033326	no crisis	0.066714	no crisis	0.383712	no crisis
April 2017	0.378680	no crisis	0.081884	no crisis	0.360783	no crisis
May 2017	0.036419	no crisis	0.094243	no crisis	0.365219	no crisis
June 2017	0.037659	no crisis	0.104278	no crisis	0.364218	no crisis
July 2017	0.037093	no crisis	0.112421	no crisis	0.364379	no crisis
August 2017	0.037469	no crisis	0.119025	no crisis	0.364327	no crisis
September 2017	0.037271	no crisis	0.124381	no crisis	0.364329	no crisis
October 2017	0.037391	no crisis	0.128725	no crisis	0.364325	no crisis
November 2017	0.037325	no crisis	0.132248	no crisis	0.364325	no crisis
December 2017	0.037364	no crisis	0.135106	no crisis	0.364324	no crisis

7. Conclusion

SWARCH (3.1) model is the appropriate model for bank deposits and real exchange rate indicators, meanwhile for terms of trade indicator, the the appropriate model is SWARCH (3.2) model. Based on the models, it can be predicted that there is no financial crisis in Indonesia in year 2017.

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