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CREDIT DOWNTURN IN THE AFTERMATH OF INDONESIAN CRISIS 1997 REVISITED: AN APPLICATION OF ARDL BOUNDS TESTING APPROACH

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A b s t r a k

Studi ini bertujuan mengestimasi persamaan jangka panjang permintaan kredit dan penawaran kredit di Indonesia dengan menggunakan teknik pengujian kointegrasi yang relatif baru, yaitu teknik autoregressive distributed lag (ARDL) bounds testing. Data yang digunakan adalah data kuartalan pada periode 1985Q1-2004Q2.

Hasil estimasi menunjukkan bahwa permintaan kredit dan penawaran kredit memiliki hubungan jangka panjang (terkointegrasi) dengan faktor-faktor yang mempengaruhinya. Selain itu, pengujian CUSUM dan CUSUMSQ menunjukkan bahwa koefisien kedua persamaan jangka panjang tersebut memiliki stabilitas. Plot estimasi permintaan kredit dan penawaran kredit menunjukkan bahwa lambatnya proses pemulihan penyaluran kredit setelah krisis di Indonesia lebih banyak disebabkan oleh lemahnya permintaan kredit.

Keywords: ARDL, cointegration, bounds testing, ECM, credit, Indonesia

JEL Classification: C32, C52, E51

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I. INTRODUCTION

The existing empirical works on credit downturn suggest that the root of the declining credit disbursement in Asian countries after the crisis is still in debate (among others Ghosh and Ghosh, 1999; Agenor, Aizenman and Hoffmaister, 2000). Some argued that it was caused by credit crunch which stimulated the phenomenon of credit rationing and resulting in the inward shifting supply of credit by banks (supply side constraint). Others believed that decreasing in bank lending was stirred by dwindling demand for credit (demand side constraint) resulted from contraction in aggregate demand and output after the crisis.

As a developing economy, financing to business sectors in Indonesia has been dominated by bank credits. At this juncture, the sluggish growth of bank credit after the crisis 1997 (henceforth the crisis) was blamed as root of the belated recovery of Indonesian economy, relative to South Korea and Thailand. Despite significant improvement in macroeconomic indicators and problems in the banking industry were gradually recovered, increase in bank credits is insufficient to push the economy back to its level prior to the crisis. Banks became more risk averse and attitude toward risk in the business sector were the reason of their reluctance to lend. Concurrently, efforts by banking authority to urge the banking system met the prudential regulation, i.e., CAR 8% and NPLs 5% at the end of 2001 and legal lending limit (maximum credit allowed to one debtor), were suspected as another reason of banks' aversion to lend. This slow growth of bank credits offers an interesting background to be discussed (see Figure II.1).

The present paper extends and complements the existing studies, by evaluating the root of credit downturn after the crisis for the case of Indonesia. This paper employs recent technique of the cointegration analysis, namely the autoregressive distributed lag (henceforth ARDL) bounds

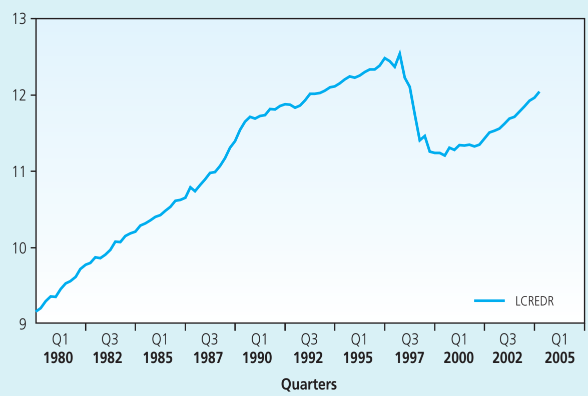

Figure II.1. Real Credit of the Banking System (1993=100)

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testing approach to estimate the long-run demand and supply equations, its stability and short-run dynamics as well.

The paper will proceed as follows. In Chapter II, the empirical methodology is to be discussed and Chapter III reports the estimation results and analyses the root of the credit downturn after the crisis whereas Chapter IV contains our concluding remarks.

II. MODEL SPECIFICATION AND ESTIMATION TECHNIQUES

II.1. Empirical Approach of Existing Studies

Existing empirical studies on estimation of demand for and supply of credit are essentially based on the demand and supply function framework. Several alternative specifications have been used. Assuming that credit market is in the disequilibrium, as demand for credit is not always equal to supply of credit, Pazarbasioglu (1996), Ghosh and Ghosh (1999), Agung *et, al.*, (2001) and Harmanta and Ekananda (2005) employed switching regression through maximum likelihood estimation method. Subsequently, they compared demand and supply with actual credit to determine which one is the constraint. Even though they found that variables under the study are integrated for different order, Agung *et al.*, (2001) and Harmanta and Ekananda (2005) proceed to estimate the demand and supply equations in the level form by assuming all the variables are cointegrated.

Alternatively, Agenor, Aizenman and Hoffmaister (2000) exploited a two-step econometric approach, looking especially at the credit supply function. Bank demand function for excess liquidity assets was calculated and then used to project data following the crisis period, on the assumption of no-structural break. Afterward, a comparison between the estimated and actual excess liquidity assets is made to identify the root of credit slowdown. A significant divergence of the two should suggest involuntary accumulation of excess reserve and they concluded a demand-induced cause of credit slowdown. Differently, Domac and Ferri (1999) attempted to investigate the existence of a credit view by looking at the spread between lending rate and risk free rate. They claimed that evidence of a widened spread accompanied by a drop in real bank credits confirmed an extensive credit crunch whose adverse effects on SMEs were noticeably larger. In fact, their shortfalls lie in the determinants of the spread used since changes in the prudential regulations or an expected associated cost of lending can also lead to higher spread.

II. 2. Empirical Specification and Variables

In the present analysis, we adopt a time series approach to estimate the credit demand and credit supply functions of the Indonesian economy. Our empirical analysis starts with two equations for the steady-state level (equilibrium) of real credit demand ($LCREDR^d$) and real credit supply ($LCREDR^s$),

$$LCREDR_t^d = \alpha_0 + \alpha_1 ICREDR_t + \alpha_2 LGDPR_t + \alpha_3 LFX_t + \varepsilon_t \quad \text{(II.1.a)}$$

$$LCREDR_t^s = \beta_0 + \beta_1 ICREDR_t + \beta_2 LLCAPR_t + \beta_3 ISBIR_t + \beta_4 LFX_t + \nu_t \quad \text{(II.1.b)}$$

where $ICREDR$ is real interest rate of credit, $LGDPR$ is real GDP (base year is 1993), $LLCAPR$ is real lending capacity of the banks (which derived from total liabilities minus cash in vault, minus capital, minus statutory reserve requirement), $ISBIR$ is real interest rate of Central Bank's securities (Sertifikat Bank Indonesia) which is a primary instrument in the open market operation, LFX is exchange rate (IDR/USD), and both ε_t and ν_t represent equilibrium error. All the variables are in the log form except for $ICREDR$ and $ISBIR$ and in quarterly basis. Our observation is ranging from 1984Q1 to 2005Q2 and the models are estimated for period 1985Q1-2004Q2 since we reserve 4 periods for construction of lag and forecast respectively.

The equations are derived from the standard demand and supply theory (see also Pazarbasioglu, 1996; Gosh and Gosh, 1999; Agung, et. al., 2001; and Harmanta and Ekananda, 2005). Normally, within this framework, we see demand for credit as a function of income (GDP), price (interest rate of credit) and proxy of substitute price to domestic credit (exchange rate)[1]. Therefore, we expect the coefficient of $LGDPR$ is positive and those of $ICREDR$ and LFX are negative. On the other hand, we view that determinants of supply of credit are lending capacity, interest rate of credit, interest rate of central bank certificate (an alternative for banks' investment since SBI were a major component of liquid assets held by banks), and other factor (exchange rate). We project that the coefficients of $LLCAPR$ and $ICREDR$ are positive, while those of $ISBIR$ and LFX are negative.

Within this specification, we contend that the credit demand and credit supply will adjust to its steady-state level in the long-run. Thus, (II.1.a) and (II.1.b) may be equivalently viewed as the long-run equations for real credit demand and real credit supply. It is important to note, since we are dealing with time series analysis, estimation of relationship in levels between variables such as (II.1.a) and (II.1.b) are justified as long as variables appearing in both equations are stationary. Should a part or all of them, in fact, are not stationary then those non stationary variables should be cointegrated. That is, to avoid problem of the so-

[1] In this framework, we view exchange rate as indirect proxy to price of credit from foreign sources. The higher the LFX means depreciation of IDR and from "the Law of one price" view point this should be followed by an increase in the domestic interest rate. To this end, domestic borrower will perceive that price of credit from foreign sources is cheaper relative to that of domestic one. Therefore, we observed an increase in private foreign debt prior to the crisis when the IDR had steadily depreciated against USD. In this understanding, we expect that an increase of LFX suggests a decrease of price of foreign credit thus it will reduce the demand for domestic credit.

called "spurious" regression[2], it is important to verify the integration or cointegration properties of variables under study. However, it has been known that the standard tests for unit roots, among others ADF and PP tests, generally suffered from the lack of power to differentiate between stationary and near stationary process. In the light of the uncertainty in pre-testing procedures, we employ another approach, namely ARDL bounds testing approach, to test for cointegration properties of variables under review.

II.3. ARDL Bounds Testing Approach

In empirical economics, considerable attention has been granted to verify the existence of relationship in levels between variables. In general, this analysis has been based on the use of cointegration techniques. Two main approaches in the cointegration analysis have been widely used, namely the two-step residual-based procedure for testing the null of no-cointegration (two-step Engle-Granger cointegration test as this method was developed by Engle and Granger, 1987) and the system-based reduced rank regression approach as developed by Johansen (1988) and Johansen and Juselius (1990). It is important to note that those two approaches require an adequately long time series and a pre-testing on the integration property of the variables under review since the $I(1)$ variables are reasonable to be tested for cointegration. In the light of those problems, the third technique was developed by Pesaran and Shin (1997) and Pesaran *et al.,* (2001) based on F-statistic in the ARDL framework.

In validating the estimations of (II.1.a) and (II.1.b), we are benefited from the recently developed ARDL framework in cointegration analysis, namely the bounds testing for the existence of relationship between variables in levels. The statistic underlying the procedure is the familiar Wald or F-statistic in a generalized Dickey-Fuller type regression, which is used to test the significance of lagged levels of the variables under review in a conditional unrestricted equilibrium correction model (from now on ECM). The advantage of this approach is two fold as it does not involve pre-testing integration property of variables under study. In particular, the test for the existence of a relationship among variables in level, i.e., cointegration test, is directly applicable irrespective of whether the underlying regressors are purely $I(0)$, purely $I(1)$, or mutually cointegrated (Pesaran *et al.,* 2001:1). Moreover, the ARDL approach can be applied to a relatively short period of series, it estimates the long-run and short-run components of the model simultaneously thus removing problems associated with the omitted variables and autocorrelation and it can distinguish between dependent and independent variables (Narayan, 2004:7).

[2] In the presence of non-stationary variables, Granger and Newbold (1974) suggest that there might be a spurious regression with high R^2 and t-statistics that appear to be significant, but the results are without any economic meaning.

Pesaran *et al.,* (2001) showed that the asymptotic distributions of critical values for the *F*-test are non-standard under the null hypothesis that there exists no relationship in levels between included variables, irrespective of whether the regressors are purely *I*(0), purely *I*(1) or mutually cointegrated. There are two sets of critical values[3] for the *F*-test which assume all the regressors are, on the one hand, purely *I*(1) and these are referred to as the upper bound critical values, and, on the other hand, purely *I*(0) and these are referred to as the lower bound critical values. Since these two sets of critical values provide critical value bounds for all classifications of the regressors into purely *I*(1), purely *I*(0) or mutually cointegrated, hence a bounds testing procedure is applied. If the computed Wald or *F*-statistic falls outside the critical value bounds, i.e., bigger than the upper bound or smaller than the lower bound, a conclusive inference can be drawn without needing to know the integration/cointegration status of the underlying regressors. However, if the Wald or *F*-statistic falls inside these bounds, inference is inconclusive and knowledge of the order of the integration of the underlying variables is required before conclusive inference can be drawn (Pesaran *et al.,* 2001:11).

Suppose that with respect to our model, we predict that there are two long-run relationships, namely among ***LCREDR***, ***LGDPR***, ***ICREDR*** and ***LFX*** on the one hand and among ***LCREDR***, ***LLCAPR***, ***ICREDR***, ***ISBIR*** and ***LFX*** on the other hand. Indeed, equations (II.1.a) and (II.1.b) represent the long-run relationships of variables under consideration. Since our point of interest is the long-run relationship in the form of demand and supply equations, the following ECMs are estimated:

$$\begin{aligned}\Delta LCREDR_t^d &= \alpha_0 + \sum_{p=1}^{n} \beta_p \Delta LCREDR_{t-p} + \sum_{p=0}^{n} \gamma_p \Delta ICREDR_{t-p} + \\ &\sum_{p=0}^{n} \varphi_p \Delta LGDPR_{t-p} + \sum_{p=0}^{n} \phi_p \Delta LFX_{t-p} + \pi_1 LCREDR_{t-1} + \pi_2 ICREDR_{t-1} \\ &+ \pi_3 LGDPR_{t-1} + \pi_4 LFX_{t-1} + \varepsilon_t\end{aligned} \qquad \text{(II.2.a)}$$

$$\begin{aligned}\Delta LCREDR_t^s &= \alpha_0 + \sum_{p=1}^{n} \beta_p \Delta LCREDR_{t-p} + \sum_{p=0}^{n} \gamma_p \Delta ICREDR_{t-p} + \\ &\sum_{p=0}^{n} \varphi_p \Delta LLCAPR_{t-p} + \sum_{p=0}^{n} \theta_p \Delta ISBIR_{t-p} + \sum_{p=0}^{n} \phi_p \Delta LFX_{t-p} + \pi_1 LCREDR_{t-1} \\ &+ \pi_2 ICREDR_{t-1} + \pi_3 LLCAPR_{t-1} + \pi_4 ISBIR_{t-1} + \pi_5 LFX_{t-1} + \nu_t\end{aligned} \qquad \text{(II.2.b)}$$

where all variables are as previously defined, Δ is difference operator, n is the order of ARDL model (ARDL($n,n,\ldots,n$)), π_i (for i=1,2,…,5) denotes the coefficients of lagged levels variables where is coefficient that represents the speed of convergence to the long-run equilibrium and both ε_t and ν_t are white-noise disturbance terms.

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[3] Pesaran and Pesaran (1997) and Pesaran et al.,(2001) provided critical values generated for sample sizes of 500 and 1000 observations and 20,000 and 40,000 replications respectively, while Narayan (2004) provided critical values generated for sample sizes ranging from 30 to 80 observations and 40,000 replications.

The null hypothesis of the bounds testing for our model is that there exists no relationship in levels (no cointegration) between included variables. Hence, the null hypothesis and its alternative for the demand equation can be stated as:

$$H_0 : \pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$$

$$H_1 : \pi_1 \neq \pi_2 \neq \pi_3 \neq \pi_4 \neq 0$$

while for the supply equation, those can be written as:

$$H_0 : \pi_1 = \pi_2 = \pi_3 = \pi_4 = \pi_5 = 0$$

$$H_1 : \pi_1 \neq \pi_2 \neq \pi_3 \neq \pi_4 \neq \pi_5 \neq 0$$

Once cointegration is confirmed, we move to the second stage and estimate the long-run coefficients of the demand for and supply of credit and the associated ARDL-ECMs.

III. RESULT AND ANALYSIS

III.1. Cointegration Test

Before conducting the cointegration test, the optimal lag length (n) of lagged changes variables need to be selected. In this stage, we will make use of the Akaike's Information Criterion (AIC) or Schwarz's Bayesian Criterion (SC). Even though it is opened to set either a same lag length, for example ARDL($n,n,\ldots,n$), or a different lag length, ARDL($n,n_2,\ldots,n_5$), for all lagged changes variables without affecting the result of the test (Pesaran *et al.*, 2001:11), for simplicity we apply a similar lag length approach. As mentioned before, for comparability of the results in selecting optimal lag order, we estimate (II.2.a) and (II.2.b) for period 1985Q1 to 2004Q2 where the first four observations are reserved for construction of lag variables. Additionally, it is important to note that the assumption of serially uncorrelated errors is essential for the validity of the

Table II.1
Statistics for Selecting the Lag Order of Demand and Supply Equations*
(ARDL Model with unrestricted intercept and no trend)

Lag Order	Demand Equation				Supply Equation			
	AIC	*SC*	$F_{SC}(1)$	$F_{SC}(4)$	*AIC*	*SC*	$F_{SC}(1)$	$F_{SC}(4)$
1	102.06	92.64	0.85	1.11	138.36	127.58	0.08	1.71
2	99.32	88.71	0.44	2.82**	135.15	117.47	4.45**	3.11**
3	97.54	82.22	18.41*	5.12*	134.88	111.31	1.16	1.95
4	107.00	86.97	0.04	0.84	156.40	126.95	0.14	0.51

* Notes: AIC and SC denote Akaike's Information Criteria and Schwarz's Bayesian Criteria for a given lag order. (1) and (4) are *F* statistics from LM tests for no residual serial correlation against orders 1 and 4. The *F* version statistic is chosen by considering that it is more suitable to our case with number of observations (*T*) equal to 78. *, ** and *** denote significant at 0.01, 0.05 and 0.10 levels respectively.

bounds tests, therefore this concern must be incorporated in determining the appropriate lag length of the ARDL model. The associated statistics are presented in Table II.1.

For the demand equation, as might be expected, AIC selects lag order which is higher compare to that selected by SC. AIC shows that the optimal lag order is 4 with the value of its statistic is 107.00, while SC suggests lag order 1 as the optimal one with the value of its statistic is 92.64. The F_{SC} statistics also suggest using a relatively high lag order: 4 or more. In the same manner, for the supply equation, AIC suggest to use lag order 4, while SC suggest to use 1. However, the F_{SC} statistics show that it is appropriate to use lag order 3 or 4. In view the importance of the assumption of serially uncorrelated errors for the validity of the bound tests, it seems prudent to select n to be 4 for both of equations. Nevertheless, for completeness, in what follows we report test results for n = 1 to 4. The computed *F*-statistics for several lag orders is reported in Table II.2.

As can be seen, the test outcome confirms the existence of cointegration between variables under review for both the credit demand and credit supply equations. The *F*-statistics for any given lag order in both of the equations are high enough to reject the null. In particular, the *F* statistic of lag order 4 of credit demand equation as 3.60 is higher than the upper bounds for 10 percent level of significance. While for the credit supply equation, the *F* statistic of lag order 4 as 3.94 is higher than the upper bounds for 5 percent level of significance. Indeed, having these results we are able to reject the null and conclude that demand for credit is cointegrated with its determinants and equally, supply of credit is also cointegrated with its affecting factors. This result justifies us to retain the lagged level of variables in (II.2.a) and (II.2.b).

Table II.2
F*-statistic for Testing the Existence of a Levels Credit Equation

Lag Order	F-Statistic of Credit Demand	F-Statistic of Credit Supply
1	21.97*	19.55*
2	11.07*	6.49*
3	5.46*	6.17*
4	3.60***	3.94**

* Notes: Critical values for the *F*-test are taken from Narayan (2004) with number of observation *T=78* and number of regressors *k=3* and *k=4*. Lower and upper bounds for 0.01, 0.05 and 0.10 levels are 4.048-5.092, 2.946-3.862 and 2.482-3.334 respectively. The symbols *, **, and *** denote that the statistic lies above the 0.01, 0.05 and 0.10 upper bound respectively.

III.2. Long-Run Demand and Supply Equations

In the second stage, we retain the lagged level of variables and estimate (II.2.a) and (II.2.b) with maximum lag order are set at 4. We end up with the final models as selected by

AIC which are ARDL(4,4,2,4) for the demand equation and ARDL(4,2,1,4,4) for the supply equation. The long-run equation of demand and supply of credit are as follows:

Long-Run Credit Demand Equation

$$LCREDR_t^D = -13.158 + 0.029\ ICREDR_t + 2.585\ LGDPR_t - 0.584\ LFX_t + \varepsilon_t$$

(3.880)* (.033) (.446)* (.206)*

Long-Run Credit Supply Equation

$$LCREDR_t^S = -0.940 + 0.047\ ICREDR_t + 1.312\ LLCAPR_t - 0.049\ ISBIR_t - 0.436\ LFX_t + \nu_t$$

(.966) (.032) (.145)* (.030) (.165)* *

Note: numbers in parenthesis are absolute value of standard error. *, ** and *** denote significant at 0.01, 0.05 and 0.10 level respectively.

For the long-run demand equation, we found that the coefficients of GDP and exchange rate are as expected and highly significant. However, the coefficient of credit interest rate is positive and not significant. This result is similar to that of Agung *et. al.*, (2001) and suggests that the interest rate is not constraint for the business sector to demand credit from banks. In the long-run, we verify that real GDP affect the real demand for credit significantly, where 1 percent growth in real GDP will increase real demand for credit as 2.59 percent. This relation also suggests that banks credit is still a luxury goods in the consumption bundle of consumers.

In the long-run, all the signs of variables in the supply equation are as expected but only lending capacity and exchange rate have significant effect to the credit supply. We found that lending capacity and exchange rate are significant at 0.01 and 0.05 levels respectively and carry positive and negative signs. From the estimated coefficients, we can expect that in the long-run, real credit supplied is not sensitive to the changes of credit interest rate and SBI rate. However, it is pretty responsive to the changes of lending capacity and exchange rate by having elasticity as 1.31 and 0.44 respectively.

III.3. Equilibrium Correction Models (ECMs) of Demand and Supply

The estimates of the ECMs selected by AIC are reported at Table II.3. The long-run equation of demand and supply of credit are used to generate the associated error correction terms (ECT_{t-1}). The adjusted R^2 for the short-run dynamic of demand and supply models are 0.72 and 0.90 respectively, suggesting that such ECMs fit the data reasonably well. Importantly, the error correction coefficients for both the equations carry the expected negative sign and are significant at 5 percent level respectively. This reinforces the finding of cointegration as provided by the bounds *F*-test.

It is important to note that error correction coefficient of supply equation (0.091) is higher than that of demand equation (0.076). This finding suggests both the demand and supply of credit have a relatively lower speed of convergence to the equilibrium. However, it can be seen that the speed of adjustment of the credit supply to converge to its steady-state level, once shocked or disequilibrium occurred, is higher than that of the credit demand. This fact has an important implication on the design of policy efforts to affect the credit level in the economy, since any attempts to stimulate the credit outstanding would be much more effective from the supply side.

We also use those ECMs in forecasting the rate of change of credit conditional upon current and past changes in its determinants (the results are reported in Table II.4). For the demand equation, we found the root mean squares of forecast error of around 3.94 percent per quarter compares favorably with the value of the same criterion computed over the estimation period (4.22 percent). The model is reasonably well to forecast the rate of change of credit in the 2004Q3 to 2005Q2. The same evidence is found for the supply equation where the root mean squares of forecast error of around 3.18 percent per quarter compares with the value of the same criterion computed over the estimation period (2.45 percent).

We perform several diagnostic tests to examine the validity of the models. The demand equation passes the diagnostic tests against non-normal errors, heteroskedasticity and ARCH. However, it fails the functional form misspecification test at the 0.05 level which may be linked to the presence some non-linear effects or asymmetries in the adjustment of the real credit demand that our linear specification is incapable of taking into account. Differently, the supply equation passes all the diagnostic tests except for the non-normal errors test at the 0.01 level. In fact, the supply model is still reliable given the number of our observation since this test belongs to the large sample property.

Finally, we examine the stability of the long-run coefficients together with the short-run dynamics for both models. In particular, we apply the CUSUM and CUSUMSQ to the residuals of models in Table II.3. Specifically, the CUSUM test make use of the cumulative sum of recursive residuals based on the first set of *n* observations and is updated recursively and plotted against break points. If the plot of CUSUM statistics stays within the critical bounds of 5 percent significance level, the null hypothesis that all coefficients in the ECMs are stable cannot be rejected. A similar procedure is used to carry out the CUSUMSQ test, which is based on the squared recursive residuals.

Figure II.3 and II.4 show a graphical representation of the CUSUM and CUSUMSQ plots applied to the ECMs of both models. The results show that the plots generally lie within the critical bounds, indicating no evidence of any significant structural instability for both models.

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Table II.3
Equlibrium Correction Form of the Models

Demand Equation				Supply Equation			
Regresor	**Coefficient**	**Standar Error**	**P-Value**	**Regresor**	**Coefficient**	**Standar Error**	**P-Value**
$\Delta LCREDR_{t-1}$	-0.155	0.102	.135	$\Delta LCREDR_{t-1}$	0.014	0.068	.835
$\Delta LCREDR_{t-2}$	0.194	0.103	.064	$\Delta LCREDR_{t-2}$	0.171	0.064	.009
$\Delta LCREDR_{t-3}$	0.260	0.105	.016	$\Delta LCREDR_{t-3}$	0.242	0.065	.000
$\Delta ICREDR_{t}$	-0.007	0.002	.003	$\Delta ICREDR_{t}$	-0.003	0.002	.150
$\Delta ICREDR_{t-1}$	0.001	0.002	.560	$\Delta ICREDR_{t-1}$	-0.003	0.002	.173
$\Delta ICREDR_{t-2}$	0.003	0.002	.077	$\Delta LLCAPR_{t}$	0.848	0.071	.000
$\Delta ICREDR_{t-3}$	-0.004	0.002	.024	$\Delta ISBIR_{t}$	-0.97E-3	0.002	.611
$\Delta LGDPR_{t}$	0.393	0.246	.114	$\Delta ISBIR_{t-1}$	0.003	0.002	.098
$\Delta LGDPR_{t-1}$	0.640	0.231	.007	$\Delta ISBIR_{t-2}$	0.001	0.80E-3	.118
ΔLFX_{t}	-0.127	0.058	.031	$\Delta ISBIR_{t-3}$	-0.001	0.86E-3	.106
ΔLFX_{t-1}	0.188	0.068	.008	ΔLFX_{t}	-0.197	0.039	.000
ΔLFX_{t-2}	-0.075	0.079	.344	ΔLFX_{t-1}	0.084	0.052	.113
ΔLFX_{t-3}	-0.230	0.082	.006	ΔLFX_{t-2}	-0.028	0.064	.668
				ΔLFX_{t-3}	-0.155	0.053	.005
Intercept	-1.003	0.601	.100	*Intercept*	-0.085	0.095	.372
ECT_{t-1}	-0.076	0.033	.025	ECT_{t-1}	-0.091	0.041	.032
$\bar{R}^2 = .72$		$\hat{\sigma} = .048$		$\bar{R}^2 = .90$		$\hat{\sigma} = .028$	
F_{SC} (1)=.74[.39]		F_{SC} (4)=1.60[.19]		F_{SC} (1)=.58[.45]		F_{SC} (4)=.95[.44]	
F_{FF} (1)= 6.08[.02]		χ^2_N (2)=1.64[.44]		F_{FF} (1)= .43[.51]		χ^2_N (2)=20.96[.00]	
F_{HET}(1)=.26[.61]		F_{ARCH} (4)= .46[.76]		F_{HET}(1)=1.15[.29]		F_{ARCH} (4)= .35[.56]	

* Notes: The regression is based on the conditional ECM [2.a and 2.b] using $ARDL(4,4,2,4)$ and $ARDL(4,2,1,4,4)$ specification for demand and supply equations respectively, dependent variable is $\Delta LCREDR_t$ which estimated over 1985Q1-2004Q2, and the equilibrium correction term (ECT_{t-1}) is given in the long-run equation. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient and $\hat{\sigma}$ is the standard error of the regression, $F_{SC}(1)$, $F_{SC}(4)$, $F_{FF}(1)$, $\chi^2_N(2)$, $F_{HET}(1)$, and $F_{ARCH}(4)$ denote *F* statistics from LM test for no residual serial correlation order 1 and 4, Ramsey RESET test for no functional form mis-specification, Jaque-Berra test for normal distribution of errors, White test for homoscedasticity of residual, and LM test for no serial correlation on residual squared (ARCH) for order 4 respectively with *p*-values given in [.].

III.4. Credit Downturn after the Crisis 1997

In determining the root of the credit downturn after the crisis 1997, we employ the aforementioned long-run real credit demand and real credit supply equations. To do so, we estimate credit demand and credit supply based on long-run equations and subsequently both of estimated variables are plotted together to examine the forcing factor to actual credit level. We follow the same line as previous studies (for instance Ghosh and Ghosh, 1999; Agung *et, al.*, 2001 and Harmanta and Ekananda, 2005) in defining the forcing factor is the minimum value between demand and supply of credit. Specifically, if the supply is lower than demand, hence the forcing factor to credit actual for that period is supply of credit and *vice versa*. The plots of credit demand (CREDEM) and credit supply (CRESUP) are presented in Figure II.2.

Some interesting features need to be highlighted from Figure II.2.

- Prior to 1992Q2, the plots suggest that credit supply had been the forcing factor to the credit outstanding in the Indonesian economy. However, between period 1992Q2-1994Q1, it was the credit demand serving as the driver to the credit outstanding. Subsequently, credit supply had come back to its position as the determinant of credit actual. In fact, this behavior remained constant until 1998Q3. Nevertheless, between period 1998Q4 to 2000Q2 the circumstance changed as the credit demand became the constraint to the credit actual. Afterward, the credit supply somehow has served as the key factor to credit outstanding until the end of our observation.
- In particular to the crisis period, we can verify that as the crisis took place in Indonesian economy at the third quarter of 1997 both credit demand and credit supply dropped sharply with demand dropped initially. Moreover, we see that the supply was able to recover faster than the demand. This reinforces our finding that the speed to converge of credit supply is higher compare to that of credit demand.

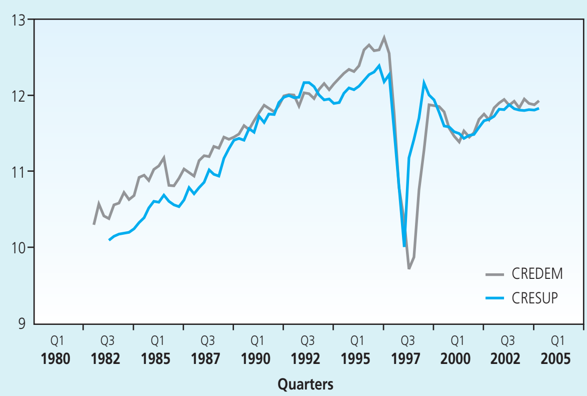

Figure II.2. Plot of The Credit Demand and Credit Supply Based on ECM

- Finally, based on the plots we can conclude that in the crisis period (1997Q3-1998Q3) credit supply operated as the constraint to credit actual even though both the supply and demand dropped in tandem. However, the slow growth of the credit disbursement after the crisis (1998Q4-2000Q2) was a demand behavior rather than supply constraint. This finding is different from Agung *et. al.*, (2001) who found that the root of the credit downturn after the crisis was the supply constraint, but we arrive at similar result as Harmanta and Ekananda (2005).

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IV. CONCLUSION

We examined the long-run credit demand and credit supply in the Indonesian economy using quarterly data over the period 1985Q1-2004Q2. By employing a relatively new cointegration technique, we were able to verify a long-run relationship between both real credit demand and real credit supply and their determinants. Both CUSUM and CUSUMSQ tests also confirm the stability of long-run coefficients of both credit equations. Furthermore, this study ensures that the speed to converge of credit supply is relatively higher relative to that of demand, but the error correction terms in both equations suggest the slow speed of adjustment to the equilibrium.

In specific, this study confirms that the root of low credit disbursement during the post crisis period is primarily driven by lack of demand for credits rather than its supply constraints. This outcome implies that any policy measures aimed at encouraging banks to expand credit disbursement without considering problems in the demand side will loose its effectiveness. Indeed, an integrated approach between demand stimulus and supply inducement seems to be appropriate to bring the credit outstanding back to its level prior to the crisis.

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APPENDIX

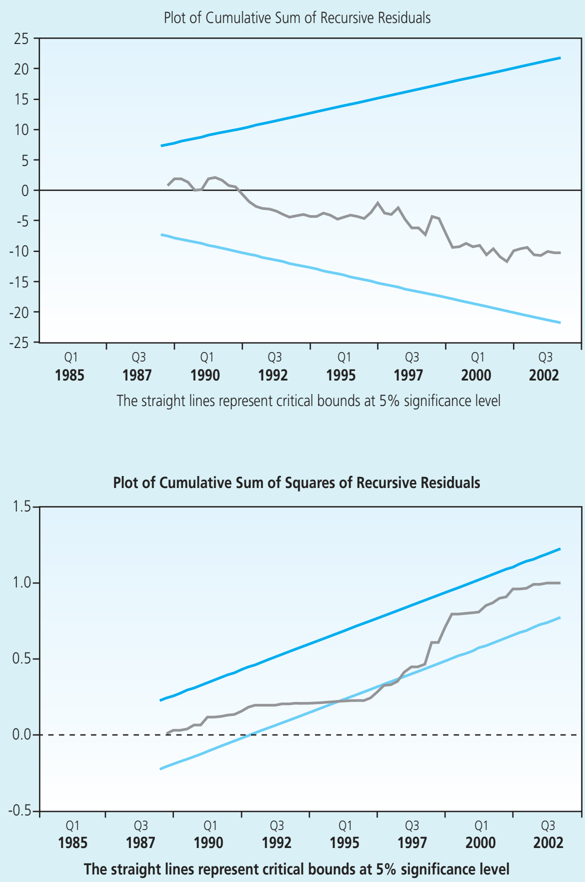

Figure II.3. Plots of CUSUM and CUSUMSQ Statistics for Coefficients Stability Demand

Table II.4
Dynamic Forecasts for the Change in LCREDR based on Demand Equation

Observation	Actual	Prediction	Error
2004Q3	.065400	.049212	.016188
2004Q4	.078200	.022111	.056089
2005Q1	.039000	.037311	.001689
2005Q2	.076500	.023470	.053030
Summary Statistics for Resisls and Forecast Errors			
	Estimation Period 1985Q1 to 2004Q2	**Forecast Period 2004Q3 to 2005Q2**	
Mean	.7414E	.031749	
Mean Absolute	.033742	.031749	
Mean Sum Squares	.001786	.00155	
Root Mean Sum Squares	.042266	.039443	

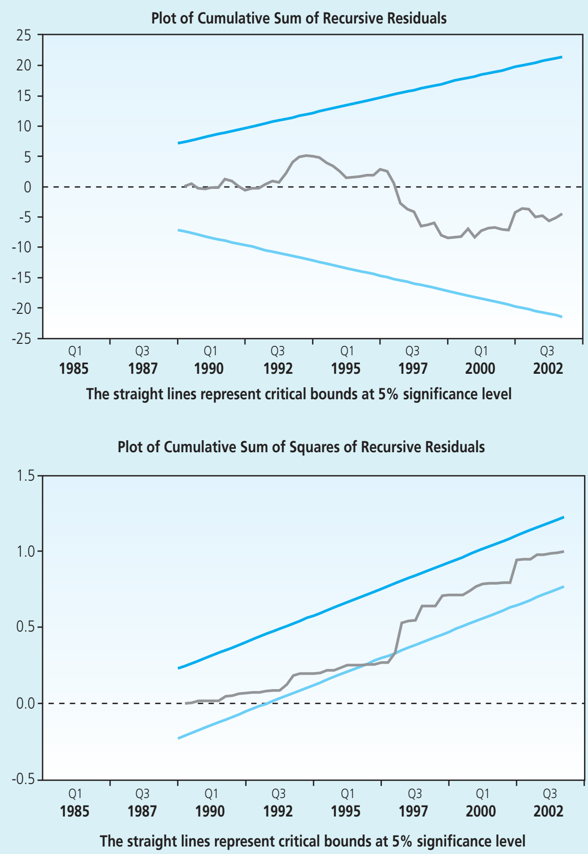

Figure II.3. Plots of CUSUM and CUSUMSQ Statistics for Coefficients Stability Supply

Table II.4
Dynamic Forecasts for the Change in LCREDR based on Supply Equation

Observation	Actual	Prediction	Error
2004Q3	.065400	.030950	.034450
2004Q4	.078200	.034868	.043332
2005Q1	.039000	.024571	.014429
2005Q2	.076500	.048604	.027896
Summary Statistics for Residuals and Forecast Errors			
	Estimation Period 1985Q1 to 2004Q2	**Forecast Period 2004Q3 to 2005Q2**	
Mean	.2290E-9	.030027	
Mean Absolute	.017754	.030027	
Mean Sum Squares	.6011E-3	.0010127	
Root Mean Sum Squares	.024517	.031823	