Early Detection of South Korean Financial Crisis using MS-GARCH Based on Term of Trade Indicator

Husna Afanyn Khoirunissa[1], Sugiyanto[2], and Sri Subanti[3]

[1,2,3]Department of Statistics, Universitas Sebelas Maret, Surakarta, 57126, Indonesia

[1]husnafanyn@student.uns.ac.id, [2]sugiyanto61@staff.uns.ac.id, [3]srisubanti@staff.uns.ac.id

Abstract. The 1997 Asian financial crisis, which occurred until 1998, had a significant impact on the economies of Asian countries, including South Korea. The crisis brought down the South Korean currency quickly and sent the economy into sudden decline. Because the impact of the financial crisis was severe and sudden, South Korean requires a system which able to sight crisis signals, therefore that, the crisis will be fended off. One in all the indicators that can detect the financial crisis signals is that the term of trade indicator which has high fluctuation and change in the exchange rate regime. The mixture of Markov Switching and volatility models, Generalized Autoregressive Conditional Heteroscedasticity (GARCH), or MS-GARCH could explain the crisis. The MS-GARCH model was built using data from the South Korean term of trade indicator during January 1990 until March 2020. The findings obtained in this research can be inferred that the best model of the term of trade is MS-GARCH (2,1,1). Term of trade indicator on that model could explain the Asian monetary crisis in 1997 and also the global monetary crisis in 2008. The smoothed probability of term of trade indicators predicts in April till December 2020 period, there will be no signs of the monetary crisis in South Korea.

Keywords: financial crisis, MS-GARCH, South Korea, term of trade indicator

1. Introduction

South Korea is a rustic that has an open financial device. Economic openness can be represented by international trade activities in a country. The existence of international trade activities affects economic growth in a country so that fluctuations in the trade rate affect fluctuations in economic growth in that country. In middle 1997 to 1998, South Korea experienced an Asian financial crisis that started in Thailand. At that time, Thailand floated the baht currency which caused the transmission to other Asian countries. The countries most affected were Indonesia, South Korea, Malaysia, Thailand and the Philippines. In 2008–2009, there was a global financial crisis when the downturn in the US subprime lending market culminated with the bankruptcy of Lehman Brothers and the international banking crisis.

According to Kaminsky et al. [1], 15 crisis indicators are used as references in indicating a crisis in a country, one of which is the term of trade indicator. The reason for choosing the term of trade indicator as the indicator used in this univariate time series analysis is because the term of trade indicator is a representation of international trade activities that affect an opened country's economic growth. The term of trade is an

indicator that measures the success and benefits of the activity of exchanging goods and services through international trade based on exports and imports. The increase in the term of trade indicates positive developments in foreign trade. An indicator of the South Korean term of trade is utilized in this study to predict a monetary crisis in that country in the near future. The examination starts with data modeling using the Autoregressive Moving Average (ARMA), as a time series stationary model. The ARMA requires the premise of non-heteroscedasticity to be satisfied. The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was introduced by Bollerslev [2] as a model that integrates past variance to explain future variance. Volatility models, on the other hand, have not been able to account for shifting conditions. Hamilton introduced the Markov switching model in 1989 as a time series data model that can detect diversities in circumstances that arise in economic indicators [3].

Chang et al. [4] used a combination of Markov switching and volatility models to examine the volatility and exchange rate of the Korean stock market, as well as the global currency crisis, using Markov switching autoregressive conditional heteroscedasticity (SWARCH). Sugiyanto and Hidayah [5] were using a composite of the Markov switching and the GARCH models to detect financial crises using an indicator of interest rates on loans and deposits. According to the findings of that study, the MS-ARCH(2,1) model for the real interest rate on deposits indicator and the MS-GARCH(3,1,1) model for the lending interest rate/deposit interest rate indicator might explain the financial crisis in Indonesia. As a result, these models were used to forecast Indonesia's financial catastrophe in 2019. The MS-GARCH model will be used to detect financial crises based on indicators of South Korea's terms of trade in this study.

2. Materials

2.1. Augmented Dickey Fuller (ADF) Test. The ADF test was performed to assess the data stationarity [6]. The ADF test's null hypothesis is that time series data are not stationary, while the alternative hypothesis is that time series data are stationary. The ADF test statistic is denoted as

$$ADF_{test} = \frac{\widetilde{\phi}-1}{\sigma(\widetilde{\phi})} \tag{1}$$

where $\widetilde{\phi}$ and $\sigma(\widetilde{\phi})$ are parameter estimator and the standard deviation of the autoregressive model, respectively. If p-value of the ADF test statistic is less than α, the

null hypothesis should be rejected. If the data is not stationary, it is necessary to transform it.

2.2.   Log Return Transformation. According to Tsay [7], the return has better statistical properties than the actual data. In economic analysis, the return value is more emphasized than the actual value, and the formula is

$$R_t = \frac{z_t - z_{t-1}}{z_{t-1}} \tag{2}$$

R_t represents return value at time-t, z_t represents observational data at time-t, and z_{t-1} represents observational data at time t-1. It is possible to write the log return transformation as

$$r_t = ln(1+r_t) = ln\left(\frac{z_t - z_{t-1}}{z_{t-1}}\right). \tag{3}$$

2.3.   Autoregressive Moving Average (ARMA) Model. ARMA model is a stationary time series model which combines Autoregressive (AR) model and Moving Average (MA) model [8]. The ARMA model can be written as

$$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \dots + \phi_p r_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} \tag{4}$$

where ϕ_i, $i=1, 2, \dots, p$ is the AR model parameter, θ_i, $i=1, 2, \dots, q$ is the MA model parameter, and a_t is the residual of ARMA models at time-t.

2.4.   Information Criteria. The optimum model is chosen based on information criteria. One of the information criteria approaches is the Akaike Information Criterion (AIC). The AIC is formulated by Akaike [9]

$$AIC = -2\frac{l}{T} + 2\frac{h}{T} \tag{5}$$

where l represents the log-likelihood function, h represents the number of parameters to be estimated, and T represents the total number of observations.

2.5.   Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model. The GARCH model is a volatility model that utilizes previous variation to explain variance in the future, according to Bollerslev, who initially identified it in 1986 [2]. The GARCH(m,s) model is defined as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \tag{6}$$

where m$\geq$0, s$\geq$0 for $i=1,2, ..., m$ and $j=1,2, ...,s$. σ_t^2 is the conditional variance of the residual at time-t [7].

2.6.   Dynamic Time Warping (DTW). DTW is a method for describing the best resemblance between collections by computing the shortest distance between them. A dynamic program method based on the distance accumulation matrix can be used to determine the DTW distance of two-time series. After we have determined the optimum number of clusters, we could search for a Markov switching model using the same number as the best number of clusters.

2.7.   Markov Switching Model. Markov switching is a type of time series data modeling that can be used to explain how events or states change. Hamilton [3] said that the Markov switching model for the state at time-t in the time series approach can be expressed as

$$r_t - \mu_{st} = \sum_{i=1}^{p} \phi_i r_{t-i} + a_t \tag{7}$$

where r_t is the observed variable, a_t is the residual of conditional mean ARMA($p,0$) model, and μ_{st} is the mean of the Markov switching model depending on the state (s_t).

2.8.   The Mixture of Markov Switching and GARCH Model. According to Gray [10], the mixture model of Markov switching and GARCH, MS-GARCH, can be written as

$$\sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t} a_{t-i}^2 + \sum_{j=1}^{s} \beta_{j,s_t} \sigma_{t-j}^2 \tag{8}$$

where m and s are the orders of the GARCH model.

2.9.   Transition Probability Matrix. According to Hamilton [3], s_t is an unobserved random variable with the values $1, 2, 3, ..., k$ assuming it follows a first-order Markov chain process with a transition probability p_{ij}. The transition probability s_t is equal to a certain value of j which depends on the s_{t-1} value of i and can be written in the following form

$$\Pr\left(s_t = j | s_{t-1} = i, s_{t-2} = k, ...\right) = \Pr\left(s_t = j | s_{t-1} = i\right) = p_{ij} \tag{9}$$

where P can be written in matrix form in equation (10):

$$P = \begin{pmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{32} \\ p_{13} & p_{23} & p_{33} \end{pmatrix} \tag{10}$$

2.10.   Smoothed Probability. Smoothed probability is the probability value of a condition at time t based entirely on observational data from start to finish. The smoothed probability value can be represented in equation (11) based on Kim and Nelson [11]:

$$Pr(S_t=j|\Omega_T;\theta) = \sum_{i=1}^{T} Pr\left(S_t=j\middle|S_{t-1}=i,\ \Omega_T;\theta\right) = \sum_{i=1}^{T} Pr\left(S_t=j, S_{t-1}=i\middle|\ \Omega_T;\theta\right) \quad (11)$$

The anticipated value of the smoothed probability at-$t+1$ is formulated as equation (12), according to Guidolin and Pedio [12]:

$$Pr(s_{t+1}=i|\Omega_T;\theta) = \sum_{j=1}^{S} p_{ij}\, Pr(s_t=j|\ \Omega_T;\theta) \quad (12)$$

where $Pr(s_t=j|\ \Omega_T;\theta)$ is the smoothed probability value when t for state j and p_{ij} is the transition probability of a state. Short-term indicators of a crisis on an economic indicator can be predicted by looking at the sign of the smoothed probability's expected value.

3.   Results and Discussion

Data on South Korea's term of trade indicator was obtained from the website of the International Monetary Fund (IMF) [13]. The term of trade is defined as

$$N = \frac{P_x}{P_m} \times 100 \quad (13)$$

where *Px* is export price index and *Pm* is import price index. The data taken is monthly data from January 1990 to March 2020. The period of January 1990 to March 2019 is used as training data while April 2019 to March 2020 is used as test data.

The stages in obtaining predictions for financial crisis signals in South Korea start from determining the appropriate data pattern through data plotting, stationarity testing, determining the best ARMA pattern based on the smallest AIC of each model combined with the order of the disconnected ACF and PACF lag combinations. Figure 1 illustrates a time series plot of the term of trade, which indicates that the data is not stationary because there is a fluctuation from time to time. Furthermore, the ADF test reveals a probability value greater than 0.05. This indicates that the data is not stationary, necessitating the use of the log return transformation.

Figure 2 shows that the log return transformed data does not indicate that the data is stationary. The probability value in the ADF test is substantially less than 0.05, indicating that the data is stationary. After the data has stabilized, ACF and PACF tests are run on each data set to determine which ARMA model should be utilized. The ACF

and PACF plots from the log return converted data in Figure 3 and Figure 4 identify the highest order ARMA model.
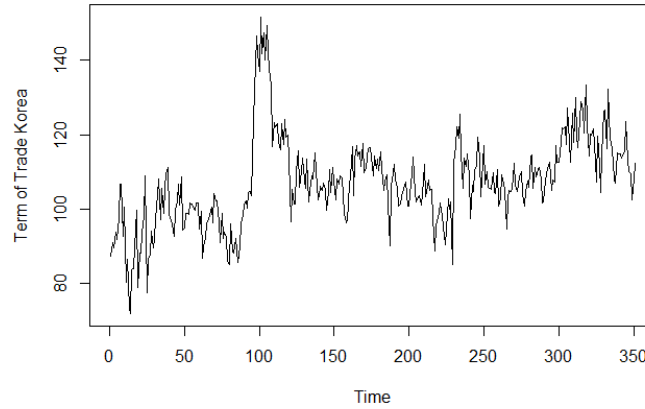

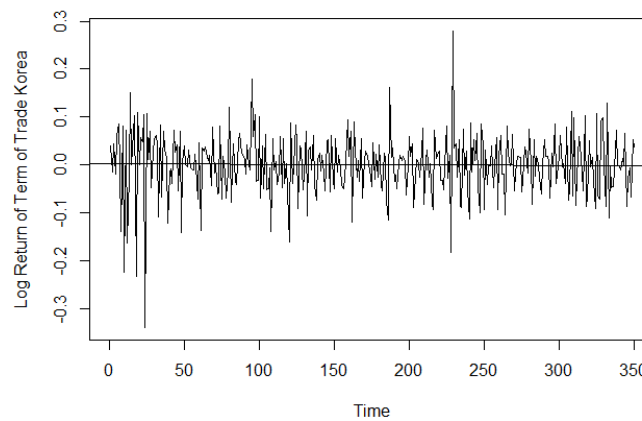Figure 1. South Korean term of trade indicator plot

Figure 2. A line plot displaying the term of trade indicator's transformation

The ACF plot in Figure 3 shows that the ACF value is disconnected and exits the confidence band at lag 1. Figure 4 shows that the PACF value is disconnected after the second lag. Consequently, the usable ARMA models are ARMA(1,0), ARMA(1,1), ARMA(2,0), and ARMA(2,1). Estimated parameters of each ARMA model are shown in Table 1.
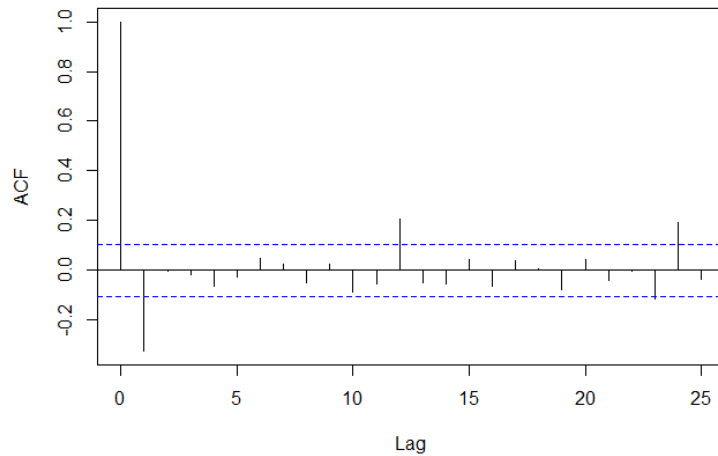
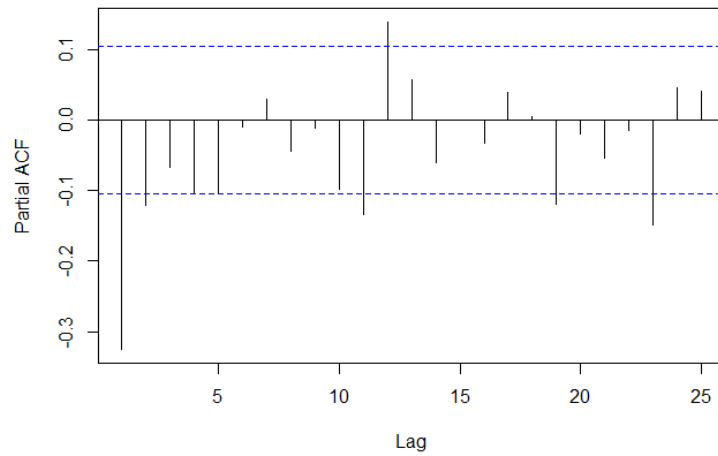Figure 3. ACF plot of the log return transformation data

Figure 4. Partial ACF plot of log return transformation data

Table 1. Parameter estimate of ARMA models

Model	Parameter	Coefficient	Probability	AIC
ARMA(1,0)	ϕ_1	-0.325784	1.14e – 10	-952.83
ARMA(1,1)	ϕ_1	0.2474916	0.0863	-961.67
	ϑ_1	-0.6271914	2.11e-07	
ARMA(2,0)	ϕ_1	-0.365484	5.97e-12	-954.99
	ϕ_2	-0.121228	0.0225	
ARMA(2,1)	ϕ_1	0.5772	< 2e-16	-965.51
	ϕ_2	0.2481	2.07e-05	
	ϑ_1	-0.9818	< 2e-16	

In Table 1, some parameters are not significant so that the ARMA model with insignificant parameters is ignored. The ARMA model is obtained with three significant parameters: ARMA(1,0), ARMA (2,0), and ARMA (3,0). (2,1). The ARMA model with the smallest AIC is obtained using the AIC information criteria, which is ARMA (2,1). However, in this study, the simple principle of the model is considered so that the ARMA (2,0) or AR (2) model is used. The ARMA(2,0) model on the transformation data log return of the South Korean term of trade indicator is written in equation (15):

$$r_t = 0.00087 - 0.3654 r_{t-1} - 0.1212\ r_{t-2} + \varepsilon_t \tag{15}$$

where r_t is the log return of the South Korean term of trade indicator at time t.
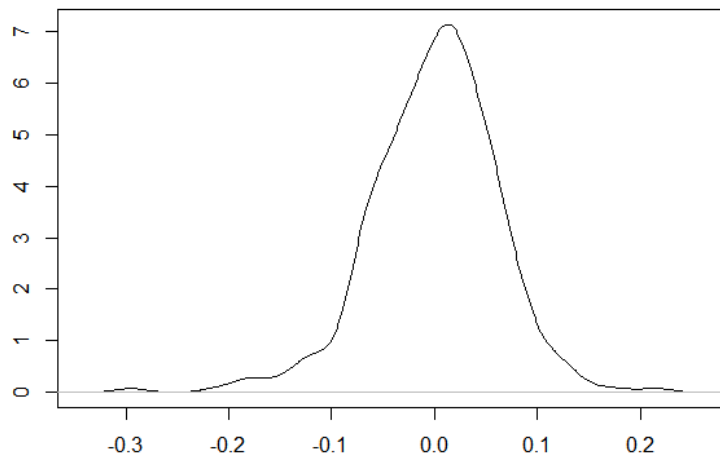

Figure 5. ARMA model residual curve

Figure 5 demonstrates that the ARMA model's residual distribution has a high peak, indicating that it is a leptokurtic distribution. Since this pattern shows that there is a range value that differs from the residual, the residuals must be grouped. The DTW distance algorithm is used to properly group time series data. The best number of clusters is found based on the grouping findings, which is two clusters as shown in Figure 6.

The next step is to run the Lagrange multiplier test on the model residual to see whether the assumption of heteroscedasticity is correct. A probability value less than 0.05 is achieved in this test, indicating that the ARMA model residual includes a heteroscedasticity effect. Overcoming the heteroscedasticity effect may be possible with the correct volatility model. The simplest GARCH model, namely GARCH, was used in

this research as the volatility model (1,1). As a result of this the GARCH(1,1) model is used in conjunction with the model described in equation (15):

$$\sigma_t^2 = 0.001474 + 0.257788a_{t-1}^2 + 0.356986\sigma_{t-1}^2 \tag{15}$$
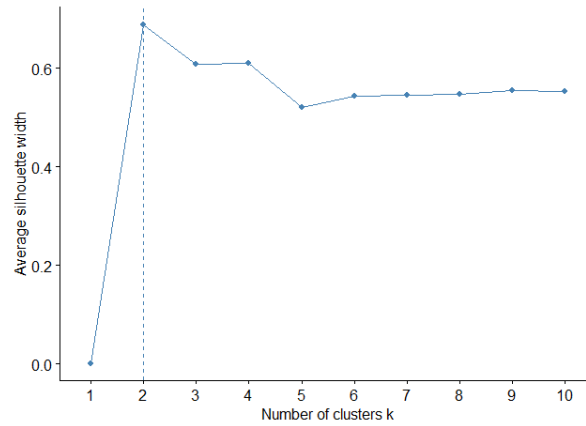

Figure 6. The optimal number of clusters.

After the volatility model in equation (15) is obtained, then a diagnostic check is finished on the GARCH(1,1) residual model which consists of a normality, autocorrelation, and heteroscedasticity effect test. The residual probability in the Kolmogorov-Smirnov test is greater than 0.05, indicating that the residual volatility model is normally distributed. The Ljung-Box test on the volatility model generates a probability value greater than 0.05, indicating that the model's residual no longer contains autocorrelation. The probability value in the volatility model is also greater than 0.05, indicating that the residual volatility model is homogeneous, according to the Lagrange multiplier test.

For the South Korean term of trade, changes in states that originate in the Markov switching model are assumed to follow a first-order Markov chain with a transition probability p_{ij} with $i, j = 1,2$. Low and high volatility are the two states of the Markov switching mixture model and the GARCH(1,1). As a result, the MS-GARCH(2,1,1) model is found. The transition probability matrix's form reveals the likelihood of changing state.

The transition probability matrix on the South Korean trade exchange rate indicator is written in equation (16):

$$P_1 = \begin{pmatrix} 0.9816 & 0.0184 \\ 0.1347 & 0.8653 \end{pmatrix} \tag{16}$$

The likelihood of surviving in low states is 0.9816, whereas the probability of surviving in high states is 0.8653, as per matrix equation (16). Change from low to high states has a probability of 0.1347, whereas change from high to low volatility has a probability of 0.0184. Equations (17) and (18) represent the mean and variance values of each state, respectively..

$$\mu_t = \begin{cases} -0.000001607, \text{ for state 1} \\ 0.000024066, \text{ for state 2} \end{cases} \tag{17}$$

$$\sigma_t^2 = \begin{cases} 0.00009189, \text{ for state 1} \\ 0.00003482, \text{ for state 2} \end{cases} \tag{18}$$

When the crisis occurred in 1997–1998, it was detected at the lowest smoothed probability, and a crisis was determined if the smoothed probability value was larger than 0.92. Figure 7 shows a plot of smoothed probability values.
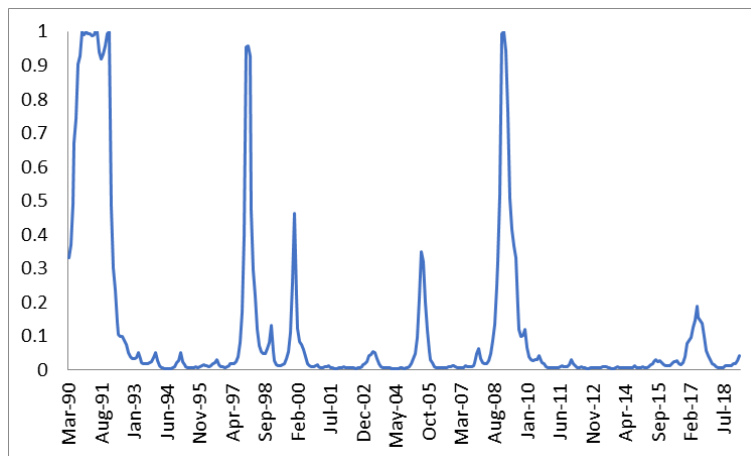

Figure 7. Smoothed probability of trade indicator

Figure 7 indicates that 21 smoothed probability values in South Korea are greater than 0.92. A financial crisis is detected by the model at the end of 1990–1991, the end of 1997–1998, and the end of 2008–2009. According to Kihwan [14], South Korea in 1990–1991 experienced a deteriorating balance of transactions due to increased inflation, appreciation of the Korean Won, and the world economic recession, so that South Korea recorded a deficit of $ 8.7 billion. The MS-GARCH(2,1,1) model on the South Korean term of trade indicator could detect crisis signs during the Asian and global financial crises of 1997–1998. Furthermore, a smoothed probability value prediction is carried out in the period March 2019 – March 2020 which is represented in Table 2.

Table 2. Prediction Value of Smoothed Probability of Test Data

Monthly Period	Prediction	Crisis Conditions	Actual	Crisis Conditions
April -19	0.041817	No Crisis	0.008208	No Crisis
May -19	0.053815	No Crisis	0.009923	No Crisis
June -19	0.063976	No Crisis	0.014772	No Crisis
July -19	0.072581	No Crisis	0.025903	No Crisis
August -19	0.079869	No Crisis	0.051832	No Crisis
September -19	0.086041	No Crisis	0.056851	No Crisis
October -19	0.091268	No Crisis	0.083854	No Crisis
November -19	0.095695	No Crisis	0.141152	No Crisis
December -19	0.099444	No Crisis	0.235733	No Crisis
January -20	0.102619	No Crisis	0.388313	No Crisis
February -20	0.105308	No Crisis	0.291357	No Crisis
March -20	0.107585	No Crisis	0.265465	No Crisis

The predicted and actual conditions are identical, as shown in Table 2. In addition, the MS-GARCH(2,1,1) is utilized to predict future financial crises. Table 3 shows the expected value of smoothed probability in South Korea.

Table 3. Monthly Smoothed Probability Prediction Value of April – December 2020

Period	Prediction	Crisis Conditions
April -20	0.110131	No Crisis
May -20	0.112283	No Crisis
June -20	0.114101	No Crisis
July -20	0.115638	No Crisis
August -20	0.116937	No Crisis
September -20	0.118035	No Crisis
October -20	0.118963	No Crisis
November -20	0.119748	No Crisis
December -20	0.120411	No Crisis

Table 3 shows that the smoothed probability prediction value is steady, indicating that the MS-GARCH(2,1,1) model of the term of trade indicator predicts that no financial crisis will occur between April and December 2020. Next, the plotting is carried out.

Figure 8 shows the result of the simulation on the value of the future smoothed probability.
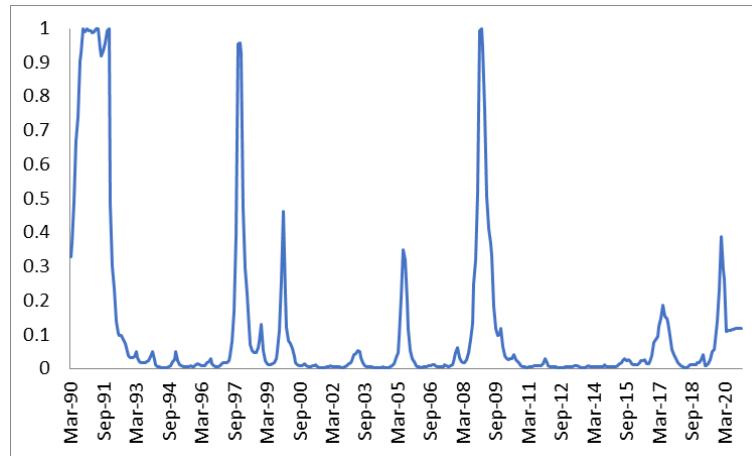

Figure 8. Future smoothed probability of trade indicator

Figure 8 shows that in the period April – December 2020 it is predicted that there will be no crisis. The data used in this research is the ratio of the export price to the import price. In 2020, when there was a global pandemic due to the COVID-19 virus, the two indicators both dropped so that the comparison between the two was balanced. As a result, the term of trade indicator had a balanced comparison value, and the term of trade indicator was unable to alert a financial crisis in the case of a COVID-19 pandemic.

4. Conclusion

The composite Markov switching model and the GARCH volatility model that is appropriate for the South Korean term of trade indicator is MS-GARCH(2,1,1). In South Korea, this indicator detects the 1990-1991 crisis, the 1997-1998 Asian crisis, and the 2008 global financial crisis. The combination model was used to detect crises in April – December 2020 based on term of trade indicator and the results showed that there will no crisis signal in that period in South Korea.

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