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The Role and Importance of Credit in Banking Crises: An Analysis of Developed and Emerging Economies

K. Batu Tunay*
Marmara University; Institute of Banking and Insurance; Department of Banking; Istanbul, Turkey; E-mail: kbatutunay@hotmail.com

ABSTRACT

Uncontrolled credit rises have the capacity to cause serious banking crises. Global banking crises have led to discussions on credit-to-GDP gaps and new credit modelling structures. In this study, both developed and emerging economies are analyzed with regard to increased credit, non-performing loans, and credit-to-GDP gaps. Panel logit models are used, as well as z-score and capital adequacy variables. The results indicate that increasing bank credit is an integral factor in banking crises. Furthermore, increases of non-performing loans also pose major systemic risks. The financial strength of banks is essential to preventing financial crises. This is not valid for capital adequacy regulations. Instead of minimizing banking system risk, on the contrary, high and firm capital adequacy ratio regulations actually cause a system to be more fragile.

JEL Classification: G01; G21; C23.

Keywords: Bank Crises; Systemic Risk; Credit; Panel Logit Models.

**Corresponding author; Marmara University; Institute of Banking and Insurance; Department of Banking; Istanbul, Turkey; E-mail: kbatutunay@hotmail.com*

1. INTRODUCTION

There has been an increase of analytical studies concerning banking crises and financial stability. Studies by applied economists and financial analysts have examined different dimensions of these subjects using a variety of different approaches. Despite many supervision and regulation processes, banking crises are typically unexpected and can last for long periods. Thus, researchers have found the subject a necessity to analyze. While the rise of banking crises has primarily been due to problems with mortgage loans than other types of loans, credit nexuses have yet to be analyzed in-depth in relation to such crises.

The effects of credit crises have been analyzed since the 1970s. The traditional view concerning credit booms is that they can cause bank crises to escalate. Research done since the middle of the 1990s suggests that increases of credit can be followed by crises. During periods when an economy is expanding, there can be sudden increases of credit that during contraction periods can lead to losses and banking system crises. Credit issues and non-performing loans are well-known determinants of such issues.

Empirical studies have shown that credit growth and non-performing loans are determinants of banking sector crises. If the “twin crises” hypothesis is valid, then banking crises can be followed by money crises. Indeed, in the global economy, financial and economic ties can lead to debt crises. To stress the point, capital market crises have inversion potential. Even though this approach appears to be an extreme one, many researchers believe that local crises can turn into global ones. It is obvious that credits show cyclicality and importance during that time. Researchers that support this view argue that credits that involve during the economic activity when there is volatility and crises.

Following Basel III, systemic banking crises have been considered one of the primary causes of economic crises. The measurement of credit provided to the private sector and its relationship to GDP is considered a main indicator of banking crises. While this new approach has been discussed, however, it also brought a new dimension to the credit-crises nexus.

The aim of this study is to analyze the effects of non-performing loans and credit-to-GDP gaps on banking crises. Using a panel logit model, a dataset on developed and emerging economies is analyzed. In the model, z-score reflects the strength of a bank, and capital adequacy ratio, which represents systematic safeness, is utilized as control variables.

2. LITERATURE REVIEW

Bank credit trends are considered to be strong indicators of economic crises. Minsky (1972) and Kindleberger (1978) were two of the first scholars to state this, and since then, several studies have shown credit increases to be related to or the direct cause of crises. Borio and Lowe (2002), Frömmel (2006), Riiser (2005, 2008), Rheinberger and Summer (2008), Gerdesmeier (2009), and Misina and Tkacz (2009) have each shown that while financial systems have become cyclically unstable due to real estate pricing, a major factor in such instability is credit.

Several studies have shown that instabilities in banking systems are indeed due to increases of bank credits [Sachs et al. (1996), Dermirgüç-Kunt and Detragiache (1998, 2002), Borio and Lowe (2002, 2004), Lorenzoni (2008), Alessi and Dekten (2009), Borgy et al. (2009), Berglöf et al. (2010), Drehmann et al. (2010), Dell'Arricia et al. (2012), Schularick and Taylor (2012), Mendoza and Terrones (2008, 2012), Wilms et al. (2014), Boyd et al. (2015), and Wosser (2015)]. These studies have shown that crises appear more frequently following credit booms than during normal periods, and that such crises are typically followed by economic recessions. Dell'Arricia et al. (2012) state that one third of credit booms are followed by crises, and that three to five of the six years following them typically involve economic recession.

While increases of credit loan volume have been observed prior to financial crises, they have also been observed to decrease immediately following a crisis. This can be perceived as an increase in credit risk. Wosser (2015) has shown that most cases appear immediately after a banking crisis, which causes banks to be more conservative in providing loans. It is very seldom that a group of credit owners does not make payments, and therefore cause a bank to be in distress. However, in 2007, the speculative ballooning of the mortgage market led many customers to be unable to cover their liabilities, thus leading to credit crunch.

Credit volume, credit regulations, the quality of credit policies, and the pace of credit availability to the private sector each reflect the fragility or stability of a banking system and can be used to prevent potential crises. Credit availability to the private sector can be used to determine the level and size of a financial system (Bergörf et al. 2010, Giannone et al. 2011). However, it is useful to analyze the development of a financial system and the size during a crisis. For this reason, the velocity of bank credits to GDP has been considered in different econometrical models. Schularick and Taylor (2012), Mendoza and Terrones (2012), Boyd et al. (2015), Wosser (2015) are examples of related literature.

Liquidity, credit risk procyclicality, and macroeconomic imbalances have also been examined by authorities and researchers. It is generally accepted that asset prices and bank credits have been ignored as procyclicality before crises, which is possible to observe in the deregulations implemented against such procyclicality for capital. Procyclicality issues can be understood as early warning signs of banking crises. In 2010, the Basel Supervision and Regulation Committee examined credit to GDP trend diversions, or credit-to-GDP gaps, to determine procyclical bank capital demand. Several researchers, such as Drehmann et al.(2011), van Norden (2011), De Bonis and Silvestrini (2013), Drehmann and Tsatsaronis (2014), and Borio (2014) have pointed out that credit gaps are important in forecasting bank crises. Alternatively, Giese et al. (2014) argue that, in examining past findings, credit gaps cannot be regarded as a warning sign of bank crises.

Indicators regarded as warning signs have been criticized by scholars such as Edge and Meisenzahl (2011a, 2011b), Gersl and Seidler (2011), Repullo and Saurino (2012), Kelly et al. (2013), Shin (2013), and Farrell (2014). Edge and Meisenzahl (2011a, 2011b), Gersl and Seidler (2011), Kelly et al. (2013), and Farrell (2014) argue that gap measurement can be misevaluated, and in relation to credit volume, can be minimized or maximized, causing a cost. However, other scholars in developed, market-based economies have found credit gaps to be less predictive of banking crises than financial systems.

Studies have also examined stock return performance both during and prior to financial crises to determine the divergence of returns in different periods. Choudhry and Jayasekera (2014), Chan-Lau et al. (2015), Min et al.

(2016), and Allegret et al. (2017) are examples of such studies. John and Park (2016) take bank crises as an early warning sign. In the literature, the use of bank stock returns as early financial warning signs represents a new approach. Li and Ongena (2015) have shown that bank credit policies typically become more conservative during periods of crises, as well as analyzed how bank stock returns change during such periods. In such studies, GARCH models, linear and dynamic panel data models, and SVAR models have been used.

The majority of studies on the effects of bank stock shares show them to have a significant impact. Kim et al. (2016) found that financial crises affected all stock returns and increased volatility. Allegret et al. (2017), in their analysis of the stock returns of 15 countries, found that crises had a negative effect during debt crises in Europe. However, studies of the USA have not found similar results. Chan-Lau et al. (2015) studied 68 banks in Europe and USA during a period of global financial crisis and found that bank stock returns had low performance. However, ones with strong equity and low leveraged banks showed acceptable performance. Sohn and Park (2016) and Repullo and Saurino (2012) analyzed credit deficit and credit growth as early warning sings. In the measurement of credit growth and credit growth ratio, they used the Hodrick-Prescott filter, with its divergence used as a cyclical variable.

3. DATA AND METHODOLOGY

3.1 MODELLING AND ANALYSIS

When modelling binary structure, analyzing with regard to probabilities is most common. For this reason, the dependent variable y_{it} , and when there is a binary structure, then all the observations will be evaluated in terms of a “1” or “0”. The model that should be used is a linear probability model:

$$\begin{aligned} y_{it} &= \beta_1 + \beta_2 x_{it} + \cdots + \beta_K x_{Kit} + c_i + u_{it} \\ &= \mathbf{x_{it}}\boldsymbol{\beta} + c_i + u_{it} \end{aligned} \tag{1}$$

In equation (1), y_{it} is the binary response variable, $\mathbf{x_{it}}$ constant term is 1xK observed as the vector of the observed explanatory variables, $\boldsymbol{\beta}$ is the 1xK parameter vector, indirectly unobserved and individual effect, u_{it} is the independent variable, and averaged zero represents residuals (Söderbom, 2009).
Equation (1) has two dependent variables. Such a model is valid for random sampling. When y equals 1, then the unconditional probability will be expressed as follows:

$$E(y) = \Pr(y = 1)$$

The conditional probability of y, y conditionally is expected to equal the value of y:

$$\Pr(y_{it} = 1 | x_{it}, c_i) = E(y_{it} | \mathbf{x_{it}}, c_i; \boldsymbol{\beta})$$

The movements of the equation with regard to the probability of y being “1” or “0” can be expressed as follows:

$$\begin{aligned} &\Pr(y_{it} = 1 | x_{it}, c_i) = \mathbf{x_{it}}\boldsymbol{\beta} + c_i \\ &\Pr(y_{it} = 0 | x_{it}, c_i) = 1 - (\mathbf{x_{it}}\boldsymbol{\beta} + c_i) \end{aligned} \tag{2}$$

Equation number (2) is a binary response model. In the model, the probability of having y=1 is a linear function of $\mathbf{x}$ in the independent vectors. For this reason, equation (2) can be understood as a linear probability model. The model’s parameters were estimated using the ordinary least squares (OLS) estimator (Söderbom, 2009).
The two nonlinear models are given as a y value of “0” and “1,” respectively:

$$\begin{aligned} &\Pr(y_{it} = 1 | \mathbf{x}) = G(\beta_1 + \beta_2 x_2 + \cdots + \beta_K x_K) \\ &\Pr(y_{it} = 1 | \mathbf{x}) = G(\mathbf{x}\boldsymbol{\beta}) \end{aligned} \tag{3}$$

In equation (3), G represents all real values between 0 and $0 < G(z) < 1$. In our example, the estimated probability is $0 < G(\mathbf{x}\boldsymbol{\beta}) <1$. G increases as accumulative density function(cdf) and monotonously increases within the z index as **x**:

$$\mathbf{x}\boldsymbol{\beta} \to \infty \quad \Rightarrow \quad \Pr(y_{it} = 1|\mathbf{x}) \to 1$$
$$\mathbf{x}\boldsymbol{\beta} \to -\infty \quad \Rightarrow \quad \Pr(y_{it} = 1|\mathbf{x}) \to 0$$

As G is nonlinear, it can not be analyzed by OLS. In the literature, the most common one that is used is logistic distribution. The logit model is given below:

$$G(\mathbf{x}\boldsymbol{\beta}) = \frac{\exp(\mathbf{x}\boldsymbol{\beta})}{1+\exp(\mathbf{x}\boldsymbol{\beta})} = \Lambda(\mathbf{x}\boldsymbol{\beta}) \tag{4}$$

In equation number (4), when $\mathbf{x}\boldsymbol{\beta}$ is accepted as scalar between 0 and 1, the cumulative distribution is a function of the logistic variable.
Panel logit models are used for unobserved individual effects. In this regard, the panel binary choice model is a latent variable defined as:

$$\begin{aligned} y_{it}^{*} &= \mathbf{x_{it}}\boldsymbol{\beta} + c_i + u_{it} \\ y_{it} &= 1[y_{it}^{*} > 0] \end{aligned} \tag{5}$$

$$\Pr(y_{it} = 1|x_{it}, c_i) = G(\mathbf{x_{it}}\boldsymbol{\beta} + c_i) \tag{6}$$

In equation (5), y_{it}^{*} is the secret variable. In equation (6), $G(.)$ functions as the logistic logit cumulative distribution function. In logit models, fixed or random effects are tested in terms of maximum likelihood (Söderbom, 2009; Williams 2016).
In this study, as the effect of bank credits on baking crises was analyzed, the $\mathbf{x_{it}}$ descriptive variable vector was formed as follows:

$$\mathbf{x_{it}} = \left\{\Delta Crd_{it}, Crd_{it}^{Gap}, \Delta NPL_{it}, z_{it}, RC_{it}\right\} \tag{7}$$

In equation (7), ΔCrd_{it} represents the ratio of credit to GDP, Crd_{it}^{Gap} is the credit-to-GDP gap, and ΔNPL_{it} is nonperforming loan ratio, which indicates an increase. These variables comprise the factors of credit that impact bank crises. The control variable z_{it} reflects bank strength, and RC_{it} is the capital requirement amount by Basel, which reflects strength against systemic risk.

3.2. DATA SET

In this study, a dataset of 46 developed and developing countries (see Table 1) was used. The data, collected by IMF and Financial Soundness Indicators in 2016, covers the period of 1999 to 2014. The total number of observations included in the data is 4,416. Credit-to-GDP gap is measured by the ratio of credit available to the private sector to GDP using the Hodrick-Prescott filter through cyclical component. Descriptive statistics are presented in Table 2, and the correlation coefficients are given in Table 3. At 18% and 20%, the correlation coefficients indicate that banking crises are strongly related to credit growth, credit gaps, and nonperforming loans.

Table 1. Analyzed Countries

Developed Economies		Emerging Market Economies	
Australia	Italy	Argentina	Romania
Austria	Japan	Brazil	Russian Federation
Belgium	Korea, Rep.	Bulgaria	South Africa
Canada	Netherlands	Chile	Thailand
Denmark	New Zealand	China	Turkey
Estonia	Norway	Czech Republic	Ukraine
Finland	Portugal	Greece	Venezuela, RB
France	Slovak Republic	Hungary	
Germany	Spain	India	
Hong Kong SAR, China	Sweden	Indonesia	
Iceland	Switzerland	Malaysia	
Ireland	United Kingdom	Mexico	
Israel	United States	Poland	

Table 2. Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Bank Crisis	0.1345	0.3414	0.0000	1.0000
ΔCrd_{it}	76.8376	48.1767	0.0000	262.4577
Crd_{it}^{Gap}	-0.0664	12.6905	-81.2600	85.8400
ΔNPL_{it}	4.9182	6.0745	0.0000	38.6000
z_{it}	10.4213	6.8879	-12.6100	40.7500
RC_{it}	13.9261	4.3692	0.0000	41.8000
Obs.	736			

Table 3. Correlation Coefficients

	Bank Crisis	ΔCrd_{it}	Crd_{it}^{Gap}	ΔNPL_{it}	z_{it}	RC_{it}
Bank Crisis	1.0000					
ΔCrd_{it}	0.2281	1.0000				
Crd_{it}^{Gap}	0.1850	0.3634	1.0000			
ΔNPL_{it}	0.2310	-0.1340	-0.0466	1.0000		
z_{it}	-0.1319	0.0790	-0.0111	-0.2660	1.0000	
RC_{it}	-0.0016	-0.2272	-0.0917	0.1199	-0.1030	1.0000

3.3. RESULTS

In the first part of the analysis, panel logit models (7) and (8), the explanatory variables, and random and fixed effects were used in the estimations. A Hausman test was then applied in order to determine which model was more efficient. The results are given in Table 4, where the fixed effect provided robust results. This model is taken as the basis, and the maximum likelihood estimator was used. The results are given in Table 5.

Table 5 shows the results concerning the developed and emerging economies. A reference model was determined for all variables. For comparison, both the reference model and the significant measures are given. Insignificant parameters have been removed.

Table 4. Hausman Tests

	All Sample	Developed Economies	Emerging Economies
χ^2	11.123	13.931	13.591
	[0.0490]	[0.0161]	[0.0184]

Note: p values of Chi-square tests are shown in square brackets

Table 5. ML Estimations of the Panel Logit Models

	All Sample		Developed Economies		Emerging Economies	
	B.Crisis	B.Crisis	B.Crisis	B.Crisis	B.Crisis	B.Crisis
ΔCrd_{it}	-0.0084		-0.0184	-0.02034	-0.0109	-0.0115
	(-1.300)		(-2.160) **	(-2.500) **	(-1.640) *	(-1.760) *
Crd_{it}^{Gap}	0.0571	0.0498	0.0728	0.0758	0.0554	0.0550
	(3.910) ***	(3.810) ***	(4.050) ***	(4.230) ***	(5.800) ***	(5.790) ***
ΔNPL_{it}	0.1087	0.1219	0.0709		0.1040	0.1005
	(2.930) ***	(3.330) ***	(0.980)		(2.890) ***	(2.740) ***
z_{it}	-0.2613	-0.2704	-0.2258	-0.2293	-0.2209	-0.2013
	(-4.530) ***	(-4.710) ***	(-3.570) ***	(-3.620) ***	(-3.620) ***	(-3.440) ***
RC_{it}	0.1155	0.1152	0.2232	0.2246	0.0756	
	(2.570) ***	(2.570) ***	(3.500) ***	(3.580) ***	(1.580)	
LR Tests:						
χ^2	83.280	8.490	56.680	55.670	114.730	112.260
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: (***), (**), (*) showed significant z tests at levels of 1%, 5%, and 10%, respectively. p values of Chi-square tests are shown in square brackets.

Observing the results, credit growth in developed and emerging countries is significant and negative parameter values are present. These findings are contrary to those of the traditional approach. Nonperforming loans in all countries, including emerging countries, are found to positively affect. No such observation was found for developed countries. This result suggests that developed countries possess strong regulations and supervision that prevent high risk of financial failure due to nonperforming loans. In emerging countries, regulation and supervision remain inefficient and is therefore a sensitive issue. Furthermore, a positive and significant relation was found between credit gaps and banking crises. Moreover, the variable had a positive effect in all models.

The z-score as a control variable was a negative coefficient, with the coefficients being similarly high in both developed and emerging countries. The z-score reflects the general solvency levels of banks and when the there is an increase in the financial strength against crises.

4. CONCLUSION

In this study, bank crises and credits within 46 developed and emerging countries were analyzed. The results of the study's panel logit model were found to be different than those of the prior literature. First, contrary to prior findings, uncontrolled credit growth was found to be an important factor in causing bank crises. Second, credit gaps were found to be a leading cause of systematic banking crises, which is developed by BIS.

The dependent variable as the z-score and capital requirement ratio was found to be significant.The z-score was expected to provide a negative coeffient, however, opposite to capital adequacy, it provided positive coefficient values. The z score proves that, for banking systems to be protected from crises, it is important for banks to have safe and sound structures. When banks are sound, a banking system will be safe as well. More specifically, strict adequacy requirements are the most significant form of security against crises. In order to protect competition power and profitability, strict capital adequacy requirements allow banks to enter into new and risky involvements. Some banks both in the EU and USA experienced it accordingly. The results indicate that the authorities should not apply strict rules but reasonable ones. Moreover, regarding the systemic ties of the banks, individual financial strength should not be ignored. Bank credits should be recorded and examined, as they represent the main elements of financial strength.

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