

Effect of Credit Risk on the Efficiency of Banks in Member Countries of the Economic and Monetary Community of Central Africa (Cemac)

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Abstract

The objective of this article is to determine the effect of credit risk on the efficiency of banks in the member countries of the Economic and Monetary Community of Central Africa (CEMAC). To achieve this goal, we used the stochastic boundary method to determine the efficiency score of CEMAC banks. Based on this score, we applied the Tobit model to show the effect of credit risk on the efficiency of banks over the period 2004-2017. The results obtained reveal that CEMAC banks are inefficient in terms of cost and that the credit risk measured from the ratio between bad debts and loans granted negatively influences the efficiency of these banks.

Keywords: Credit risk; efficiency; CEMAC

Introduction

Efficiency is a key concept for financial institutions that is studied by various authors (Du and Sim, 2016; Bopkin, 2013). However, the range of issues that influence banks' ability to obtain information about the market and about borrowers themselves can also affect bank efficiency. Customer information is a critical component for the bank in selecting credible customers. Indeed, the existence of information asymmetries, whether ex ante or ex post, increases the risk of customer insolvency (of credit repayment).

Thus, several researchers have shown substantial interest in this subject (Pastor, 1999 and Win, 2018). This topic has attracted considerable interest because the quality of bank assets is an important indicator that signals bank failures and influences bank efficiency (Mester 1996).

The increase in distressed loans observed in recent years poses an efficiency problem for CEMAC banks. Thus, the objective of this article is to determine the effect of credit risk on bank efficiency. This paper hypothesizes that credit risk negatively influences the efficiency of banks. The paper is subdivided into three sections. The first reviews the literature on the effect of credit risk on bank efficiency, the second reviews the methodology employed by the literature, and the third reviews the results and policy implications.

I- Literature review of the effect of credit risk on bank efficiency.

The study of the effect of credit risk on bank efficiency has been the subject of two main approaches (Hugues et al. 1996; Fiordelisi et al. 2011). The first focuses on credit risk as a source of inefficiency, and the second focuses on credit risk as a source of bank efficiency.

The first approach is based on the theory of bank mismanagement. According to this theory, a bank has a low level of efficiency because of poor management decisions that translate into poor credit management (Keeley, 1990; Arellano and Bond, 1991). As a result, inefficiency in bank management leads to bad loans. This theory states that poor management of a credit institution leads to a deterioration in the quality of a bank's portfolio. Credit risk is essentially due to managerial inefficiency arising from a lack of monitoring of operating expenses and the credit quality of customers. For example, a high level of nonperforming loans is justified by ineffective borrower credit risk management skills and a lack of collateral (Podpiera and Weil, 2008).

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The second approach is based on the economic or "skimping" behavior of banks. Based on this, profitable banks may appear more efficient in a short period of time by using fewer resources for monitoring and underwriting loans (Williams, 2004). In this case, a high level of nonperforming loans leads to an increase in efficiency. Consistent with this view, both loan quality and efficiency are affected by the share of resources specified for loan underwriting and monitoring. This theory shows that nonperforming loans lead to efficiency for a short time.

According to this theory, costs are reduced by reducing underwriting, monitoring and control of borrowers. This is achieved by devoting fewer resources to collateral evaluation. This suggests that banks are efficient for a short period of time.

Empirically, work on the relationship between credit risk and bank efficiency has shown conflicting results under a number of assumptions. Most research, such as the work of Berger and Humphrey (1992) and et al (2010), shows that there is a negative relationship between bad loans and bank efficiency. In contrast, other research by Lown and Peristiani (1996) indicates that there is a positive relationship between credit risk and bank efficiency.

In terms of early work, Williams (2004) studied a sample of European banks over the period 1990-1998 and concluded that these banks follow the mismanagement hypothesis. Subsequently, Karim et al. (2010) highlight the effect of credit risk on bank efficiency. They estimate efficiency using the stochastic frontier approach and tobit regression to determine the effect of nonperforming loans on bank efficiency. On the one hand, the results indicated an average efficiency score of 87.68% for the full sample and also indicate that there are no significant differences between commercial banks in Singapore and Malaysia. On the other hand, the tobit regression results clearly indicate that nonperforming loans reduce bank efficiency. These results are consistent with those of Altunbas et al. (2000) and Fan and Shaffer (2004), who found that nonperforming loans lead to inefficiency in the banking sector.

The second group of authors showed that credit risk positively influences the efficiency of banks. The work of Nguyen and Simioni (2015) is intended to explore the relationship between delinquency and efficiency in Vietnamese commercial banks over the period 2007-2013. These authors use data envelopment analysis (DEA) to measure banking efficiency as suggested by Coelli et al. (2005). They apply the Tobit model to identify the reciprocal effects of delinquent claims on banking efficiency. The results show that the efficiency of Vietnamese commercial banks is 52.6 per cent and that there is a positive relationship between these claims and efficiency. These results support the economic behavior hypothesis. Other authors such as Batir et al. (2017) analyzed banks in Turkey using the DEA method, the intermediation approach and Tobit regression to identify factors that could influence bank efficiency. The DEA results indicate that the average efficiency of participating foreign banks is higher than the efficiency of conventional banks each year, while spending and loan quality have a significantly negative relationship with the efficiency of conventional banks, they have a clearly positive impact on foreign banks.

According to the review of the theoretical and empirical literature, lessons have been learned at a theoretical level, and the majority of authors, such as Podpiera and Weil (2008), explain the relationship between credit risk and bank efficiency using the theory of mismanagement. This theory can be supported by the lack of control of loans and costs at the level of bank management (Berger and De Young, 1997). Credit risk is then linked to a problem in monitoring operating expenses and the quality of borrowers' loans. At the empirical level, most works, as exemplified by Karim et al. (2010), employ the notion of efficiency to assess the quality of bank management and predict risks. This work supports the effect of credit risk on bank efficiency using the stochastic frontier approach and Tobit regression.

II- Methodology of the effect of credit risk on bank efficiency

To analyze the effect of credit risk on the efficiency of banks in CEMAC, we adopt a two-step methodological procedure. We measure bank efficiency in the first step and analyze the factors that may influence its evolution in the second. This methodology has been employed effectively in various banking contexts in developed and developing countries (Karim et al. 2010; Ramli et al. 2018). Thus, in this section, we will determine efficiency scores and analyze the effect of credit risk on bank efficiency.

II.1. Determining efficiency scores

To determine efficiency scores, various methods have been adopted following the work of Farrell (1957). This analysis considers the efficiency scores for each country and does not assume that the border is common to all banks.

This research adopts the parametric method of a stochastic frontier. In addition, the parametric method of a stochastic frontier makes it possible to apprehend the efficiency beyond the static framework by taking into account the evolution of the environment.

We opt for a cost function that it imposes no restrictions on the functional form (Aigner et al., 1977; Meeusen and Van den Broeck, 1977).

The level of cost-efficiency is derived from the estimation of a total cost function based on the level of output(s), the price of inputs, an error term (v_{it}) and inefficiency. The form of the stochastic cost frontier of Battese and Coelli (1995) is represented by the following equation (1):

$$y_{it} = \alpha + X'_{it}\beta + Z'_{it}\gamma + \varepsilon_{it} \quad (1)$$

Where y_{it} is the total cost in logarithms of country i at time t , X'_{it} is the price matrix of outputs and inputs in logarithmic form, and Z'_{it} are bank- and environment-specific variables for country i at time t (related to inefficiency). Then the random error is defined as follows: $\varepsilon_{it} = v_{it} + \mu_{it}$, where μ is the unconditional average given to ε_{it} and takes a value between 0 and 1, and v_{it} is the usual error term.

Equations (2) and (3) give the shapes of these models under these two specifications.

$$\begin{aligned} \ln CT_{it} = & \beta_0 + \sum_{j=1}^n \beta_j \ln z_{it} + \sum_{k=1}^m \beta_k \ln x_{kit} + \frac{1}{2} \sum_j^n \sum_l^m \beta_{jl} \ln z_j \ln z_l + \frac{1}{2} \sum_k^m \sum_p^m \beta_{kp} \ln x_{kit} \ln x_{pit} \\ & + \frac{1}{2} \sum_j^n \sum_k^m \beta_{jk} \ln z_{it} \ln x_{kit} + \beta_{qt} + u_{it} + v_{it} \quad (2) \end{aligned}$$

$$\ln CT_{it} = \beta_0 + \sum_{j=1}^n \beta_j \ln(z_{it}) + (v_{it} - \mu_{it}) \quad (3)$$

In equations (2) and (3) $\ln CT_{it}$ is the logarithm of the total cost; $\ln z_{it}$ is the logarithm of the j th output ($j=1,2,\dots,n$); $\ln x_{kit}$ is the logarithm of the prices of the inputs ($k=1,2,\dots,m$); t is the year of observation; β denotes the estimated coefficients; v_{it} are random variables associated with measurement errors in the output variable or the effect of explanatory variables not specified in the model; and u_{it} represents the values of nonnegative random variables associated with the inefficiency of the inputs used in relation to the level of outputs and inputs held nearly fixed.

II.1.1. Choice of inputs and outputs

The selection of outputs and inputs is a subject of controversy among scholars. Indeed, there is no consensus on how outputs and inputs should be selected. In the face of this dilemma, two approaches are used: the production approach by Benston (1965) and Bell and Murphy (1968) and the intermediation approach by Sealy and Lindley (1977).

The intermediation approach is considered the most appropriate for measuring bank efficiency in CEMAC in this paper. There are several reasons for this choice. First, it is believed that this approach better reflects banking activity in the CEMAC region: significant collection of deposits and a nearly proportional supply of credit. Thus, the choice of variables is motivated both by the literature (the intermediation approach) and by the availability of data on the banking sector in CEMAC.

II. 1.2 Definition and measurement of variables

a) Bank Outputs

The outputs offered by CEMAC banks are classified into two categories.

- Total bank credit (TC). These include total customer credit (the discount portfolio, customer accounts receivable, credits on special resources and other customer credits). The use of this variable is also widespread, as it reflects the very *raison d'être* of banks (Bem and Kouezo, 2009).
- Total margins on miscellaneous operations (MO). Since the work of Rogers (1998), this variable has been increasingly incorporated into models estimating bank efficiency.

b) Banking inputs

The abovementioned outputs are produced by combining the production factors, namely: the labor factor "L"; the physical capital factor "K" and the financial capital factor "F". The different forms of deposits that make up financial capital are considered as an input, as stipulated by proponents of the intermediation approach. These factors of production are measured as follows:

- Labor input (L): Labor input is measured by the number of employees (De Bandt and Davis, 2000). The total number of employees seems to be the most widely adopted measure of this input.
- However, since these data are difficult to obtain, apart from in certain works, we use total assets following Lapteacru and Lahet (2014). Indeed, these authors believe that the larger the bank is, the more employees it has.
- Physical capital (K): The measurement of physical capital poses a problem in the literature due to specific characteristics of banks. The works on efficiency by De Bandt and Davis (2000) and Chaffai and Dietsch (1998, 1999) do not agree on its measurement. De Bandt and Davis (2000) measured physical capital by fixed assets plus the nondepreciated depreciation account. In contrast, Chaffai and Dietsch (1998, 1999) approximate the measure of physical capital by the value of buildings and other equipment owned by banks, which usually provides an estimate of the value of physical capital. In this research, we join Chaffai and Dietsch (1999) in measuring the value of physical capital based on capital expenditures.
- Financial capital (F): Financial capital is approximated by financial resources, which are in turn approximated by total deposits. These include total short-, medium-, and long-term deposits, with the deposit variable being one of the most widely used variables in the calculation of bank efficiency.

c) Bank production costs

The endogenous variable is defined as the total cost (TC). It includes both financial and operating costs. Operating costs correspond to the expenditure on labor and physical capital:

Labor cost (LC) = wage bill (i.e., personnel costs).

Cost of physical capital factor (CK) = the ratio of other operating costs to the net operating ratio (NOR/GNP).

Finance costs (FC) are defined by interest expense or by expenses on customer transactions.

Therefore, **TC** = cost of labor factor + cost of physical capital factor + cost of financial capital factor.

d) Bank input prices

Once the costs of each bank input have been determined, we can evaluate the prices of these inputs using the formulas given by Karim et al (2010).

The formulation of these prices can be summarized as follows:

$$P_L = \frac{CL}{L} = \frac{Chp}{TA}$$

$$P_K = \frac{CK}{K} = \frac{CNE}{Depi}$$

$$P_F = \frac{CF}{F} = \frac{COC}{TD}$$

The cost function selected will include the variables presented in equations (5) and (6) described in Table 1.

Table 1: Description of variables in the SFA model

	Description	Type of variables
C	Total cost	Dependent
	Input prices	
PL	The price of labor input (PL) is calculated using total personnel costs (Chp) for total assets (ΓA) ² (Karim et al., 2010; Lapteacru and Lahet, 2014).	Independent
PK	The price of the physical capital factor (PK) takes the ratio of other operating expenses (CNE) to total fixed assets or capital expenditure (Depi)	
FCP	The financial capital factor (FCP) price is calculated by dividing total interest expense or customer transaction charges (COC) by total deposits (TD)	
	The outputs	
TC	Total bank credit	
MO	Miscellaneous operating margins	

Source: Karim et al.(2010) and Lapteacru andLahet(2014)

II.1.3. Presentation of the empirical cost-effectiveness model

The stochastic cost frontier model is used to determine the efficiency score of banks. The efficiency measure shows the position of banks in CEMAC countries relative to the frontier.

Since we do not know the true specification of these two functional forms, we present empirical models of the two functional forms represented by equations (5) and (6) for the translogarithmic function and the Cobb-Douglas function.

$$\ln C_{it} = \beta_0 + \beta_1 \ln TC_{it} + \beta_2 \ln MO_{it} + \beta_3 \ln PL_{it} + \beta_4 \ln PK_{it} + \beta_5 \ln PF_{it} + \frac{1}{2} \beta_6 (\ln TC_{it})^2 + \frac{1}{2} \beta_7 (\ln MO_{it})^2 + \frac{1}{2} \beta_8 (\ln PL_{it})^2 + \frac{1}{2} \beta_9 (\ln PK_{it})^2 + \frac{1}{2} \beta_{10} (\ln PF_{it})^2 + \beta_{11} \ln TC_{it} \times \ln MO_{it} + \beta_{12} \ln TC_{it} \times \ln PL_{it} + \beta_{13} \ln TC_{it} \times \ln PK_{it} + \beta_{14} \ln TC_{it} \times \ln PF_{it} + \beta_{15} \ln MO_{it} \times \ln PL_{it} + \beta_{16} \ln MO_{it} \times \ln PK_{it} + \beta_{17} \ln MO_{it} \times \ln PF_{it} + \beta_{18} \ln PL_{it} \times \ln PK_{it} + \beta_{19} \ln PL_{it} \times \ln PF_{it} + \beta_{20} \ln PK_{it} \times \ln PF_{it} + \varepsilon_{it} \quad (5)$$

$$\ln C_{it} = \beta_0 + \beta_1 \ln TC_{it} + \beta_2 \ln MO_{it} + \beta_3 \ln PL_{it} + \beta_4 \ln PK_{it} + \beta_5 \ln PF_{it} + \varepsilon_{it} \quad (6)$$

With

C_{it} : The function of the estimated cost of bank i in year t

TC_{it} : The total credits of banks in country i in period t

MO_{it} : The operating margins of banks in country i in period t

PL_{it} : The price of bank is labor input at period t

PK_{it} : The price of the physical capital factor of banks in country i and period t

PF_{it} : The price of a bankis thefinancial capital factor at period t

ε_{it} : The random error term

II.2 Choice of model for analyzing the effect of credit risk on efficiency

²A true wage price is the ratio of total wage expenditure to the number of employees. This latter figure is difficult to obtain. As in the vast majority of works, we use the total number of employees in the denominator. Indeed, the larger the bank is, the more employees it has.

To assess the effect of credit risk on efficiency, several regressions are used. Since the objective of this article is to determine the effect of credit risk on bank efficiency, the authors identify several models, including ordinary least squares (OLS) and tobit. Tobit regression is more suitable for this analysis than a simple least squares regression because it allows regressions with a limited dependent variable. Thus, the tobit model proposed by Tobin (1958), used by Rosett and Nelson (1975) and later adopted by Greene and Hensher (2003) makes it possible to describe the relationship between a dependent variable and a set of exogenous variables.

II.2.1 Theoretical model of the effect of credit risk on bank efficiency

The Tobit model is used in this research since the efficiency scores fall between zero and one. This model implies the notion of selection, which results from the fact that the ability to observe a phenomenon is not independent of the phenomenon itself.

Specifically, the tobit model assumes an unobservable latent variable, EFF_i^* , linearly related to a set of independent variables, X_i , through a coefficient vector. More formally, the standard Tobit model can be defined as follows:

$$EFF_i^* = \beta' X_i + \varepsilon_i, \varepsilon_i \sim N(0, \sigma^2) \text{ if } 0 < EFF_i^* < 1 \quad (1)$$

$$EFF_i = 0 \text{ if } EFF_i^* = 0$$

$$EFF_i = 1 \text{ otherwise}$$

Here EFF_i^* representing represents the scores of the stochastic frontier efficiency estimation, β represents a vector of parameters to be estimated, X is a vector of explanatory variables, and ε_i represents a normally distributed error term.

II.2.2 Choice of variables for the level of bank inefficiency

The choice of variables is important when using an econometric model. Referring to previous empirical work (Koju et al., 2018), we define the variables used in this research.

- SCR: The ratio of distressed loans to total loans; the more banks accumulate distressed loans, the more inefficient they are in terms of cost (Athanasoglou et al., 2008).
- Credit-to-deposit ratio (CDR): This measures total loans granted relative to total deposits received. A higher credit-to-deposit ratio indicates that deposits are mobilized to generate revenue and increase efficiency. However, a lower loan-to-deposit ratio indicates inefficiency in resource allocation and low profit. Based on the empirical work of Jameel (2014) and Anjom and Karim (2016), the credit-to-deposit ratio has a negative relationship with distressed claims.
- Inflation: Consumer price index; low inflation provides a favorable environment for banks to improve their efficiency (Vu and Nahm, 2013)
- LGDP: The logarithm of gross domestic product; the level of GDP affects the efficiency of banks (Thoraneenitiyan and Avkiran, 2009).
- CNE: The net cost-to-income ratio is the ratio between net banking income and overhead.
- ROE: Return on equity measures the ratio of banks' equity to net income. Authors such as Akin et al. (2009) and Vu and Nahm (2013) report a positive relationship between efficiency and ROE.
- Interest Margins (IM): This is the difference between the interest received and the interest paid by a bank, i.e., the difference between the interest rate at which banks lend and the interest rate at which they refinance themselves (Were and Wambua, 2014).

II.2.3 Empirical model for the analysis of the effect of credit risk on efficiency

The Tobit regression model used to estimate the effect of credit risk on efficiency is as follows:

$$EFF_{it} = \alpha_0 + \delta_1 RCS_{it} + \alpha_1 RCD_{it} + \alpha_2 inflation_{it} + \alpha_3 CNE_{it} + \alpha_4 lPIB_{it} + \alpha_5 MI_{it} + \varepsilon_{it}$$

II.2.4 Data sources and descriptive analyses

This test mainly uses data from COBAC's annual reports from 2004 to 2017 from the banks of six (6) CEMAC³ countries. The data on the ratios of the claims in distress to credits granted are used as measures of the credit risk of the banks of CEMAC.

³They are Cameroon, Central African Republic, Chad, Republic of Congo, Equatorial Guinea and Gabon.

The descriptive statistics for the different inefficiency variables are summarized in the following table. In addition, statistics on the efficiency scores of banks are issued after the functional form specification tests.

Table 2: Descriptive statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
SCR	13.0126	8.3623	1.3863	34.5650
CDR	71.2334	28.4986	25.9395	177.3103
Inflation	3.1652	3.2777	-7.4000	17.8390
IGDP	10.5754	6.1904	5.7054	24.3167
ROE	20.6140	12.8969	-9.9202	65.7643
IM	8.4490	1.7968	5.6400	14.5100
CNE	52.5256	9.3912	24.4400	73.6800

Source: Author's calculation

The above table reveals that most of the variables are distributed in a dispersed manner because the standard deviations of these different variables are found to be lower than their means. However, there is a fairly significant difference between the minimums and maximums of the variables studied.

When estimating the stochastic frontier, the choice of a functional form is necessary. To make this choice, we pose the following test to be able to choose between the functional forms of the stochastic cost frontier model:

$$\left\{ \begin{array}{l} H_0: \beta_{11} = \beta_{22} = \beta_{33} = \beta_{12} = \beta_{13} = \beta_{23} = 0 \Rightarrow \text{Specification Cobb Douglas} \\ H_1: \exists_{ij} \beta_{ij} \neq 0 \Rightarrow \text{Specification translog} \end{array} \right.$$

Under the null hypothesis (H0), the parameters associated with the squared and cross-term variables are not significantly different from 0, suggesting a Cobb-Douglas specification. Table 3 sets out the specification hypothesis test

Table 3: Hypothesis testing of model specification

	Cobb Douglas	Translog
Log likelihood (lnL)	8.7429	52.5955
LR = -2*(lnL _{Cobb} - lnL _{Translog})		87.71
Value read from table		23.21
Decision		Rejection of H ₀

Source: Author's calculation

The value of the LR statistic obtained is 87.71, higher than the value read on the Chi-Square table at the 1% level at 10 degrees of freedom (23.21). Consequently, we adopt the translog functional form for the specification of the stochastic frontier. Thus, the following table shows the descriptive statistics of the variables in the translog cost function.

Table 4: Descriptive statistics of the translog cost function

Variable	Mean	Standard Error	Minimum	Maximum
Outputs				
TC	776876.8	725981.2	60188	3078827
MO	38800.83	30156.37	1247	123077
Inputs				
TA(L)	1402430	1176755	59485	4601043
Depi(K)	88421.18	95910.22	3306	384363
TD(F)	1190537	969966.7	33945	3537216
Input costs				
chp (CL)	22538.04	23052.62	1331	103784
CNE(CK)	52.52563	9.391176	24.44	73.68
COC(CF)	21625.4	44096.71	715	198586
Input prices				
PL	0.01756	0.009978	0.005914	0.091992
PK	0.002255	0.003207	0.000142	0.016824
PF	0.013427	0.013259	0.002255	0.059473

Source: Author's calculation

III. Economic policy outcomes and implications

This subsection is composed of two points, namely the presentation of the results and the economic policy implications.

III.1 Presentation of results

The results obtained are presented in two different ways. The first results obtained refer to the results of the estimation of the stochastic cost frontier. The second results show the effect of credit risk on the efficiency score of CEMAC banks. These are presented in Table 5.

III.1.1 Results of the translog function

The results of the translog cost function are presented in Table 5.

Table 5: Results of the estimation of the banks' translog cost function

Variables	Coefficients	Standard Error
ITC	1.989**	0.948
IMO	-3.791***	1.331
IPL	6.357***	1.610
IPK	-2.589**	1.279
IPF	-1.577**	0.794
ITC_ITC	0.233*	0.129
IMO_IMO	0.300	0.310
IPL_IPL	0.493**	0.218
IPK_IPK	-0.0763	0.257
IPF_IPF	0.128*	0.0705
ITC_IMO	-0.230*	0.130
ITC_IPL	0.464*	0.242
ITC_IPK	0.141	0.147
ITC_IPF	-0.127	0.129
IMO_IPL	-1.474***	(0.258)
IMO_IPK	-0.122	(0.241)
IMO_IPF	0.507***	(0.127)
IPL_IPK	-0.638***	(0.197)
IPL_IPF	-0.141*	(0.0749)
IPK_IPF	0.231**	(0.0974)
Diagnostic statistics		
Sigma_u 0.0642		
Sigma_v 0.0609		
lambda 1.0540		
Prob > chi2 = 0.000		
Log likelihood =84.436		

Source: Author's calculation; *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The results of this table show that the coefficients of outputs and input prices are significant at the 1% and 5% levels. The coefficient of the price of labor (PL) is the highest (6.357). The estimation of the stochastic cost function allowed the calculation of the banks' cost efficiency scores. The average cost efficiency score for all CEMAC banks is 92.38%, which means that banks can further reduce their input mix by 7.62% to improve their efficiency level. This score is between 0.65 and 0.99.

Table 6: Descriptive statistics of the average score of the banks

Variables	Mean	SD	Minimum	Maximum
Efficiency score	0.9238	0.0765	0.6576	0.9980

Source: Author's calculation

The results obtained from the Tobit regression are as follows.

Table 7: Results of estimates of the effect of credit risk on bank efficiency

Variables	Coefficient	Standard Error
RCS	-0.003***	0.001
RCD	0.001***	0.000
Inflation	0.001***	0.001
CNE	-0.002	0.000
IPIB	0.006	0.001
ROE	0.001***	0.000
MI	-0.002	0.004
Constant	0.875***	0.068
Parameters		
sigma_u	0	0.0405
sigma_e	0.0559***	0.00438

Source: Author's calculation

Wald chi2 (7) = 75.79

Log likelihood = 118.296 Prob > chi2 = 0.000 Note: The values in brackets indicate significant p-values at the 1% (***) and 5% (**) levels.

An analysis of this table reveals the presence of several variables significant at the 1% level that have a negative or positive influence on bank efficiency. Thus, the results obtained show on the one hand that CEMAC banks are inefficient in terms of cost. Indeed, the scores of CEMAC banks are between 0.657 and 0.997. Thus, the result found relative to the border yields a difference of 0.3% to 34.3%.

There is an overuse of inputs of the order of 0.3% to 28% depending on the country. On the other hand, the credit risk negatively influences the efficiency of CEMAC banks. This result can be explained by the fact that banks use more deposits or inputs to monitor credit. Thus, mismanagement within these banks may stem from the poor assessment of borrowers' credit risk. Therefore, inefficiency is usually accompanied by poor risk management and thus by an increase in bad loans. These results confirm the results obtained by other authors in different banking sectors. This literature has shown that poor asset quality is the main source of bank failure (Kamgna and Dimou, 2008; Karim et al., 2010; Partovi and Matousek, 2019).

The results suggest that specific policy implications are worth pursuing. They can be broadly defined in terms of minimizing expenditure in terms of inputs. Banks can reduce their spending by 0.3% to 28% to adopt the most efficient choices. Indeed, they must reduce costs by implementing an optimal input reduction policy to achieve optimality. Input reduction can be achieved by taking into account the price of labor (PL). Another important improvement is strengthening the banks' information asymmetry reduction tools. Indeed, banking efficiency through credit risk is managed by effective control of information asymmetries.

Conclusion

The objective of this paper is to determine the effect of credit risk on the efficiency of CEMAC banks. Based on data from COBAC's annual reports between 2004 and 2017, we estimate their cost efficiency. The efficiency scores are then used in the second stage of the Tobit analysis to determine the effect of credit risk on banking efficiency. The empirical results of the efficiency frontier estimates indicate scores between 0.765 and 0.997 for all CEMAC banks. This result shows that banks have not been able to manage to maximize their outputs given the available inputs. Consequently, improvement in the banks' efficiency is linked to a reduction in production costs.

The Tobit regression results clearly indicate that increasing the level of distressed claims reduces cost efficiency. Consequently, CEMAC banks are called upon to improve their efforts to build up sufficient provisions to cover themselves against potential risks. From these results, banks can achieve optimality by implementing a policy of cost reduction and addressing information asymmetry.

References

- Altunbas, Y., Liu, M. H., Molyneux, P., & Seth, R. (2000). Efficiency and risk in Japanese banking. *Journal of Banking & Finance*, 24(10), 1605-1628.
- Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics*, 6(1), 21-37.
- Akin, A., Kiliç, M., & Zađm, S. (2009). Determinants of Bank Efficiency in Turkey: A Two Stage Data Envelopment Analysis. In *International Symposium on Sustainable Development* (pp. 32-41).
- Anjom, W., & Karim, A. M. (2016). Relationship between non-performing loans and macroeconomic factors with bank specific factors: a case study on loan portfolios—SAARC countries perspective. *ELK Asia Pacific Journal of Finance and Risk Management*, 7(2), 1-29.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, 58(2), 277-297.
- Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of international financial Markets, Institutions and Money*, 18(2), 121-136.
- Batir, T. E., Volkman, D. A., & Gungor, B. (2017). Determinants of bank efficiency in Turkey: Participation banks versus conventional banks. *Borsa Istanbul Review*, 17(2), 86-96.
- Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical economics*, 20(2), 325-332.
- Bell, F. W., & Murphy, N. B. (1968). Economies of scale and division of labor in commercial banking. *Southern Economic Journal*, 131-139.
- Bem, J., & Kouezo, B. (2008). Les déterminants de l'efficacité des banques de la CEMAC. *Document de Travail de la COBAC, DT*, 8(02).
- Benston, G. J. (1965). Branch banking and economies of scale. *The Journal of Finance*, 20(2), 312-331.
- Berger, A. N., & Humphrey, D. B. (1992). Measurement and efficiency issues in commercial banking. In *Output measurement in the service sectors* (pp. 245-300). University of Chicago Press.
- Bopkin, G. A. (2013). Ownership structure, corporate governance and bank efficiency: an empirical analysis of panel data from the banking industry in Ghana. *Corporate Governance: The International Journal of Business in Society*, 13(3), 274-287.
- Chaffai, M. (1998). Estimation des inefficiences techniques et allocatives des banques de dépôts tunisiennes: une frontière de coût fictif. *Économie & prévision*, 136(5), 117-129.
- Chaffai, M. E., & Dietsch, M. (1999). Mesures de l'efficacité technique et de l'efficacité allocative par les fonctions de distance et application aux banques européennes. *Revue économique*, 633-644.
- Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer Science & Business Media.
- De Bandt, O., & Davis, E. P. (2000). Competition, contestability and market structure in European banking sectors on the eve of EMU. *Journal of Banking & Finance*, 24(6), 1045-1066
- Du, K., & Sim, N. (2016). Mergers, acquisitions, and bank efficiency: Cross-country evidence from emerging markets. *Research in International Business and Finance*, 36, 499-510.
- Fan, L., & Shaffer, S. (2004). Efficiency versus risk in large domestic US banks. *Managerial Finance*.
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, 120(3), 253-281.
- Fiordelisi, F., & Molyneux, P. (2011). The determinants of shareholder value in European banking. *Journal of Banking & Finance*, 34(6), 1189-1200.

- Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological*, 37(8), 681-698.
- Hughes, J. P., W. Lang, L.J. Mester, and C-G. Moon,(1996) "Efficient Banking Under Interstate Branching", *Journal of Money, Credit, and Banking*, 28 (November 1996).
- Jameel, K. (2014). Crucial factors of nonperforming loans evidence from Pakistani banking sector. *International Journal of Scientific & Engineering Research*, 5(7).
- Kamgna, S. Y., & Dimou, L. (2008). Technical Efficiency of the Banks of the CEMAC. MPRA Paper, (9603).
- Karim, M. Z. A., Chan, S. G., & Hassan, S. (2010). Bank efficiency and non-performing loans: Evidence from Malaysia and Singapore. *Prague Economic Papers*, 2(1), 118-132.
- Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American economic review*, 1183-1200.
- Koju, L., Koju, R., & Wang, S. (2018). Macroeconomic and Bank-Specific Determinants of Non-Performing Loans: Evidence from Nepalese Banking System. *Journal of Central Banking Theory and Practice*, 7(3), 111-138.
- Lapteacru, I., & Lahet, D. (2014). Efficiency et pouvoir de marché des banques en Thaïlande suite aux crises financières. *Revue économique*, 65(5), 675-698.
- Lown, C., & Peristiani, S. (1996). The behavior of consumer loan rates during the 1990 credit slowdown. *Journal of Banking & Finance*, 20(10), 1673-1694.
- Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International economic review*, 435-444.
- Mester, L. J. (1996). A study of bank efficiency taking into account risk-preferences. *Journal of banking & finance*, 20(6), 1025-1045.
- Moon, C. G., & Hughes, J. P. (1997). Measuring bank efficiency when managers trade return for reduced risk (No. 199520).
- Nguyen, P. A., & Simioni, M. (2015). Productivity and efficiency of Vietnamese banking system: new evidence using Färe-Primont index analysis. *Applied economics*, 47(41), 4395-4407.
- Partovi, E., & Matousek, R. (2019). Bank efficiency and non-performing loans: Evidence from Turkey. *Research in International Business and Finance*, 48, 287-309.
- Pastor, J. M. (1999). Efficiency and risk management in Spanish banking: a method to decompose risk. *Applied financial economics*, 9(4), 371-384.
- Podpiera, J., & Weill, L. (2008). Bad luck or bad management? Emerging banking market experience. *Journal of financial stability*, 4(2), 135-148.
- Ramli, N. A., Mohammed, N. I., Hussin, S. A. S., & Khairi, S. S. M. (2018, July). Investigating the effect of non-performing loans on technical efficiency in Malaysian banking sector. In *AIP Conference Proceedings* (Vol. 1982, No. 1, p. 020008). AIP Publishing LLC.
- Rogers, K. E. (1998). Nontraditional activities and the efficiency of US commercial banks. *Journal of Banking & Finance*, 22(4), 467-482.
- Rosett, R. N., & Nelson, F. D. (1975). Estimation of the two-limit probit regression model. *Econometrica: Journal of the Econometric Society*, 141-146.
- Sealey Jr, C. W., & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *The journal of finance*, 32(4), 1251-1266
- Thoraneenitiyan, N., & Avkiran, N. K. (2009). Measuring the impact of restructuring and country-specific factors on the efficiency of post-crisis East Asian banking systems: Integrating DEA with SFA. *Socio-Economic Planning Sciences*, 43(4), 240-252.
- Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: journal of the Econometric Society*, 24-36.
- Vu, H., & Nahm, D. (2013). The determinants of profit efficiency of banks in Vietnam. *Journal of the Asia Pacific Economy*, 18(4), 615-631.
- Were, M., & Wambua, J. (2014). What factors drive interest rate spread of commercial banks? Empirical evidence from Kenya. *Review of development Finance*, 4(2), 73-82.
- Williams, J. (2004). Determining management behavior in European banking. *Journal of Banking & Finance*, 28(10), 2427-2460.
- Win, S. (2018). Banks' lending behavior under repressed financial regulatory environment. *Pacific accounting review*.