Chapter 3. Credit Market Development and Economic Growth: Empirical Evidence*

3.1. Introduction

Does credit market development promote economic growth? Most recent empirical studies conclude that it does; see, e.g., King and Levine (1993a, 1993b). However, other studies reach a different conclusion. For example, De Gregorio and Guidotti (1995) have found divergent effects of financial market development on economic growth between high-income and low- and middle- income countries. More specifically, by using total domestic credit to the private sector divided by GDP as the indicator of financial market development (referred to as *CREDIT*[1] hereafter), De Gregorio and Guidotti find that the development of financial markets has no effect on economic growth in high-income countries, while it has a strongly positive effect in low- and middle-income countries.

As our previous two chapters offer a good explanation of this conflicting result, the objective of this chapter is to further provide evidence in supporting our theoretical conjectures and to clarify the source of some divergent empirical results in the literature. Specifically, as shown in Figure 1.3 (referred to as F3 hereafter), the relationship between credit market development and economic growth may well be that, at the low levels of credit market development, the growth rate increases as credit markets develop. However, once a critical level of credit market development has passed, the growth rate will decrease along with development of credit markets because consumers derive a larger proportion of total credit, thereby reducing the total available resource for investment and thus economic growth. The positive relationship between credit markets and growth will arise again only after credit markets are further developed (that is, in *Area IV* of F3).

Ideally, empirical investigation of this issue would start with a data set identifying both total credit to firms and total credit to consumers separately. However, there is no available data set which satisfies this requirement. As recent literature has argued that *CREDIT* is a

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reasonable measure of the level of financial market development[2], in this chapter we follow the literature by using *CREDIT*[3] as the indicator of credit market development to test our theoretical implications. Our theoretical work has the novel implications that there could be structural breaks in the relationship between credit market development and economic growth. Finding such structural breaks in the data could both support our theoretical models as well as provide insights into some of the contradictory findings of earlier studies.

The Chow test is the primary test used here to determine whether a structural change occurs in the growth regression. The use of the Chow test requires prior information about when the structural change takes place; unfortunately, our theoretical models do not offer the specific level for which the relationship between credit market development and growth will change. To overcome this problem, we simply use the average level of *CREDIT* in all countries as an assumed break point. The average of *CREDIT* in the time period of the 1960-1989 of 91 countries is 0.246. Any countries whose *CREDIT* is higher than 0.246 will be characterized as the (relatively) high-credit country. We then test whether the relationship between credit market development and economic growth changes between high-credit and low-credit countries. Under this situation, our test results, therefore, may be best interpreted as testing a structural change in this relationship between relatively high-credit and relatively low-credit countries. We also conduct a sensitivity analyses by varying the assumed break points. Moreover, to validate our results, we also employ CUSUM and CUSUM squares tests to complement Chow test, as both tests are more general in that they do not require any prior information[4].

We test our theoretical implications based on the same data set as King and Levine (1993b). We find that a structural change is not detected over the time period 1960-1989. This result, at the first glance, seems inconsistent with a non-linear relationship between credit market development and economic growth. However, carefully examining the data,

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[1] In King and Levine (1993a, 1993b), this indicator is termed as *PRIVATE*.

[2] De Gregorio and Guidotti have offered some reasons to why this indicator is a good proxy of financial market development.

[3] This *CREDIT* must proxy both for developments of the consumer as well as firm credit markets.

[4] However, neither test is ideal in this situation, as we can observe in Section 4.

we further find that the distribution of *CREDIT* of high-credit countries in 1960-1989 is mainly clustered in the low levels. Note that, according to our theoretical models, the structural break will take place only when credit markets of high-credit countries are sufficiently developed; that is, when *CREDIT* is large enough. In other words, the levels of *CREDIT* in the high-credit category are still too low; thus, the data is probably unable to indicate the presence of a structural break. As the next step, we then restrict our consideration to the time period of the 1980s, where the difference of the average *CREDIT* between the relatively high-credit and low-credit countries are bigger than that of in 1960-1989. We find evidence for a structural change in this period. The results of misspecification tests between these two periods also show that the regression of 1980s is more appropriate. Consequently, the empirical evidence we derive in this chapter supports our theoretical implications.

This chapter is organized as follows. Section 2 describes the data and further tests the results of King and Levine (1993a, 1993b). In Section 3, we apply Chow test to examine the structural change in 1960-1989 and 1980s, and perform a sensitivity analyses of our results. In section 4, we illustrate our results by applying CUSUM and CUSUM squares tests. The conclusions and some further extensions are provided in Section 5.

3.2. Credit Market Development and Economic Growth : Re-examining King and Levine's Results

As mentioned, we use the data set of King and Levine (1993b)[5] and perform essentially the same regressions to begin our investigation. The data contains about 119 countries during the 1960-1989 period; however, due to lack of financial data and elimination of major oil exporters we are left with only about 90 countries. King and Levine employ a large variety of financial and growth indicators, showing that there exists an overall positive relationship between financial market development and economic growth. Because we focus on credit market development, we will restrict ourselves to using *CREDIT* as the

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[5] The data is available at the web site of World bank: http://www.worldbank.org.

indicator of financial market development.

Table 3.1. Regression results of King and Levine (1993a), N=91.
(t-statistics in parentheses, dependent variable: average real per capita GDP, 1960-1989)

Regression	1	2	3	4	5	6
Constant	.043	. 034	.033	.028	.034	.028
	(6.29)	(4.58)	(3.95)	(3.09)	(3.8)	(3.03)
CREDIT	.029	.090	.026	.076	.022	.072
	(2.77)	(3.32)	(2.49)	(2.49)	(1.99)	(2.39)
$CREDIT^2$		-.062		-.049		-.05
		(-2.41)		(-1.723)		(-1.78)
LRGDP60	-.0126	-.013	-.012	-.012	-.01	-.010
	(-3.98)	(-4.22)	(-3.62)	(-3.66)	(-3.05)	(-3.11)
LSEC	.0077	.0064	.008	.0067	.005	.0039
	(4.16)	(3.44)	(4.28)	(3.386)	(2.38)	(1.7)
CIVIL	-.00215	-.0024	-.00243	-.002	-.001	-.0012
	(-1.48)	(-1.75)	(-1.46)	(-1.54)	(-.689)	(-.88)
ASSA	.00086	.00154	.00149	.0003	.0011	-.00007
	(.258)	(.47)	(.429)	(.08)	(.34)	(-.021)
REVC	-.012	-.007	-.017	-.004	-.01	-.008
	(-1.66)	(-0.98)	(-2.1)	(-.5)	(-1.27)	(-1.05)
GOV			.026	.004	-.007	-0.29
			(.072)	(.1)	(-.178)	(-.71)
PI			-.00001	-.00001	.000003	.000009
			(-.57)	(-.037)	(.121)	(.316)
TRD			.0086	.007	.013	.011
			(1.453)	(1.26)	(2.12)	(1.93)
LAM					-.0098	-.009
					(-2.0)	(-2.05)
AFA					-.012	-.013
					(-2.27)	(-2.3)
R^2	.413	.45	.44	.46	. 48	.50

As economic growth likely depend on many factors, not just financial market development, King and Levine (referred to as KL hereafter) include other explanatory variables in their regressions: log of initial real per capita GDP (*LRGDP*), log of secondary school enrollment rate in initial year (*LSEC*), the ratio of government consumption over GDP (*GOV*), inflation rate(*PI*), and the ratio of imports plus exports over GDP (*TRD*). The dependent variable is real per capita GDP growth rate (*GYP*).

We first investigate whether the data implies that the effect of credit market development on economic growth differs in different levels of *CREDIT*, as is suggested by our theoretical models. The test results for the 1960-1989 period are reported in Table 3.1. In the table, regressions 1, 3, and 4 are the same as KLs', and regressions 2, 4, and 6 include a square term of *CREDIT* into KLs' regressions. In all regressions, we find that the coefficients of the *CREDIT* squared are negative and significant at 5% level, so that the effect of credit market development on economic growth is decreased as credit markets develop (that is, at higher levels of *CREDIT*), though the total effect is still positive. Our findings are thus consistent with those of De Gregorio and Guidotti (1995). To illustrate this point more clearly, let us take a look at regression 6. Combining effects of *CREDIT* and $CREDIT^2$, the results of regression 6 indicate that if *CREDIT* is greater than 0.72, then the growth rate will decrease as credit markets develop further. However, in the data, there are only two countries whose *CREDIT* is greater than 0.72. As our theoretical models predict that the growth rate may be a cubic function of *CREDIT* (see F3), we also add a cubic term of *CREDIT* into the regressions; however, even though the sign of the coefficient of $CREDIT^3$ is correct (positive), it is not significantly different from 0. Recall that, as shown in F3, the cubic part of the relation will be observed only at high levels of *CREDIT*, where there are so few observations that it is unlikely that this would be detected.

The relationship between the growth rate and *CREDIT* in 1960-1989 can be further clarified by Figure 3.1[6]. Note that the y-axis of the growth rate is the residuals derived by regressing the growth rate on the explanatory variables except *CREDIT*. From this figure, it is evident that the distribution of *CREDIT* is concentrated at the low levels. If a structural break exists at relatively higher levels of *CREDIT*, this is unlikely to be detected. The logical next step to take is to restrict attention to a time period where *CREDIT* is more extensively

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[6] Note that the vertical line in the figure is the average of *CREDIT*.

distributed.

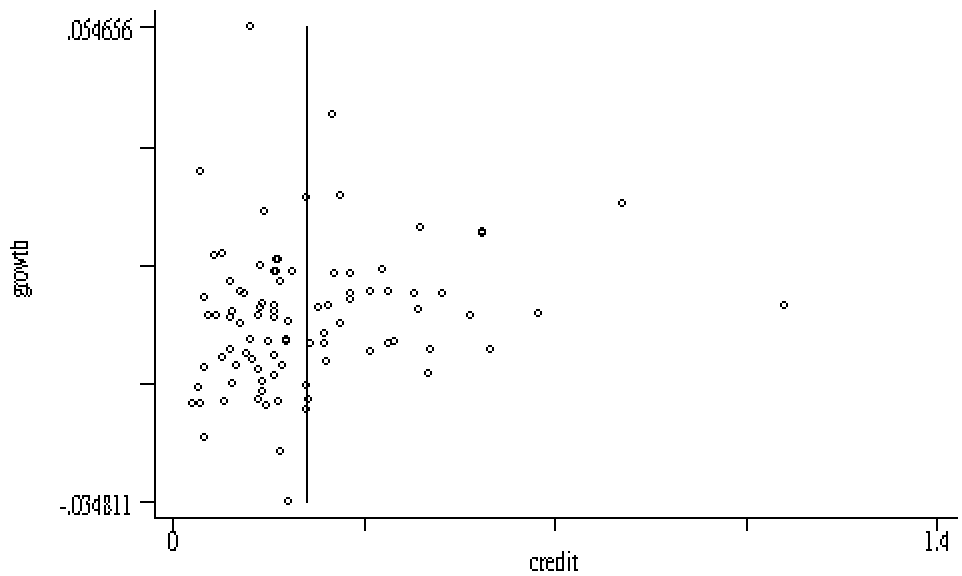

Figure 3.1 The Growth Rate and *CREDIT* in 1960-1989

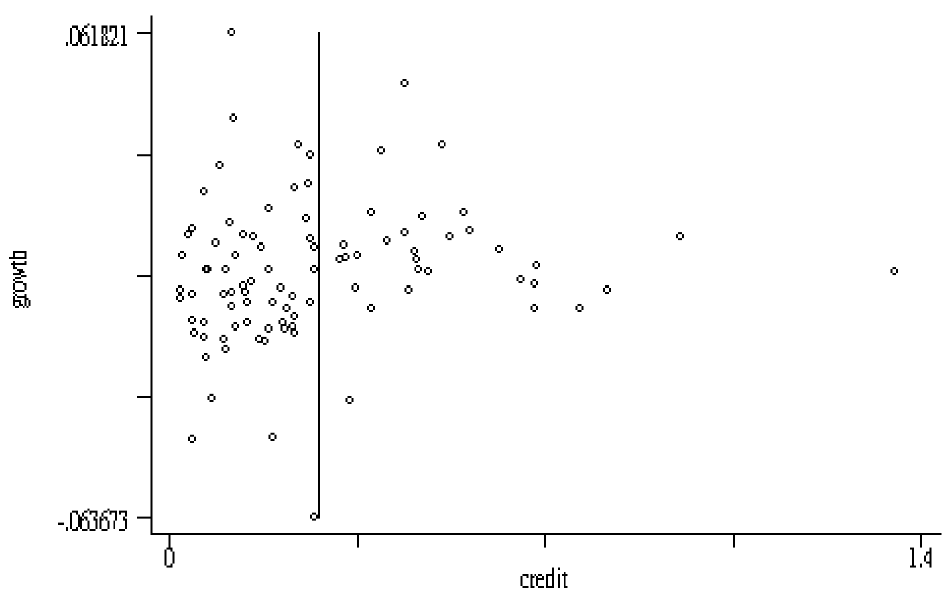

Figure 3.2. The Growth Rate and *CREDIT* in 1980s

Figure 3.2 is the relationship between the growth rate and *CREDIT* in the time period of 1980s. Over this time period, *CREDIT* is more widely distributed and thus this data should be more appropriate to test our theory. Note that the average of *CREDIT* is 0.246 in

1960-1989 and 0.276 in the 1980s. For the relatively high-credit countries (those with *CREDIT* above the average), the average *CREDIT* is 0.41 in 1960-1989 and 0.56 in the 1980s. Clearly, the average level of credit market development is higher in the 1980s than in 1960-1989, making this time period the more appropriate one to use to test our theory.

Table 3.2 Misspecification Tests (p-value)

[Reject Rule: P-value < Significant Level]

Time Period	60-89	80s
1. Normality		
Skewness	.000143	.175
Kurtosis	.00000	.00105
2. Functional Form		
a. RESET	.688	.502
b. KG2 Test	.337	.147
c. Individual Test		
$+ CREDIT^2$	.0887	.031
$+CREDIT^2 + CREDIT^3$	.237	.099
3. Homoskedasticity		
a. RESET Test	.891	.580
b. KG2 Test	.497	.391
4. Parameter Stability		
a. Conditional Variance	.93	.644
b. Conditional Mean	.527	.298
5. Joint Test (Functional form, Independence, and Stability of beta)		
Overall Test	.229	.488

The conclusion that the time period of the 1980s is more appropriate to test our theory is further suggested by the misspecification testing. Table 3.2 reports the results of several misspecification tests between the time periods 1960-1989 and the 1980s[7]. From Table 3.2, we see that the skewness assumption of normality is appropriate in the 1980s but not in 1969-1989, and that the p-value of kurtosis assumption is greater in the 1980s than in

[7] See Appendix F for the test approaches and hypotheses.

1960-1989, though it is still rejected. These results suggest that the normality assumption is more reasonable in 1980s than in 1960-1989.

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Related to the functional form, results indicate that using the 5% significance level we should reject the hypothesis that the coefficient of $CREDIT^2$ in 1980s is equal to 0 while in 1960-1989 we fail to reject it. Moreover, we should also reject the joint hypothesis that the coefficient of $CREDIT^2$ and $CREDIT^3$ is equal to 0 under the 10% significance level in 1980s. The null hypothesis of all other misspecification tests are not rejected for either period. To sum up, the misspecification testing results are largely consistent with the conjecture that a linear regression for the 1980s is misspecified.

Finally, to give a rough idea about the relationship between *CREDIT* and the growth rate in 1980s, we plot Figure 3.3. In addition to the y-axis of the growth rate, in this diagram the x-axis variable is the residuals derived from regressing *CREDIT* on all other independent variables. The curves is drawn by specifying 5 bands along the x-axis (credit) to group data and calculating medians of the growth rate and *CREDIT*[9], then smoothing the curve. This figure certainly suggests that there is a nonlinear relationship between *CREDIT* and economic growth.

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[8] See Appendix A for the test approaches and hypotheses.

[9] STATA offers a command for this graphing.

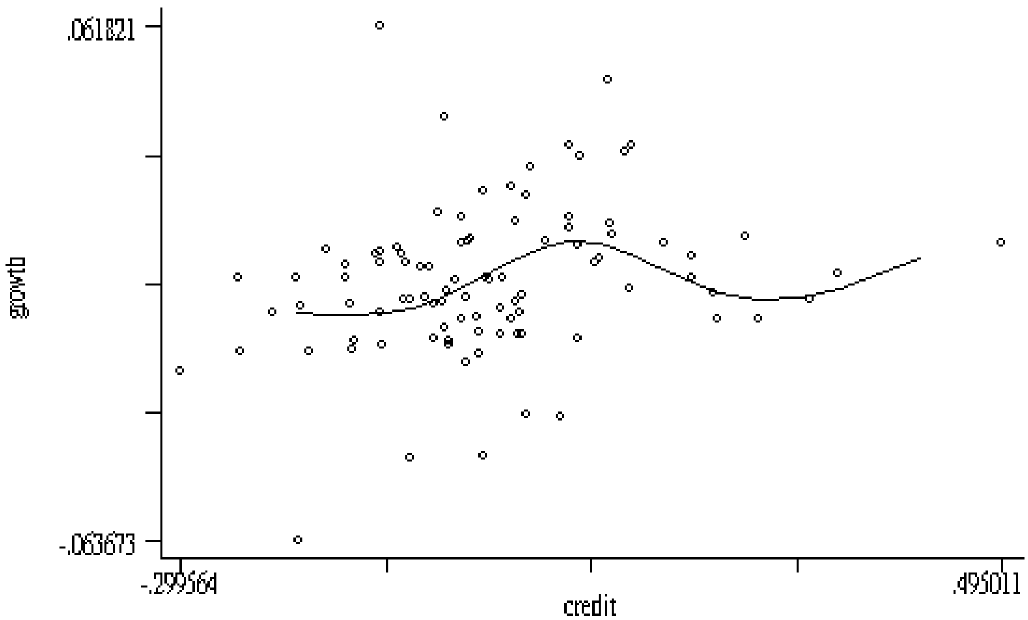

Figure 3.3 The Relationship between the Growth Rate and *CREDIT* in 1980s

3.3. Tests of Structural Change

In this section, we apply Chow test to formally test for a structural change in the relationship between credit market development and economic growth. The regression equation we use to test is the same as regression 3 in Table 3.1. As we are only interested in *CREDIT* , not the entire set of explanatory variables, we should use a t test instead of an F test as noted by Amemiya (1985).

We now derive the test statistics as follows[10]. Suppose that the regression 3 is expressed as follows:

$$y = X\beta + u , \qquad (3.1)$$

where

$$y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} ,\ X = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix},\ \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}, \text{ and } u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}.$$

The total number of observations is T for the whole sample, T_1 for the group 1 (the relatively low-credit countries), and T_2 for the group 2 (the relatively high-credit countries). Assume further that the *i*th columns of X_1 and X_2 are *CREDIT* and denoted as x_{1i} and x_{2i}, respectively, and that $X_{1(i)}$ and $X_{2(i)}$ are the remaining *K-1* explanatory variables, where *K* is total number of independent variables. We then define $M_{1(i)}$, $\tilde{x}_{1(i)}$ and $\tilde{y}_1$ as follows:

$$M_{1(i)} = I - X_{1(i)}(X_{1(i)}{}' X_{1(i)})^{-1} X_{1(i)}$$

$$\tilde{x}_{1(i)} = M_{1(i)} x_{1(i)}$$

$$\tilde{y}_1 = M_{1(i)} y_1 .$$

Similarly, $M_{2(i)}$, $\tilde{x}_{2(i)}$, and $\tilde{y}_2$ are defined. The coefficient of x_i in group 1 (that is, x_{1i}) and group 2 (x_{2i}) can be derived as

$$\hat{\beta}_{1i} = \frac{\tilde{x}_{1i}\tilde{y}_1}{\tilde{x}_{1i}'\tilde{x}_{1i}} \sim N(\beta_{1i}, \frac{\sigma_1^2}{\tilde{x}_{1i}'\tilde{x}_{1i}})$$

and

$$\hat{\beta}_{2i} = \frac{\tilde{x}_{2i}\tilde{y}_2}{\tilde{x}_{2i}'\tilde{x}_{2i}} \sim N(\beta_{2i}, \frac{\sigma_2^2}{\tilde{x}_{2i}'\tilde{x}_{2i}}).$$

Assuming $\sigma_1^2 = \sigma_2^2 = \tilde{\sigma}$, we derive the following test statistic:

$$\frac{\hat{\beta}_{1i} - \hat{\beta}_{2i}}{(\frac{\tilde{\sigma}^2}{\tilde{x}_{1i}'\tilde{x}_{1i}} + \frac{\tilde{\sigma}^2}{\tilde{x}_{2i}'\tilde{x}_{2i}})} \sim t_{(T_1+T_2-2*K)}, \qquad (3.2)$$

where

$$\tilde{\sigma}^2 = \frac{y'[I - X(X'X)^{-1}X']y}{(T_1 + T_2 - 2*K)}.$$

Obviously, the effectiveness of this test depends on whether the assumption of $\sigma_1^2 = \sigma_2^2$ holds or not. To release this assumption requires deriving the alternative estimators of σ_1^2 and σ_2^2. One natural alternative of estimators of σ_1^2 and σ_2^2 are $\tilde{\sigma}_1^2 = \frac{y_1'M_1y_1}{(T_1 - K)}$ and $\tilde{\sigma}_2^2 = \frac{y_2'M_2y_2}{(T_2 - K)}$, respectively. Hence, the test statistic similar to (3.2) is

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[10] For details, see Amemiya (1985).

derived as

$$\frac{\tilde{\beta}_{1i} - \tilde{\beta}_{2i}}{\left(\frac{\tilde{\sigma}_1^2}{\tilde{x}_{1i}'\tilde{x}_{1i}} + \frac{\tilde{\sigma}_2^2}{\tilde{x}_{2i}'\tilde{x}_{2i}}\right)} \sim t_{(V)}, \qquad (3.3)$$

where V is as follows

$$V = \frac{\left[\frac{\tilde{\sigma}_1^2}{\tilde{x}_{1i}'\tilde{x}_{1i}} + \frac{\tilde{\sigma}_2^2}{\tilde{x}_{2i}'\tilde{x}_{2i}}\right]^2}{\frac{\tilde{\sigma}_1^4}{(T_1 - K)(\tilde{x}_{1i}'\tilde{x}_{1i})^2} + \frac{\tilde{\sigma}_2^4}{(T_2 - K)(\tilde{x}_{2i}'\tilde{x}_{2i})^2}}.$$

Testing Results:

Table 3.3 shows the results. Note that we have sorted data according to *CREDIT* before we conduct the tests. As mentioned, the criterion for distinguishing the high-credit and low-credit countries is 0.246 for the time period of the 1960-1989 and 0.276 for the time period of the 1980s. In the time period 1960-1989, the first 57 observations of *CREDIT* are less than the average value of *CREDIT*, and in 1980s, they are the first 62 observations.

From the table, one can easily confirm that, under our assumption of the break point, the relationship between credit market development and growth does not change in the time period of 1960-1989. Technically speaking, this result is inconsistent with a break in the relationship; nonetheless, as we discussed in the previous section, the clustered distribution of *CREDIT* in the relatively high-credit countries could possibly lead to the failing of our theoretical implications.

Turning to 1980s, we should reject the hypothesis that $\hat{\beta}_{1i}$ is equal to $\hat{\beta}_{2i}$, especially if we drop the assumption that $\sigma_1^2 = \sigma_2^2$. In particular, note that $\hat{\beta}_{1i}$ is positive and $\hat{\beta}_{2i}$ is negative, implying that the relationship between *CREDIT* and the growth rate is different between high-credit (group 2) and low-credit (group 1) countries. This result is the same as our theoretical models predicted (see *Area II* and *III* in F3).

Table 3.3. The results of Chow test.

Time Period	1960-1989	1980s
Sample Size	$T_1 = 57, T_2 = 34$	$T_1 = 62, T_2 = 31$
1. With the assumption of $\sigma_1^2 = \sigma_2^2$		
$\hat{\beta}_{1i}$	0.03628	0.0924
$\hat{\beta}_{2i}$	0.13019	-0.0158
P-value	0.6072	0.0533
2. Without the assumption of $\sigma_1^2 = \sigma_2^2$		
$\hat{\beta}_{1i}$	0.03628	0.0924
$\hat{\beta}_{2i}$	0.13019	-0.0158
P-value	0.6072	0.0367

Sensitivity Analyses:

We have derived the empirical evidence supporting our theory by separating high-credit and low-credit countries according to the simple average level of *CREDIT* in 1960-1989 and 1980s, respectively. But this criterion is arbitrary; ideally we should let the theory to guide us the selection of a appropriate break point. It is then natural to ask if our results are robust to perturbations of the criterion for distinguishing high-credit and low-credit countries. Therefore, we use the same test as above but change the criterion for distinguishing high-credit and low-credit countries (or equivalently, the sample size of the low-credit countries) to check the robustness of our results. Note that since we have 10 independent variables, the sample of group 2 has to be at least equal to 10. The results are in Table 3.4, where the criterion for distinguishing high-credit and low-credit countries is also reported. Any countries whose *CREDIT* is less than or equal to the criterion will be characterized as low-credit countries (the sample size of low-credit countries is equal to T_1).

Table 3.4 The Sensitivity Analyses[11,12]

Period	1960-89	1980s
Criterion	*0.21(T_1=52)*	*0.21(T_1=45)*
$\hat{\beta}_{1i}$	0.0115	0.0188
$\hat{\beta}_{2i}$	0.0218	0.0256
p-value	0.84	0.92
Criterion	*0.212(T_1=54)*	*0.22(T_1=48)*
$\hat{\beta}_{1i}$	0.0049	0.0 046
$\hat{\beta}_{2i}$	0.0123	0.0204
p-value	0.88	0.81
Criterion	*0.221(T_1=55)*	*0.241(T_1=54)*
$\hat{\beta}_{1i}$	0.0197	0.06581
$\hat{\beta}_{2i}$	0.0115	0.0143
p-value	0.86	0.38
Criterion	*0.245(T_1=56)*	*0.26(T_1=56)*
$\hat{\beta}_{1i}$	0.0086	0.091
$\hat{\beta}_{2i}$	0.0117	0.013
p-value	0.94	0.15
Criterion	*0.246(T_1=57)**	*0.2631(T_1=58)*
$\hat{\beta}_{1i}$	0.0362	0.108
$\hat{\beta}_{2i}$	0.013	0.015
p-value	0.607	0.069

[11] The results reported here are without the assumption of $\sigma_1^2 = \sigma_2^2$.

[12] The sample size of group 2 are $91 - T_1$ for 1960-1989 and $93 - T_1$ for 1980s.

Table 3.4 The Sensitivity Analyses--Continued

Period	1960-89	1980s
Criterion	$0.2463(T_1=58)$	$0.273(T_1=61)$
$\hat{\beta}_{1i}$	0.022	0.272
$\hat{\beta}_{2i}$	0.0118	0.0114
p-value	0.816	0.0502
Criterion	$0.253(T_1=60)$	$0.28(T_1=62)$*
$\hat{\beta}_{1i}$	0.014	0.0924
$\hat{\beta}_{2i}$	0.0064	-0.0158
p-value	0.84	0.036
Criterion	$0.28(T_1=63)$	$0.32(T_1=63)$
$\hat{\beta}_{1i}$	0.015	0.095
$\hat{\beta}_{2i}$	0.0014	-0.019
p-value	0.71	0.024
Criterion	$0.32(T_1=69)$	$0.33(T_1=65)$
$\hat{\beta}_{1i}$	0.058	0.100
$\hat{\beta}_{2i}$	0.0006	-0.0204
p-value	0.114	0.017
Criterion	$0.37(T_1=74)$	$0.37(T_1=66)$
$\hat{\beta}_{1i}$	0.055	0.057
$\hat{\beta}_{2i}$	0.007	-0.038
p-value	0.128	0.036
Criterion	$0.4(T_1=78)$**	$0.4(T_1=71)$
$\hat{\beta}_{1i}$	0.056	0.075
$\hat{\beta}_{2i}$	-0.029	-0.045
p-value	0.035	0.00143

Table 3.4 The Sensitivity Analyses--Continued

Period	1960-89	1980s
Criterion	*0.442(* T_1 *=79)*	*0.465(* T_1 *=78)***
$\hat{\beta}_{1i}$	0.0526	0.078
$\hat{\beta}_{2i}$	-0.029	-0.088
p-value	0.0718	3.29e-06
Criterion	*0.45(* T_1 *=80)*	*0.5(* T_1 *=80)*
$\hat{\beta}_{1i}$	0.048	0.079
$\hat{\beta}_{2i}$	0.038	-0.115
p-value	0.69	1.59e-05

* means that the criterion is the same as the average level of *CREDIT* in each period.

** is the criterion under which the lowest p-value is derived (the Maximum Chow test).

We may follow the work of Alston and Chalfant (1991) to use the maximum Chow test to search for the potential break point. The test of maximum Chow test is obtained by searching across the data for the maximum F-statistic (or t-statistic), or equivalently the minimum p-value, for locating the potential break point instead of using a predetermined break point. Under the maximum Chow test, the structural break is the one when the criterion is 0.4 in 1960-1989 and 0.465 in 1980s. If the criterion is 0.4, we see that our theoretical implications are actually also supported in 1960-1989 as the null hypothesis is rejected at 0.05 level. Moreover, $\hat{\beta}_{1i}$ is positive and $\hat{\beta}_{2i}$ is negative under this criterion; consequently, our theoretical implications about the relationship between economic growth and levels of credit market development seems correct in 1960-1989.

Although our theory is supported in 1960-1989, it is very sensitive to the criterion we choose. For example, if we increase the criterion to 0.442, we will fail to reject the null hypothesis under 5 % significance level. Therefore, unless our theoretical models specify that the break point is located on 0.4, we cannot confidently conclude that our theory is correct in the time period of the 1960-1989. However, our testing results are very robust in

1980s to the changing of the criterion. In particular, the p-value is decreasing while $\hat{\beta}_{1i}$ remains positive and $\hat{\beta}_{2i}$ remains negative as we increase the criterion form 0.276, which is the average level of *CREDIT* in 1980s. Clearly, our theoretical implications are even more supported if we increase the criterion for separating high-credit and low-credit countries in 1980s. In conclusion, we have found the evidence showing that the relationship between credit market development and economic growth is positive in low levels of *CREDIT* and negative in high levels of *CREIDT* (that is, the relationship specified in the *AREA* II and III of F3).

In F3, we also indicate that the relationship between credit market development and economic growth could be positive again in the extremely high credit levels (that is, in *AREA IV* of F3). However, from Figure 3.2 and Figure 3.3, there are only about 2 countries whose credit is extremely high in 1980s. As we noted earlier, the sample size of group 2 has to be at least equal to 10. Consequently, due to data limitation, we are not able to test this conjecture.

3.4. Recursive Residuals

In the previous section, we tested the structural change of the relationship between credit market development and economic growth by arbitrarily imposing a break point. From the statistical points of view, we could let the data tell us about this information, instead of testing structural change by imposing any prior restriction. Therefore, to complement our results, we illustrate the structural change between credit market development and growth by using CUSUM and CUSUM squares (CUSUMSQ) tests. Neither tests require any prior information about the break point, and both can help us to locate the structural break point. The CUSUM and CUSUMSQ tests are appropriate for time-series data; nonetheless, we apply both tests to cross-section data[13].

Consider the usual regression model

$$Y = X\beta + u ,$$

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[13] We conduct this by sorting data according to *CREDIT*. For the detail, see Galpin and Hawkins (1984).

where Y is the ($n\times 1$) vector observations on dependent variables; X ($n\times k$) is n observations on k independent variables; β ($k\times 1$) is the regression vector to be estimated; and u is an error term assumed to be *i.i.d.*. Denote b_r as the least squares regression vector based on the first r observations, and let X and Y be partitioned accordingly; that is, $X_r' = (x_1,......,x_r)$ and $Y_r' = (y_1,.....,y_r)$. So b_r can be derived as

$$b_r = (X_r' X_r)^{-1} X_r' Y_r .$$

The recursive residuals are then defined by Brown, Durbin, and Evans (1975) as

$$w_r = \frac{y_r - x_r' b_{r-1}}{\sqrt{1 + x_r'(X_{r-1}' X_{r-1}) x_r'}}, \quad r = p+1,........,n .$$

It is known that If $u \sim N(0,\sigma^2 I_n)$, then the distribution of w_r is $N(0,\sigma^2 I_{n-k})$ and w_r is independent of w_s for $s \neq r$. If the distribution of w_r is changing over r, we should reject the null hypothesis that the coefficients remain constant for the full sample. Given the distribution of w_r specified above, two kinds of tests have been suggested by Brown *et al.* to investigate the structural change and other model assumptions. The first test –CUSUM test –is based on the cumulated sum of the residuals:

$$W_r = \sum_{r=k+1}^{r} \frac{w_r}{\hat{\sigma}},$$

where

$$\hat{\sigma}^2 = \frac{\sum_{r=k+1}^{n} (w_r - \overline{w})^2}{n-k-1}$$

and

$$\overline{w} = \frac{\sum_{r=k+1}^{n} w_r}{n-k}.$$

The confidence bounds are derived by plotting the two lines connecting the points $(k, \pm a\sqrt{n-k})$ and $(n, \pm 3a\sqrt{n-k})$, where a can be found in Greene (1993).

The second test is CUSUM of squares test, which are calculated as

$$S_r = \frac{\sum_{r=k+1}^{r} w_r^2}{\sum_{r=k+1}^{n} w_r^2}.$$

For a given *r*, the expected value of S_r [E(S_r)] is approximately equal to *(r-k)/(n-k)*. Thus, the test can be done by drawing two lines that connect the points E(S_r)$\pm c_0$, where c_0 depends on *(n-k)* and significant level and can be found in Harvey (1990). We may plot the CUSUM and CUSUMSQ against *r* (the number of residuals accumulated, CUSUM Number) to locate the potential break point.

Since we have 10 independent variables and we are only interested in *CREDIT*, we generally use the residuals derived from regressing the growth rate on other independent variables except *CREDIT* as the dependent variable and, similarly, the residuals derived from regressing *CREDIT* on all other variables as independent variable. Figure 3.5 and 3.6 are the plots of CUSUM and CUSUMSQ for the time period of 1980s.

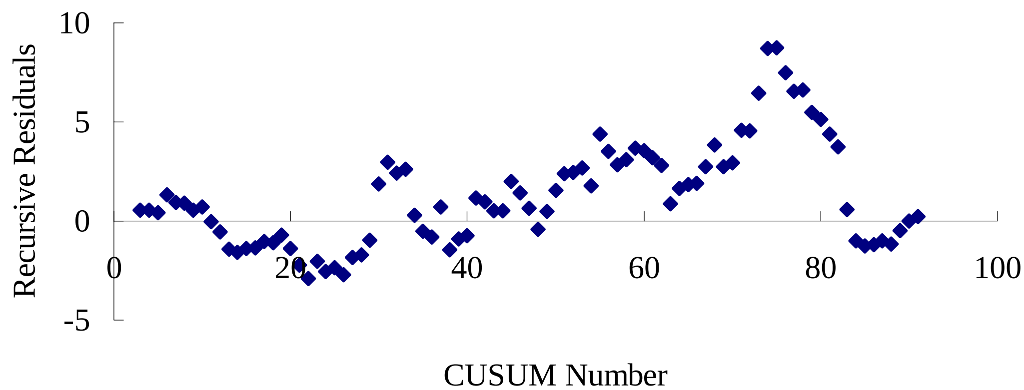

Figure 3.4 The Plot of CUSUM

Note that we do not draw the confidence bounds in Figure 3.3, as they are far away from the observations. Since any level of CUSUM does not cross the confidence bounds, we fail to reject the null hypothesis that there is no structural change. This result seems to violate our theory. Nonetheless, both CUSUM and CUSUMSQ tests are initially meant for descriptive diagnostic rather than pure significance testing. In particular, Garbade (1977), McCabe and Harrison (1979), and Ashley(1984) have recognized that CUSUM test has little power to reject the null hypothesis of stable coefficients, especially when the change occurs late at the data. Therefore, we should use the plot of CUSUM to locate the possible break points instead of using it to formally test the stability of coefficients.

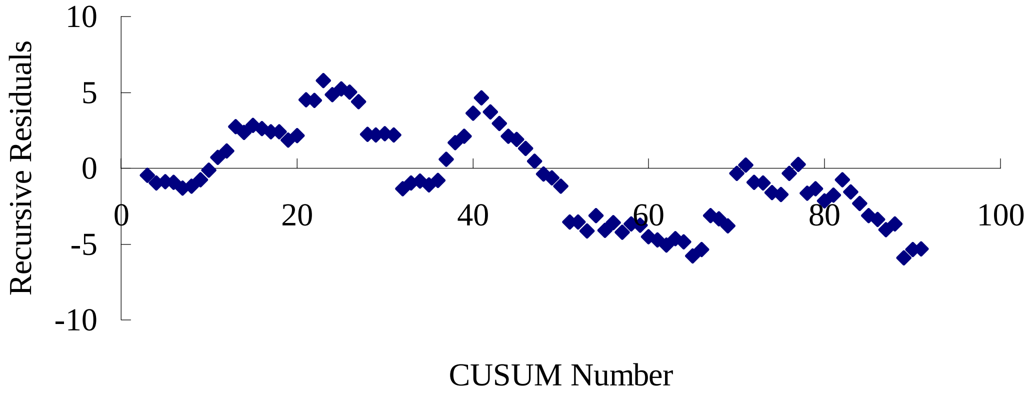

Figure 3.5 The Plot of CUSUM-Calculated Backwards

As is shown above, the expectation of recursive residuals is zero; therefore, if the coefficients are stable, the plot of CUSUM should show a random walk about the origin. From Figure 3.4, we see that the recursive residuals show a random walk around the origin until the CUSUM number equal to 64. From 64^{th} sample, the recursive residuals has an underlying positive trend (thus, far away from the origin). Another possible break point takes place at 76^{th} sample, where the recursive residuals demonstrate a negative trend. Consequently, the plot of CUSUM may suggest that there may exist structural changes in the latter part of the data. Recall that we have sorted the data according to *CREDIT* before we calculate the recursive residuals. Thus, the suggestion implies that the relationship between credit market development and economic growth differs between high and low levels of *CREDIT*.

Since the CUSUM test lacks power especially when the change takes place at the latter parts of the data, we should also calculate the recursive residuals backwards, so that the lower the CUSUM number is, the higher the *CREDIT*. Figure 3.5 is the corresponding diagram. Clearly, the figure also indicates that the relationship between credit market development and economic growth is different between high and low levels of *CREDIT*. Specifically, the CUSUM show a negative trend from the 40th sample, implying that the structural break may take place at the 40th sample. Moreover, Figure 3.5 shows that there may exist multiple break points.

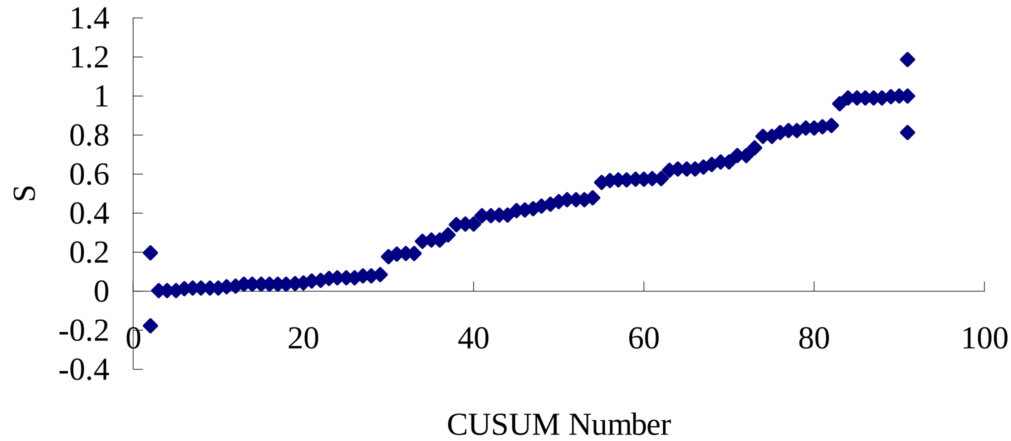

Figure 3.6 The Plot of CUSUMSQ

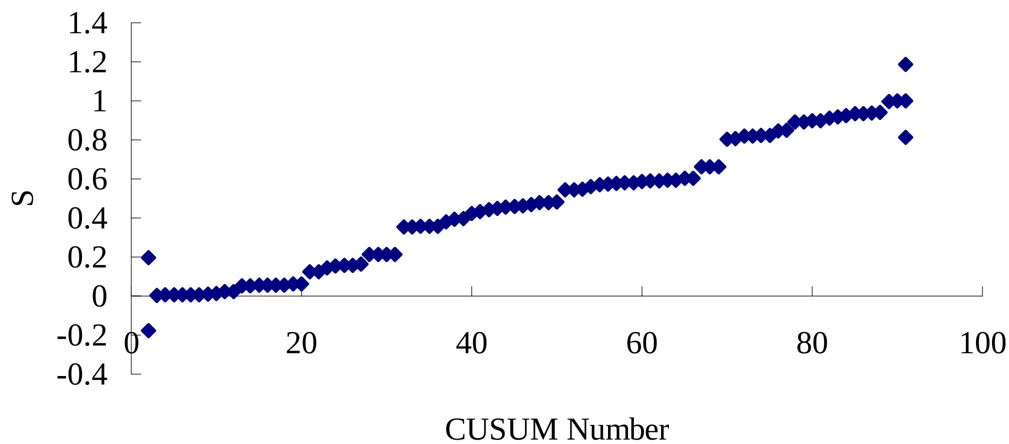

Figure 3.7 The Plot of CUSUMSQ-Calculated Backwards

The test of CUSUMSQ is plotted in Figure 3.6. Note that we have drawn 5% significance lines in the figure. From this diagram, it is obvious that the CUSUMSQ test rejects the null hypothesis, as the squares of CUSUM cross the 5% significance lines around 25th sample. This result suggests that the relationship between credit market development and economic growth is not stable over the whole sample. Figure 3.7 show the test of CUSUMSQ where the recursive residuals are calculated backwards. In this figure, we fail to reject the null hypothesis; nonetheless, the squares of CUSUM are close to the lower bound at the 20th sample, indicating that the structural break may occur at this point.

In conclusion, the plot of CUSUM does suggest that the relationship between credit market development and economic growth differs between high and low levels of credit market development. In fact, there could be multiple break points. The test of CUSUMSQ in Figure 3.6 also reject the null hypothesis that the coefficients are stable over the whole samples. In the future, we plan to employ the more general and powerful econometric technique to test this result.

3.5. Conclusions and Extensions

We have studied the relationship between credit market development and economic growth as credit markets develop. We find that the effects of credit market development on economic growth are different between countries with relatively developed and countries with relatively less developed credit markets. Specifically, we find that, at low levels of credit market development, the development of credit markets can promote growth; however, the effects of credit market development on growth are actually reversed at the high levels of credit market development. This evidence provides support of our theory.

To extend our empirical work, first, we may try to collect an updated data set in which the distribution of *CREDIT* of the high-credit countries is more extensive and therefore may enable us to test for the presence of multiple break points. Second, it could be desirable to use a more general econometric technique, which does not require any prior information about the break point. Third, our theoretical implications could be examined by using time-series data of a specific country, if the appropriate data could be found.