Financial deregulation, banking development, and the likelihood of banking fragility: the case of Indonesia

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NOTE

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5.1. Introduction

The theories of financial repression of McKinnon (1973) and Shaw (1973) have provided arguments for developing countries to deregulate their financial sector to enhance economic growth. The approaches of McKinnon and Shaw, however, are different. Shaw (1973) also considered the important role of increasing interest rates in encouraging saving and discouraging low yielding investment which in turn will increase the role of financial intermediaries. It suggests that an increase in interest rates is expected to increase saving through the banking sector and it will increase the ability of banks to extend credit to efficient investment. Therefore, credit from banks plays important role as a channel between saving through the banking sector and private investment through the credit availability effect. Hence, the relationship between financial deregulation and private investment is not direct but it is indirect through the interrelated relationship between interest rates, saving through the banking sector, credit from banks, and private investment. In those relationships, credit from banks has a key role as a channel between saving through the banking sector and private investment. It is expected that financial deregulation will increase private investment and this is the main benefit of financial deregulation. Financial deregulation, however, might contribute to increasing the likelihood of banking fragility. In addition, macroeconomic and group bank specific variables are also hypothesised to influence the probability of banking fragility.
To measure those relationships and to test the determinants of the probability of banking fragility, econometric testing will be used in this study. The selection of a particular econometrics test in this study is related to its ability to measure the relationships among the variables. Econometrics also has the ability to test the binary responses related to the dummy variable for banking fragility.

The objective of this chapter is to outline the econometric methods that will be used in this thesis. Since this study is concerned with long run relationships, the cointegration test is selected to analyse the long run relationships among variables. The evidence for the long run relationships among the variables is valid to present an error correction model. Therefore, the econometric methods in this study are based on cointegration testing and error correction mechanisms. In addition, logit and probit models are proposed for econometric testing of the determinants of the probability of banking fragility.

The organisation of this chapter is as follows. Section two presents the unit root test of the Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests. Section three discusses the procedures of the unit root test in the presence of a structural break associated with the 1997 financial and banking crises. Section four will present the cointegration test and error correction mechanism. Section five presents the logit and probit methods to test the determinants of the probability of banking fragility and the last section is the conclusion of this chapter.
5.2. The Unit Root Tests of Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF)

The unit root test for each variable is important before any estimation of modeling to examine each variable whether stationary or non-stationary. If a variable is non-stationary, the results of estimation cannot be interpreted appropriately. Therefore, unit root test for each related variable should be carried out before estimating the equation.

A time series is stationary if its mean, variance and covariance are independent of time. In other words Y is stationary if Y has a constant mean, variance, and covariance over time:

1. \( E(Y_t) = \text{constant for all } t; \)
2. \( \text{Var}(Y_t) = \text{constant for all } t; \)
3. \( \text{Cov}(Y_t) = \text{constant for all } t. \)

To analyse whether the variable is stationary or non-stationary, the unit root tests of Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests are used in this thesis.

The Dickey-Fuller (DF) test is presented as follows:

\[
Y_t = \mu + \rho Y_{t-1} + e_t, \tag{30}
\]

where \( \mu \) and \( e_t \) are an intercept and a white noise error term. The DF test is a test of the null hypothesis of a non-stationary series that is \( \rho = 1 \) against the alternative hypothesis of stationary series that is \( |\rho| < 1. \)

Equation (30) is often rewritten as follows:

\[
\Delta Y_t = \mu + \delta Y_{t-1} + e_t, \tag{31}
\]

where \( \Delta Y_t = Y_t - Y_{t-1} \) \( \tag{32} \)
If identity (32) is substituted in equation (31), then equation (31) can be written as follows:

$$Y_t - Y_{t-1} = \mu + \delta Y_{t-1} + e_t$$  \hspace{1cm} (33)

and we can rearrange equation (33):

$$Y_t = \mu + (1 + \delta) Y_{t-1} + e_t$$  \hspace{1cm} (34)

Equation (34) is equal to equation (30), and consequently $\rho = (1 + \delta)$. As a result, the procedure for the unit root test by applying the equation (31) is testing the null hypothesis of a unit root that is $\delta = 0$, and it is equivalent to $\rho = 1$ in the equation (30), against the alternative hypothesis of $\delta < 0$. The rejection of the null hypothesis of a non-stationary series indicates that the level of $Y$ is stationary, and $Y$ is identified as integrated of order zero or I(0).

If the null hypothesis of a non-stationary series cannot be rejected, it suggests that the tested time series (for example $Y$) is non-stationary. If the tested variable is indicating that it is non-stationary in its level, the tested variable might be integrated of an order higher than zero such as I(1). As an alternative, the time series variable might need to be first differenced to become stationary.

If a non-stationary time series can be converted to a stationary time series after differencing one time, for example, the series is called integrated of order one that is $I(1)$. Therefore, if the level of the variable is non-stationary, the next step is to test whether the first difference of the variable is stationary or non-stationary which is $Y$ is integrated of order one or $I(1)$.

The error term in the DF test, however, might be serially correlated. The possibility of serial correlation of the error term in the DF test is eliminated in the Augmented Dickey-Fuller (ADF) test by adding the lagged time series as an
explanatory variable. The presentation of the ADF test of the level of a variable included an intercept is as follows:

$$\Delta Y_t = \mu + \delta Y_{t-1} + \sum_{i=1}^{d} \alpha_i \Delta Y_{t-i} + e_t$$

(35)

where $\mu$ is an intercept, and $d$ is the lag-length in the estimation of the ADF test.

The null hypothesis of the ADF test is the same as the DF test that is $\delta = 0$ against the alternative hypothesis of $\delta < 0$. The procedure testing of the DF and ADF tests of each variable in this study is included an intercept.

The selection of appropriate lag-length for the ADF test is important. Too few lags may result in over-rejecting the null hypothesis when it is true (i.e., adversely affecting the size of the test), while too many lags reduce the power of the test as the unnecessary nuisance parameters reduce the effective number of observations available (p.34, Harris (1995)).

There are many approaches to selecting the lag-length ($d$) in the ADF test. The selection of lag-length can be approached by using the F-test. By using the F-test, it implies that the maximum lag-length is assumed to be unrestricted and it will gradually reduced to lower lag-lengths. Another approach to selecting the lag-length for the ADF test is based on model selection criteria such as using Akaike Information Criteria (AIC), Schwarz Bayesian Criteria (SBC), and Hannan-Quinn Criteria (HQC).

The AIC, SBC and HQC for this study are defined as the following (pp.353-354, Pesaran and Pesaran (1997)).

$$AIC_i = l_n(\hat{\theta}) - p$$

(36)

$$SBC_i = l_n(\hat{\theta}) - \frac{1}{2} p \log n$$

(37)

$$HQC_i = l_n(\hat{\theta}) - (\log \log n) p$$

(38)
where $l_n(\hat{\theta})$ and $\theta$ are the maximised values of the log-likelihood function of the model and maximum likelihood estimator of $\theta$ based on a sample size of $n$ respectively; and $p =$ the number of freely estimated parameters. Based on those definitions of model selection criteria, the highest value of AIC, SBC, or HQC is selected.

Selection of the lag-length of the ADF test in this study will be based on the selection model criteria which is the Akaike Information Criteria (AIC), Schwarz Bayesian Criteria (SBC), and Hannan-Quinn Criteria (HQC). Selection of the lag-length based on one criterion, however, might be different than for other criteria. If there is a difference in the selection of lag-length among the criteria, the lower lag-length is selected in order to save degrees of freedom.

The unit root tests of the ADF (and also DF) tests have covered the period of the 1997 financial and banking crises. The 1997 financial and banking crises have influenced the major economic variables. Therefore, the power of the ADF test might be lower if the 1997 financial and banking crises were not considered in the unit root tests for each variable. Therefore, in this study, the unit root test is also conducted by considering the presence of structural break.

5.3. The Unit Root Test Conditional on the Presence of Structural Break

Perron (1989) developed the procedure for a stationarity test by allowing a one-time change occurring at a time $T_B (1 < T_B < T)$, where $T_B$ is the break time and $T$ is total sample.

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103 Detailed discussion can be seen in Pesaran and Pesaran (1997).
Perron (1989) considered three different models as follows.

1. One that permits an exogenous change in the level of the series (model A).
   
   This model allows for a one-time change in the intercept of the trend function.

2. One that permits an exogenous change in the rate of growth (model B).
   
   This model allows a one-time change of the slope of the trend function.

3. One that permits an exogenous change in both level and growth (model C).
   
   This model allows a one-time change for both intercept and the slope of the trend function simultaneously.

The parameters of the null hypothesis of those three models is denoted as follows (p.1364, Perron (1989)):

1. Model (A): \( Y_t = \mu + dD(TB)_t + Y_{t-1} + \varepsilon_t \)  

2. Model (B): \( Y_t = \mu_1 + Y_{t-1} + (\mu_2 - \mu_1)DU_t + \varepsilon_t \)  

3. Model (C): \( Y_t = \mu_1 + Y_{t-1} + dD(TB)_t + (\mu_2 - \mu_1)DU_t + \varepsilon_t \)  

where \( D(TB)_t = 1 \) if \( t = T_B + 1 \), 0 otherwise;

\( DU_t = 1 \) if \( t > T_B \), 0 otherwise.

The trend-stationary alternative hypothesis is presented as follows (p.1364, Perron (1989)):

1. Model (A): \( Y_t = \mu_1 + \beta_t + (\mu_2 - \mu_1)DU_t + \varepsilon_t \)  

2. Model (B): \( Y_t = \mu + \beta_t + (\beta_2 - \beta_1)DT^*_t + \varepsilon_t \)  

3. Model (C): \( Y_t = \mu_1 + \beta_t + (\mu_2 - \mu_1)DU_t + (\beta_2 - \beta_1)DT_t + \varepsilon_t \)  

where \( DT^*_t = t - T_B \)

\( DT_t = t \) if \( t > T_B \), 0 otherwise, and \( T_B \) is the time break

In line with the null hypothesis, the alternative hypotheses of model A permits a one-time change in the intercept of the trend function and Perron called this model a
The notation of \((\mu_2 - \mu_1)\) represents changes in the intercept of the trend function that occurred at the break time. Model B allows a change in the slope of the trend function without any sudden change in the level at the time break, and Perron called this model a changing growth model. The notation of \((\beta_2 - \beta_1)\) refers the changes in the slope of the trend function that occurred at the time break. While model C allows a one-time change in both the level and slope of the trend function simultaneously. The notation of \((\mu_2 - \mu_1)\) and \((\beta_2 - \beta_1)\) represent the changes of intercept and slope of the trend function that occurred at the break time simultaneously.

Corresponding with the null and alternative hypothesis, Perron extended the unit root test of Augmented Dickey-Fuller (ADF) and constructed those three alternative models to examine the trend stationary of the variable as follows (pp. 1380-1381, Perron (1989)):

A. Crash model (A):
\[
Y_i = \mu_A + \beta_A DU_i + \beta^A t + d^A D(TB) + \hat{\alpha}_A Y_{i-1} + \sum_{j=1}^{k} \hat{c}_j \Delta Y_{i-j} + \hat{\epsilon}_i,
\]

B. Changing growth model (B):
\[
Y_i = \mu_B + \beta_B DU_i + \beta^B t + \gamma^B DT_i + \hat{\alpha}_B Y_{i-1} + \sum_{j=1}^{k} \hat{c}_j \Delta Y_{i-j} + \hat{\epsilon}_i,
\]

C. Where both effects are allowed (C):
\[
Y_i = \mu_C + \beta_C DU_i + \beta^C t + \gamma^C DT_i + d^C D(TB) + \hat{\alpha}_C Y_{i-1} + \sum_{j=1}^{k} \hat{c}_j \Delta Y_{i-j} + \hat{\epsilon}_i,
\]

The null hypothesis of the model is denoted as follows:

A. Crash model (A): \(\alpha^A = 1, \beta^A = 0, \theta^A = 0\);

B. Changing growth model (B): \(\alpha^B = 1, \gamma^B = 0, \beta^B = 0\);

C. Where both effects are allowed (C): \(\alpha^C = 1, \gamma^C = 0, \beta^C = 0\).

Under the alternative hypothesis of a trend stationary process, it is expected that \(\alpha^A, \alpha^B, \alpha^C < 1; \beta^A, \beta^B, \beta^C \neq 0; \theta^A, \theta^B, \gamma^B, \gamma^C \neq 0\). In addition, under the alternative
hypothesis, \( d^A, d^C, \theta^B \) are close to zero while under the null hypothesis they are expected to be significantly different from zero.

Moreover, Perron (1989) used models A, B, and C to estimate the unit root test in his study. The model only allows one break and Perron (1989) hypothesised that either the 1929 Great Crash or the 1973 oil price shock were the break time\(^{104} \). By allowing a one-time break in the unit root test, Perron (1989) found that the null hypothesis of most variables (10 out of 13 variables) could be rejected. It suggests that by allowing a one-time exogenous change in evaluating the unit root test had resulted in different conclusions. In addition, Perron has provided the asymptotic distribution of the t-statistic for those three models. Perron in his model hypothesised that the break-time is known.

Perron and Vogelsang (1992) have extended the model to the hypothesis that the break time is unknown. Perron and Vogelsang (1992) extended the unit root test by allowing a one-time exogenous change for an unknown break time\(^{105} \). The break time should occur at \( T_b \) with \( 1 < T_b < T \).

The implementation of a unit root test by allowing a one-time exogenous change assumes that the break time is known. The selection of the known break time is based on the argument that the estimation of the unit root test has covered the data for the Indonesian financial sector from 1983:1-1999:2.

\(^{104} \)Perron (1989) used the 1929 Great Crash as the break time for 13 macroeconomic time series that are used by Nelson and Plosser. Perron excluded unemployment rates from the data set of Nelson and Plosser as he argued that the unemployment rates are generally perceived as being stationary. On the other hand, the 1973:1 oil price shock is used as a break time for quarterly real GNP.

\(^{105} \)There are many ways to determine the endogenous break time. Perron and Vogelsang (1992), for example, determine the break time by choosing to minimize the t statistic for testing \( \delta = 0 \). For the discussion on determining an unknown break time can be seen in Perron and Vogelsang (1992), Zivot and Andrew (1992), Perron (1994), and Holden and Perman (1994).
During this period, there was a "big-shock" associated with the 1997 financial and banking crises. Therefore, in line with the 1929 Great Crash as the known break time of the Perron study (Perron, 1989), 1997:2 is argued as the known break time. If the 1997 financial and banking crises were not included in the unit root test, it implies that the 1997 financial and banking crises would be treated simply as one big outlier. Therefore, the existence of the 1997 financial and banking crises have to be considered in the analyses of the unit root test. The unit root test in the presence of structural break will apply the Perron (1989) model with the hypothesis that 1997:2 was the known break time. In addition, the objective of the unit root test by allowing a one-time exogenous change is to examine the trend stationary of each variable by possibility higher power (Perron (1989)).

The model by allowing both changes in intercept and trend simultaneously (model C) is selected as the 1997 financial and banking crises, at least up to 1999:2, caused a major change not only in the intercept but also in the trend. It implies that the implications of the exogenous change (the 1997 financial and banking crises) have changed the level and slope of the trend function after 1997:2\textsuperscript{106}. Therefore the procedure of testing the unit root test in the presence of structural break by using model C in (47) is by estimating the parameters of the model as follows\textsuperscript{107}:

\[ \Delta Y_i = \mu + \theta DU_i + \beta t + \gamma DT_i + dD(TB)_i + \alpha Y_{i-1} + \sum_{j=1}^{k} c \Delta Y_{i-j} + e_i \]  \hspace{1cm} (48)

\textsuperscript{106} The Indonesian financial and banking crises were started by the currency crisis on the middle of July 1997. The second quarter of 1997 (1997:2) is selected as a break time as the data is quarterly. By using 1997:2 as a break time, the changes in the level and trend are allowed in the third quarter of 1997 (1997:3).

\textsuperscript{107} See Holden and Perman (1994).
where $Y$ is the variable which to be tested. $DU$ is a dummy variable and the value is equal to one if $t > T_b$ and zero otherwise; $T_b = 1997:2$. The value of $D(TB)$ is equal to one if $t = T_b + 1$ and 0 otherwise, and $e_i$ is the error term.

The selection of lag-length for the unit root test conditional on the presence of a structural break ($k$), in this study, will be based on the F-test. The F-test is used to test whether the additional lag is significant or insignificant in the model. The estimation of the equation is estimated by using the ordinary least square (OLS) method.

If the unit root test for each variable indicates that the variable is $I(1)$, the cointegration test can be carried out. The cointegration test, however, cannot be carried out for variable $I(0)$ as the $I(0)$ time series has a constant mean while the other variable $I(1)$ tends to drift over time. Consequently, they cannot be stable over time. The variables that are included in the cointegration test might have a different order, but not one of them is $I(0)$. Therefore, the time series $I(0)$ is not included in the cointegration test but it can be included in the estimation of the Vector Auto-Regression (VAR) of the Johansen cointegration test.

5.4. Cointegration Test and Error Correction Mechanism

A non-stationary variable might have a long run relationship with other non-stationary variables and this does not create a spurious regression if the deviation of this long run relationship is stationary. It implies that those variables are cointegrated and it suggests that they have a long run relationship. The economic interpretation of cointegration is associated with two or more variables that are linked to form an equilibrium relationship in the long run (steady state), even though the series themselves in the short run may deviate from their long run equilibrium, they will
move closely together over time to the long run equilibrium (p.22, Harris (1995)). Therefore, the concept of cointegration is based on the existence of a long run equilibrium, even in the short run they might deviate but they will move back to the long run equilibrium.

To analyse whether the variables in the system of equations have a long run relationship, the cointegration test will be used. When variables are cointegrated, it implies that an equilibrium long run relationship exists among the variables. In the short run, however, there may be disequilibrium. Therefore, the error correction mechanism will be used to test the short run behaviour of its long run value. Engle and Granger (1987) have shown that any co-integrated series has an error correction representation.

The Engle and Granger approach for error correction model is often called a two step procedure test. Suppose for variable Y and X. If the residual of the estimation of variables Y and X is stationary, then Y and X are cointegrated. It implies that Y and X have a long run relationship. The testing procedure is represented as follows:

- Estimating the regression for the level of variables Y and X, allows the hypothesis of cointegration to be tested. It is called a cointegrating regression. Suppose the model is represented as follows:

\[ Y_t = \alpha_0 + \alpha_1 X_t + \epsilon_t \]  \hspace{1cm} (49)

where \( \epsilon_t \) is an error term and it is interpreted as the cointegrating linear relationship. Variables Y and X might individually be non-stationary but if the estimate of the residual error in the estimation is stationary, Y and X are said to be cointegrated and it is considered that there is no spurious regression problem.
Therefore, the residual of the estimation is examined to analyse whether the residual is stationary or non-stationary.

- The residual of the estimation is obtained as follows:

\[ e_i = Y_i - \hat{Y}_i \]  \hspace{1cm} (50)

The residual term \( e_i \) is tested for whether it is stationary or non-stationary. If the residual error in the estimation of the first step is stationary, it suggests that \( Y \) and \( X \) are cointegrated and the error correction procedure can be carried out in the second step procedure testing.

- The level of the (stationary) residual of the estimation in the first step is entered into the second step that is the error correction model (ECM). The model implicitly assumes that \( Y \) and \( X \) are both I(1). As a result, the presentation of the short run model with the error correction model is as follows:

\[ \Delta Y_t = c_0 + c_1 \Delta X_t + c_2 EC_{t-1} + \nu_t \]  \hspace{1cm} (51)

where \( \nu_t \) is the error term and \( EC \) is the estimated residual in the first step estimation of \( Y \) and \( X \), which is \( (e) \) in the first step. The coefficient of \( c_2 \) represents the parameters short run adjustment to their long run equilibrium.

The two-step procedure has covered both long run equilibriums and has an error correction mechanism if the \( c_2 \) is negative and significant.

The estimation of the first step equation (cointegrating regression), however, is not a really a long-run equation: "this is an assumption and cannot be statistically verified" (p.157, Charemza and Deadman (1993))\(^\text{108}\). The residual based cointegration

\[^{108}\text{There is another way to estimate the long run for a single equation that is the Auto-Regressive Distributive Lag (ARDL) method.}\]
test of the Engle and Granger procedure is dealing with a single equation modeling, but this test is not efficient for a multivariate case (p.291, Pesaran and Pesaran (1997)).

Johansen (1988) and Johansen and Juselius (1990) have improved the cointegration test for the multivariate case. As the long run relationship in the estimation of this study is considering the multivariate case (more than two variables which are included in the estimation of cointegration test), the Johansen cointegration method will be used in this study to examine whether the long run relationship among the variables exists or not.

The Johansen approach involves testing and analysing the cointegration analysis by linking it with the Vector Auto-Regression (VAR) model. Suppose the unrestricted VAR model is written as follows\(^{109}\):

\[
Z_t = A_1 Z_{t-1} + \ldots + A_k Z_{t-k} + u_t
\]

where \(Z_t\) as an unrestricted VAR with \((nx1)\), each of \(A_i\) is an \((nxn)\) matrix of parameters, and \(u_t\) is a vector of random errors.

Suppose the matrix of \(A\) in equation (52) is written as follows:

\[
A = \alpha . \beta^\prime
\]

Variables that are included in \(Z_t\) are non-stationary, but \(\Delta Z_t\) is stationary, the linear combinations given by \(\beta^\prime . Z_t\) are also stationary. It implies that the vector process of \(Z_t\) is cointegrated with the cointegrating vectors \(\beta^{110}\). Johansen shows that the maximum likelihood estimator of \(\beta\) can be derived as the solution of a generalised eigenvalue problem. The likelihood ratio (LR) test of the hypothesis of the number of cointegrating vectors is based on these eigenvalues. Johansen proposes two

\(^{109}\) For simplification of the model VAR, intercepts and deterministic trend are not included in the model.

\(^{110}\) Detailed discussion can be seen in (p.132, Johansen (1991)).
tests to determine the number of cointegrating vectors. First, the likelihood ratio test, which is based on the maximal eigenvalue with the null hypothesis that there are \( r \leq k \) (where \( k = 0,1,2,\ldots,k-1 \)) \(^{111}\) cointegrating vectors against the alternative hypothesis that there are \( r = k + 1 \) cointegrating vectors. Second, the likelihood ratio test, which is based on the trace test with the null hypothesis that there are \( r \leq k \) cointegrating vectors against the alternative hypothesis that there are \( r \geq k + 1 \) cointegrating vectors. The power of the LR trace test is lower than that of the LR maximal eigenvalue test (Johansen and Juselius (1990)). If the null hypothesis of no cointegrating vector can be rejected, it indicates that there is a long run relationship among the variables in the model. As a result, the error correction mechanism can be presented.

The relation of the error correction mechanism process and the Vector AutoRegression (VAR) of the Johansen approach is based on the implicit assumption that the model allows the process of \( Z_t \) to be non-stationary, and it is simplified that \( Z_t \) is integrated of order 1, therefore the \( \Delta Z_t \) \(^{112}\) is stationary.

Cointegration test of the Johansen approach has links to the Vector AutoRegression (VAR) model. Consequently, the selection of the lag-length for VAR is important in the estimation of the Johansen cointegration test. The selection of lag length (k) of VAR is associated with the objection to achieve the error term is Gaussian white noise in the Vector Error Correction Mechanism (VECM). In addition, Johansen (1995) argues that to select the lag-length of VAR, it is important to avoid too many lag-lengths and if a long lag-length is required to get white noise residuals

\(^{111}\) The exception is for the null hypothesis of no-cointegrating vector is \( r = 0 \), it is not \( r \leq 0 \). This null hypothesis of no-cointegrating vector is also applied for trace statistics.

\(^{112}\) \( \Delta Z_t \) represents the first difference of all variables that are included in the vector of \( Z_t \).
then it might be better to add another important explanatory variable in the information set.

There are many ways to determine the lag-length of VAR for estimating the Johansen cointegration test. The lag-length of VAR can be determined by a criteria selection model such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC). In addition, the selection of lag-length can also be determined by testing the restrictions using the likelihood ratio (LR) test.

The selection of lag-length of VAR for estimating the Johansen cointegration test in this study will be based on the criteria selection model that consists of the AIC and the SBC, and together with the restriction test by the likelihood ratio (LR) test. The procedure to determine the lag-length of the VAR for estimating the Johansen cointegration test is as follows (pp. 106-107, Holden and Perman (1994)):

- Estimate the unrestricted level of VAR

\[ Z_t = A_1 Z_{t-1} + \ldots + A_k Z_{t-k} + u_t \]

Initially estimate the level of VAR with a long lag-length, a large of k, and then re-estimate the same equation for successively smaller lag-lengths. In this case, the maximum lag-length chosen is 5 lag-lengths and then it is re-estimated successively with lag-lengths 4, 3, 2, 1, 0 respectively.

- The selection of lag-length for VAR is analysed based on the AIC and SBC. As the selection based on the AIC might give a different result to that based on the SBC, the lower lag-length is chosen. The selection of lag-length based on either AIC or SBC should be supported by the results of the restriction tests of the likelihood ratio (LR) test.
• The restriction test of the likelihood ratio (LR) test is carried out to analyse whether the restriction imposed in moving to a reduced lag-length is statistically acceptable. The maximum (the longest) lag-length is considered to be unrestricted, while the re-estimation for lower lag-lengths of the same level of variable of VAR is considered as the restricted estimation by using the likelihood ratio (LR) test. The LR test has a chi-square ($\chi^2$) distribution with degrees of freedom equal to the number of restrictions.

• Based on the LR test statistic and the model selection criteria, the lag-length is selected.

• As the selection of lag-length for the VAR should be related to a white noise error term, after the lag-length for the VAR was selected, the next step carried out was the residual test using the Lagrange Multiplier (LM) test for residual autocorrelation. This is calculated by regressing the estimated residual from "candidate" (selected) order of VAR on the residual lag as well as the regressors in the model VAR. The Lagrange Multiplier test is used to examine whether the individual equation has a serial correlation problem or if they are not serially correlated. The condition of the white noise residual is important since the validity of the estimation of the Johansen approach is based on the assumption of the white noise error term. Therefore, a higher value of lag-length than indicated by the criteria selection model might be required to obtain the conditions for the white noise residual. In addition, Johansen (1995) argues that the important criterion for the choice of lag-length is that the residuals are uncorrelated.
As discussed earlier, the Johansen cointegration test has links to VAR model. The model of unrestricted VAR is transformed to a cointegrating transformation\textsuperscript{113}, and it results in the presentation of the error correction mechanism as follows:

\[ \Delta Z_t = \Gamma_1 \Delta Z_{t-1} + ... + \Gamma_k \Delta Z_{t-k+1} + \Pi_k Z_{t-k} + \psi D_t + \Phi \mu + u_t \]  \hspace{1cm} (54)

where

\[ \Gamma_i = -(I - A_i - ... - A_k), \]
\[ i = 1, 2, ... , k, \]
\[ \Pi = -(I - A_i - ... - A_k) \]

In the short run, it is often the dummy variable that represents the short run shock or policy intervention which might influence the short run pattern but which might not be significant in the long run. Under this situation, the dummy variable is included the vector error correction mechanism (VECM)\textsuperscript{114}, but the dummy variable is not included in the long run relationship. Hence, the error correction mechanism is presented as follows:

\[ \Delta Z_t = \Gamma_1 \Delta Z_{t-1} + ... + \Gamma_k \Delta Z_{t-k+1} + \Pi_k Z_{t-k} + \psi D_t + \Phi \mu + u_t \]  \hspace{1cm} (55)

where \( D \) and \( \mu \) represent the dummy variable and intercept respectively.

The Johansen cointegration test and the error correction mechanism will be used to analyse the relationship for saving through the banking sector, credit from banks, private investment and their specified determinants variables respectively. From those equations together, the financial deregulation hypothesis of the relationship between interest rates, saving through the banking sector, credit from banks, and private investment will be analysed. In addition, in order to test the

\textsuperscript{113} The transformation of the model VAR to Error correction mechanism can be confirmed by adding \( Z_{t-1}, Z_{t-2}, ... Z_{t-k}, \) \textit{and} \( A_1 Z_{t-2}, A_2 Z_{t-3}, ... , A_{k-1} Z_{t-k} \) to both sides of the model VAR and then rearranged to obtain the cointegrating transformation (Charemza and Deadman (1993)). The cointegrating transformation is the presentation of the error correction mechanism.

\textsuperscript{114} see (pp.81-86, Harris (1995)).
determinants of the probability of banking fragility in this study, the logit and probit models are proposed.

5.5. The Logit and Probit Models

To estimate the probability of banking fragility, the logit and probit models are used in this study. The dependent variable is a dummy for banking fragility\(^{115}\), which has a value of one if there is banking fragility and zero if there is no banking fragility. As discussed earlier, the construction of the dummy variable for banking fragility is associated with the following criteria: if the ratio of non-performing loans to total loans exceeds 10\%, if the generalised deposit guarantees were introduced, or if there was a large scale government take over. If a minimum of one of those criteria holds, the group of banks is classified as fragile. Therefore, the dependent variable can be represented as follows:

\[
P(Y) = \begin{cases} 
1 & \text{if the group of banks is classified as fragile} \\
0 & \text{otherwise} 
\end{cases}
\]

As a result, the dependent variable is a binary quantitative response which only contains one if the group of banks is classified as fragile and zero otherwise. If the dependent variable is a binary quantitative response which contains zero and one, the most appropriate way to estimate the model is to use a logit or probit model. Hence, the logit and probit methods will be used. A probit method is used for comparison purposes to analyse the determinants of banking fragility in Indonesia.

\(^{115}\) As discussed earlier, if one group of bank either state banks or national private banks as a group is fragile, it contributes to enhancing the unsoundness of the banking system as the share of either state banks or national private banks as a group is very substantial in the Indonesian banking system during the most period of study.
Suppose that probability of observing banking fragility, $Y=1$, is represented as follows:

$$P(Y = 1)$$  \hspace{1cm} (56)$$

The probability of observing the non-existence of banking fragility, $Y=0$, can be written as follows:

$$P(Y = 0) = 1 - P(Y = 1)$$  \hspace{1cm} (57)$$

To solve the equation $P(Y = 1) = \beta X$ is not as straightforward as in the linear regression, but the $P(Y = 1)$ should be replaced by $\text{odds}(Y = 1)$. The natural logarithm of the odds, $\ln\{P(Y = 1) / [1 - P(Y = 1)]\}$, is called the logit of $Y$\textsuperscript{116}.

It is assumed that the probability of banking fragility, which is denoted as $P(Y_i = 1)$, depends on the values of $X$ independent variables. The equation for the relationship between dependent and independent variables is as follows:

$$\text{Logit}(Y) = \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_n X_{in}$$  \hspace{1cm} (58)$$

where $X_{ij}$ is the value of the $i$th independent variable related to the $j$th group of banks.

The value of $Y = 1$, is if the group of banks is classified as fragile and $Y = 0$ if the group of banks is classified as non-fragile.

The logit ($Y$) is converted to the odds: $\text{Odds}(Y = 1) = e^{\text{logit}(Y)}$, equation (58) which is the probability of the banking fragility can be rewritten as follows:

$$P(Y = 1) = \frac{e^{\beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_n X_{in}}}{1 + e^{\beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_n X_{in}}} = \frac{\sum \beta_j X_{ij}}{1 + \sum \beta_j X_{ij}}$$  \hspace{1cm} (59)$$

\textsuperscript{116} For detailed discussion can be seen in Menard (1995), pp.12-14.
Equation (59) which is the probability of occurrence (in this case the probability of the presence of banking fragility) is often written as follows:\(^\text{117}\):

\[
P(Y = 1) = \Lambda(\sum_{i=1}^{n} \beta_i X_{iy}) = \frac{\sum \beta_i X_{iy}}{1 + e^{-\sum \beta_i X_{iy}}} \tag{60}
\]

where \(\Lambda(.)\) represents the logistic cumulative distribution function. On the other hand, the probability that there is no banking fragility is represented as follows (p.12, Liao(1994)):\(^\text{118}\):

\[
P(Y = 0) = \Lambda(-\sum_{i=1}^{n} \beta_i X_{iy}) = \frac{1}{1 + e^{-\sum \beta_i X_{iy}}} \tag{61}
\]

Another type of statistical model which widely used to estimate the binary responses is a probit method. A probit model can be expressed by replaced the cumulative distribution function of error term in a logit model in equation (59) by standard normal cumulative function as follows (Liao (1994), Greene (2000)):

\[
P(Y = 1) = \Phi(\sum_{i=1}^{n} \beta_i X_{iy}) \tag{62}
\]

where \(\Phi(t)\) is the standard normal density.

On the other hand, the probability of there is no banking fragility by using a probit method is given as follows (p.21, Liao (1994)):

\[
P(Y = 0) = 1 - \Phi(\sum_{i=1}^{n} \beta_i X_{iy}) \tag{63}
\]

\(^{117}\) For example see Greene (2000), Liao (1994) among others.

\(^{118}\) Liao (1994) uses notation \(L\) instead of \(\Lambda\).
The interpretation of the sign of the coefficient parameters in the logit and probit models is the same with the standard regression model. Given a significant statistical test, a positive sign of the parameter suggests that the likelihood of response increases with the other variables held constant. On the other hand, a negative sign of the parameter indicates the likelihood of the response decreases with the other variables held constant. However, the interpretation of the estimated coefficient in the logit and probit models is different than in the standard linear regression model. The estimated coefficients in the logit and probit models do not indicate an increase (or decrease) in the probability of banking fragility associated with a one unit increase (or decrease) in the corresponding explanatory variable.

Interpreting the marginal effects of the explanatory variables in the logit and probit models is not straightforward. The marginal effect of a unit change variable (and other variables are assumed constant) can be measured as follows (p. 48-49, Demaris (1992)):

$$\beta_n(\pi_i)(1-\pi_i)$$

where \(\beta_n\) is coefficient of variable \(n\), \(\pi_i\) is the conditional probability of banking fragility. The Microfit program version 4, however, has provided "the factor for the calculation of marginal effect" to the probability model. Therefore, the marginal effect of one variable on the probability of banking fragility is measured by the coefficient of those explanatory variables multiplied by "the factor for the calculation of marginal effect" (pp. 264-265, Pesaran and Pesaran (1997)).

On the other hand, the interpretation of probit model is identical to that of logit model except for the difference in their cumulative distribution function (p.23, Liao (1994). Consequently the magnitude of the coefficients by using a logit model cannot directly be compared to the coefficient by using a probit model. To make them
comparable, the coefficients estimated by using a probit model must be multiplied by 1.814 (p.264, Pesaran and Pesaran (1997), p.25, Liao (1994)).

The results by using the logit and probit models in some cases may differ substantially especially when there is a large observation with a heavy concentration in the tails. The logit model is more appropriate for distributions with heavier tails (p.25, Liao (1994)). As the observation covers data up to 1999:2 which is included the financial and banking crises, it is argued that the observation has a distribution with a heavier tail. Consequently, a logit model is more appropriate than a probit model. Therefore, to analyse the probability of banking fragility, it will be emphasised the result by using a logit method. However, an estimation by using a probit model will also be presented for the comparison purposes. In addition, both logit and probit models are estimated by using maximum likelihood method.

5.6. Conclusion

This chapter has considered the econometric methods that will be used in this thesis. As the modern standard for econometrics, the unit root test for all related variables is carried out before estimating the equations. The objective of the unit root test is to investigate whether the variables are stationary or non-stationary. As there is a “big-shock” associated with the 1997 financial and banking crises, the unit root test should consider the existence of the 1997 financial and banking crises. The objective of the unit root test conditional on the presence of a structural break is to obtain the possibility of higher power than the conventional ADF test that ignores the existence of a structural break.

Meanwhile, to analyse the long run relationship among the variables, the Johansen cointegration test was selected. The Johansen approach provides an estimation
of the cointegration test related to the context of a vector error correction mechanism by using a cointegrating Vector Auto-Regression (VAR) model. The estimation of the Johansen cointegration test assumes the existence of a white noise of error term. Consequently, the selection of lag-length for VAR in estimating the Johansen cointegration test is important in order to obtain the white noise of error term.

On the other hand, the logit methods will be used to analyse the probability of banking fragility as it is argued that the observation has distribution with heavy tail related with the 1997 financial and banking crises. However, probit method is also used for comparison purposes. The dependent variable is a dummy variable for banking fragility, which has a value of one if there is a banking fragility and zero otherwise. In addition, the probability of banking fragility is hypothesised to depend on \( n \) explanatory variables.