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INFLUENCE OF EFFICIENCY MEASURES AND BANK CATEGORIES ON NON-PERFORMING LOANS THRESHOLD AMONG COMMUNITY BANKS IN TANZANIA

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ABSTRACT
Over the past twelve years Non-Performing Loans (NPLs) ratio in Community Banks (CBs) has been above the threshold of the overall bank industry. Operating above the NPLs industry ratio threshold connotes potential danger while the contrary is core for maintaining a safe loan portfolio. This study examined the influence of CBs' efficiency measures and bank categories on the NPLs ratio threshold using unbalanced panel data from 9 CBs in a span of 17 years. Probit regression modelled the relationship between variables. The study establishes that Technical efficiency under Constant Returns to Scale (TeCRS) increased the probability of CBs to operate within NPLs threshold, while Scale efficiency (SE) and Technical efficiency under Variable Return to Scale (TeVRs) decreased the chances. Furthermore, Co-operative Community Banks (CCBs) had lower chances to NPLs threshold compared to Non-Co-operative Community Banks (NCCBs). The results are consistent with moral hazard hypothesis. The policy implications are that, bank regulators (BOT) should control CBs' undue expansion to limit overstretching their capacity. Furthermore, CBs should fortify group lending methodologies in dealing with small borrowers. Moreover, bank regulators should reinforce capital adequacy regulations to curb excessive risk taking in CCBs in order increase probability to operate within NPLs threshold.

***Key words**: Community Banks, efficiency measures, NPLs threshold; marginal effects, Tanzania.*
***Paper type**: Research paper*
***Type of Review:** Peer Review*

1. INTRODUCTION

Community banks (CBs) have continued to bloom in various countries amid uphill battle against fierce competition, low capitalization and increasing NPLs (Petach, Weiler and Conroy, 2021; Balla and Rose, 2019; Mckee and Kagan, 2018). The size of these challenges and the extent to which they impact on CBs differ in different countries, depending on the level of the financial system in which they operate (Awo and Akotey, 2019; Adusei, 2016). While the major challenge facing CBs in highly developed financial systems have been stiff competition from well capitalized and technologically advanced bank chains, CBs in developing countries including Tanzania suffer from low capitalization and increasing NPLs (Chou and Buchdad, 2016; BOT, 2015).In Tanzania[i], increasing NPLs in CBs has been coupled with low levels of efficiency (Mataba, 2019; Mataba, Aikaeli and Kirama, 2018). BOT (2015) defines NPLs as loans whose principal or interest remains unpaid90 days or more after due date. The rule of thumb is that NPLs ratio should not exceed 5% benchmark (Kjosevski and Petkovski 2017; Malimi, 2017; BOT 2015).

Over the past 12 years, the NPLs ratio in Tanzanian CBs[ii] has been adverse when compared with the Industry Average (IA) NPLs ratio. Figure 5.1, depicts the NPLs ratio trend in CBs against the IA NPLs ratio.

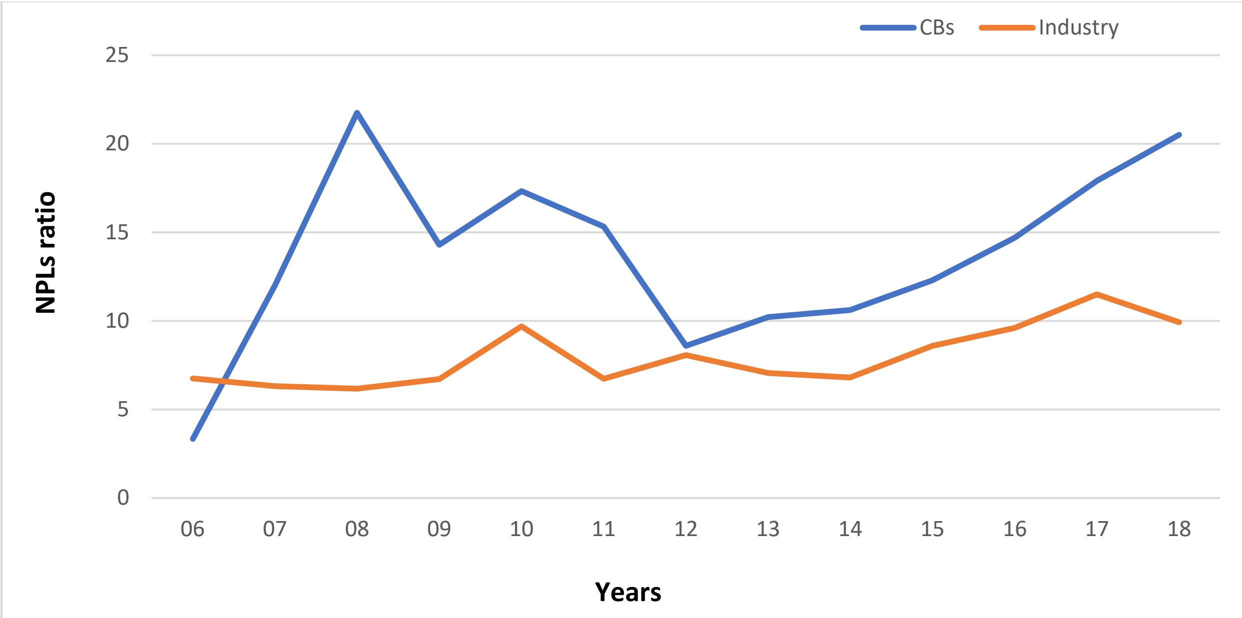

Figure 1: Comparison of NPLs ratio in CBs against industry average over 2006-2014 period

NPLs ratio in CBs increased from 3.33% in December 2006 to 21.76% in December 2008 against and industrial average (IA) of 6.75% to 6.18% respectively during the same period. Although CBs NPLs ratio seemed to subside in 2011 and 2012, the ratio was still far above the industry average NPLs ratio. For instance, while the IA NPLs ratio in 2011 and 2012 were 6.75 and 8.07% respectively, the NPLs ratio in CBs was 15.32 and 8.6% respectively. Thereafter, NPLs in CBs increased unproportionally relative to the industrial average as indicated in figure1. High NPLs ratio in Tanzanian community banks above the industry standards for such a protracted period is an indicator of evolving problem loans in the community banking sector that calls for in-depth study.

Previous studies have concluded that there is a relationship between NPLs and efficiency, albeit under different hypotheses or assumptions (Kingu, Macha and Gwahula 2018;Podpiera and Weill, 2008; Berger and DeYoung, 1997). These assumptions have generally been categorized under two main camps, namely "bad management" and "bad luck" hypotheses. However, to the author's knowledge, the NPLs-efficiency relationship studies have so far been limited to one efficiency measure, the Cost Efficiency (CE). Other efficiency measures, namely Scale Efficiency (SE) and Technical Efficiency (TE), which provide additional empirical and theoretical insights in the bank NPLs-efficiency relationships, have not been examined. This leaves gap as to the effects of other efficiency measures on NPLs.

Moreover, CBs in Tanzania exist in two categorical forms, namely; Cooperative-based Community Banks (CCBs) and Non-Cooperative Community Banks (NCCBs). Further, these CBs have been initiated in different financial (banking) reform phases, namely; first and second financial reforms in 1991 and 2002 respectively. Based on bank type and the reform phase in which the CBs were initiated, three categories of CBs were identified for the purpose of this study. These categories are Co-operative Community Banks (CCBs), Non-Cooperative Community Banks initiated in the first banking reform phase (NCCBs1), and Non-Co-operative Community Banks initiated in the second banking reform phase (NCCBs2). Thus, further inclusion of bank categories in the study might provide additional insight on the relationship between NPLs and efficiency in the community banking sub-sector.

In order to utilize an appropriate benchmarking ratio that reflects the dynamic banking industry situation in the country, this paper adopted the Industry Average NPLs ratio (IA NPLs ratio) rather than a static NPLs ratio benchmark of 5%. In this paper, NPLs threshold is defined as the NPLs ratio equal or below the IA NPLs ratio, expressed as NPLs threshold $\leq$IANPLsRt. Operating within the NPLs industrial threshold is important for gauging CBs performance against the industry and also for increasing the chances for a safe loan portfolio (BOT, 2015).

As community-based organisations, CBs are vital due to provision of financial services to the local communities (Petach, Weiler and Conroy, 2021; Mckee and Kagan, 2018; John, Gerald and Boris, 2017). Consequently, CBs have continued to attract the debate attention of policy makers, development bankers and academicians worldwide (Sofyan, 2019; Danquah, Quartey and Iddrisu, 2017; Boadi, Li and Lartey, 2016; Jagtian and Lemieux, 2016). The debate centres on CBs' regulatory costs, competitiveness, and efficiency issues. The major question has been whether CBs can endure competitive pressures in the wake of restructuring and heavy investment in technology made by larger banks in developed countries after the 2008 financial crisis. While this debate has been active in the US and other developed countries, there has been no serious debate on the plight of CBs in developing countries like Tanzania despite their importance in providing regulated financial services in the rural agricultural sector. Given that these banks face numerous challenges related to increasing NPLs and low capitalization, the study contributes to this debate by examining the relationship between efficiency and NPLs. A special contribution is centred on the relationship between efficiency and NPLs ratio threshold while reflecting on various categories of CBs.

This study expands the frontier of knowledge on the relationship between bank efficiency and NPLs ratio in two dimensions. First, unlike the previous studies which have generally dwelt on larger Traditional Commercial Banks (TCBs), the sample includes smaller banks, that is, Community Banks (CBs). Second, contrary to previous studies (Awo and Akotey, 2019; Jolevski, 2017; Sapci, and Miles, 2017; Adusei, 2016) the study investigates efficiency–NPLs relationship by involving a broader set of efficiency measures and various CBs categories. While previous studies mostly dwelt on the effect of cost and/or revenue efficiency on NPLs (Partovic and Matousek, 2019;Grmanová and Ivanová, 2018; Mataba and Aikaeli, 2016), this study focused on the effect of various efficiency measures and CBs categories on NPLs threshold using binary regression model. Studies on the effect of efficiency on NPLs threshold are important in order to establish how various efficiency components impact on the probability of CBs to reducing NPLs risk situation. Further, the effects of bank categories on NPLs threshold are vital for informed policy solutions (Petach, Weiler and Conroy, 2021;Oteng-Abayie, Affram and Mensah, 2018). Accordingly, the main objective of the paper was to examine the influence of bank efficiency measures and bank categories on NPLs threshold in CBs in Tanzania. Specifically, the paper analysed the effects of cost, technical, and scale efficiency measures and bank categories on NPLs threshold among community banks in Tanzania.

2. THEORETICAL FOUNDATIONS

2.1 Bank efficiency concepts

The bank's efficiency is a comparison between observed and optimal values of outputs and inputs. The set of the optimal outputs, given the inputs constitutes the efficient frontier. According to Farrell (1957), efficiency of any firm consists of two components: (i) technical efficiency, the ability of the firm to maximize outputs from the given set of inputs; and (ii) allocative efficiency, the ability of the firm to allocate resources in optimal proportion given their respective prices. When the two components are combined, they provide a measure of economic efficiency, which is also known as productive or overall efficiency.

An alternative measure of economic efficiency is cost efficiency. Cost Efficiency (CE) gauges how far a bank's costs deviate from the best practice bank's costs, producing at the same level of output and under the same environmental conditions (Oteng-Abayie, Affram and Mensah, 2018; Psillaki and Mamatzakis, 2017). CE can be decomposed into technical efficiency and allocative efficiency. The level of technical efficiency is usually related to managerial decision making, while allocative efficiency is usually related to regulatory environment or macroeconomic conditions (Hung-pin and Kumbhakar, 2019; Asghar, Sasaki, Jourdain, and Tsusaka, 2018; Decker, Haltiwanger, Jarmin, and Miranda, 2017; Lovell, 1993).

Technical efficiency under the assumption of constant returns-to-scale (CRS) is known as a measure of overall technical efficiency (TeCRS). The TeCRS helps to determine inefficiency due to the input/output configuration as well as the size of operations. In Data Envelopment Analysis (DEA), TeCRS has been decomposed into two components: pure technical efficiency (PTE) and Scale Efficiency (SE). The PTE, known as Technical efficiency under Variable Returns to Scale (TeVRS) is obtained by estimating the efficient frontier under the assumption of variable returns-to-scale. It is a measure of technical efficiency without scale efficiency and purely reflects the managerial performance to organise the inputs in the production process. Thus, PTE or TeVRS has been used as an index to capture managerial performance.
The ratio of TeCRS to TeVRS provides Scale Efficiency (SE) measure. The SE provides the ability of the management to choose the optimum size of resources, that is, to choose the scale of production that will attain the expected production level (Kumar and Gulati, 2008). Previous studies have examined the relationship between cost efficiency and NPLs, leaving an empirical gap on the relationship between other efficiency measures (Scale, TeCRS and TeVRS) and NPLs ratio threshold. This study sets to uncover the effect of scale and technical efficiency on performance of CBs in terms of NPLs. Consequently, the following Null Hypothesis is advanced:

> *H_{O1}: Bank efficiency measures (Scale, TeCRS and TeVRS) do not significantly influence NPLs ratio threshold in CBs.*

2.2 Information asymmetry theory
This study is guided by asymmetric information theory which was jointly developed by George Akerlof, Michael Spence and Joseph Stiglitzin the 1970s and 1980s to address market failure. Market failure refers to a situation where the pricing mechanism fails to efficiently allocate resources in the free market. The theory was developed as a plausible explanation of the market failure in the credit market. Two information problems are predominant in lending market: lack of information on the borrowers' characteristics (which leads to adverse selection) and lack of information on the value of the project (which leads to moral hazard behavior). Lenders cannot adequately assess the resolve or commitment of the borrowers to make loan repayments; and lenders have incomplete information on the value of investment projects to be financed. The theory postulates that NPLs are a result of the failure of the banking institutions' management to make informed lending decisions due to imbalanced information which may lead to NPLs in banks.

Berger's and De Young (1997) contributing to the information asymmetry theory proposed four complementing postulations, namely "bad management", "bad luck", "skimping" and "moral hazard" hypotheses in explaining the root causes of NPLs in banks. While the bad management and bad luck hypotheses attempt to explain the incidence of NPLs from both internal management failure and external influence respectively, the skimping and moral hazard hypotheses focus on the behavior of managers in controlling NPLs; and the two hypotheses are set to inform this study. Skimping relates to a state where bank managers attempt to minimize costs in order to attain cost efficiency. However, in doing so they compromise the loan appraisal and monitoring efforts, thus leading to increased NPLs. On the other hand, moral hazard behavior is associated with excessive risk taking by banks. Low capitalized bank managers could be “incentivized” by the “nothing to lose attitude” and hence involve themselves in excessive risk taking. If excessive risk-taking behaviour applies in loan issuance it may lead to increased NPLs, which in turn results into the failure to operate within the NPLs ratio threshold.

Over a span of years capitalization ratio in co-operative community banks (CCBs) has been lower comparable to similar ratios in non-co-operative community banks (NCCBs). For instance, prior to the revoke of licenses of some community banks by the Bank of Tanzania (BOT) in 2018 for failure to comply with minimum capital requirement regulation of 2014, capital adequacy ratio for CCBs was 3.68% while that of NCCBs was 4.73%. Although the capitalization ratios for both categories were lower than the required minimum of 14.5% as per the BOT capital adequacy Regulations of 2014, the NCCBs capitalization ratio was better. Based on this exposition, this study advances the following null hypothesis:

H_{O2}: Community bank categories do not significantly influence NPLs ratio threshold.

3.0 METHODOLOGY

3.1 Research Design, Study Period and Data

The study covered the period from the year 2002 to 2018 and captured the effects of first and second financial (banking) reform phases in Tanzania. The study employed explanatory sequential research design by which key results generated from analysis of secondary data were triangulated by findings generated from interviews conducted with key informants in CBs. Secondary data, which were the main source of information for this study, were obtained from Bank of Tanzania (BOT) repositories an dfrom audited accounts in respective CBs. Only community banks with industrial experience of five years and beyond were included in the sample as lower experiences of less than five years may not be appropriate for gauging bank performance. The final sample consisted of an unbalanced panel of 9 CBs in the period 2002-2018 with a total of 118-bank –year observations.

3.2 NPLs Threshold and Choice of a Model

The dependent variable, (NPLsRtP*) is binary as it assumes two states, namely NPLs threshold, which takes value=1; while NPLs above NPLs threshold takes value=0. To work out the NPLs threshold, the average of the total sum of each end of the year industry average NPLs ratio (EYIA) in the overall banking industry was calculated. End of the year industry average NPLs ratio (EYIA) was readily available in the data. The study utilized the overall banking Industrial Average NPLs ratio (IANPLsRt) in order to reflect the overall regulatory requirements which do not provide separate regulatory framework when benchmarking NPLs ratio.

Thus, NPLs threshold $\leq$ IANPLsRt= $\dfrac{\sum_{i=1}^{n} EYIA}{n}$ ……………………………………(1)

Where:
EYIA= End of year Industry Average NPLs ratio in the whole banking industry
n= number of years in the study period.

To model the relationship between the binary dependent variable and the independent variables the univariate binary response probit model was employed. One of the main advantages of probit models is that they enable a researcher to calculate marginal effects and allow the use of panel data (Qiu, Song and He, 2019; Mbembela, 2019; Maguza-Tembo, Mangison, Edris and Kenamu, 2017). In probit model the observable outcomes of the binary choice problem are represented by a binary indicator variable Y_i that is related to unobserved dependent variable Y*. The probit model for this study is expressed as:

$$Y = \begin{cases} 1 \ if \ Y^* \leq IANPLsRt \\ 0 \ otherwise \end{cases} \quad \ldots\ldots(2)$$

Modelling the conditional probability of "success", that is when $Y_i = 1$

$$\Pr(Y_i = 1 | X_{1i} \ldots X_{ki}; \beta_0, \ldots, \beta_K) = \Phi\left(\beta_0 + \sum_{k=1}^{K} \beta_K X_{Ki}\right) \quad \ldots\ldots(3)$$

Where Pr denotes probability and Φ (.) is the cumulative distribution function of the standard normal distribution. This implies that, the probability that the outcome variable Y_i is 1 is a certain function of linear combination of the independent variables (regressors). The parameters β_i are estimated by Maximum Likelihood (ML) method. The marginal effects of the regressors implies that, when you change one unit of the regressor, how much will be change in the conditional probability of the outcome variable, holding all other regressors constant at some values. The marginal effect is given by:

$$\frac{\partial \Pr(Y_i = 1 | X_{1i}, \ldots, X_{Ki}; \beta_0, \ldots, \beta_K}{\partial X_{ki}} = \beta_k \phi(\beta_0 + \sum_{k=1}^{K} \beta_k X_{ki} \quad \ldots\ldots(4)$$

Where $\phi(.)$ is the standard normal probability density function. In case of categorical independentvariables X_{ki}, the discrete change is:

$$\Delta \ X_{ki} \Pr(Y_i = 1 | X_{1i}, \ldots, X_{Ki}, \ldots, \beta_0, \ldots, \beta_K) = \beta_k \phi(\beta_0 + \sum_{l=1}^{k-1} \beta_l X_{li} + \beta_k + \sum_{l=k+1}^{K} \beta_l X_{li}) \quad \ldots\ldots(5)$$

3.3 Variable Definitions and Modelling the Relationships

Two groups of independent variables were identified, namely efficiency measures (which are continuous) and bank categories (which are categorical). Efficiency components are Cost Efficiency (CE); Technical efficiency under Constant Returns to Scale (TeCRs); Technical efficiency under Variable Returns to Scale (TeVRS); and Scale Efficiency (SE). These were obtained through DEA estimation method. Three categories of Community Banks (CBs) were identified. The first category, which serves as the reference category involves Co-operative Community Banks (CCBs). These banks were initiated in the first-generation banking reform in Tanzania. The first-generation reforms stated in 1991 when the Banking and Financial Institutions Act (BAFIA) was enacted. The second category (NCCBs1) involves Non-Co-operative Community Banks which were also initiated in the first-generation financial reforms. The last category (NCCBs2), which also entails Non-Co-operative Community Banks, includes all CBs that were initiated in the second-generation reforms which started in 2002. The second-generation reforms, which were introduced in 2002, focused on addressing banking dynamism and efficiency, increasing the depth of full-fledged market-based financial system and improving access to financial services by the majority, especially in the rural sector. The relationship between the dependent variable and efficiency measures and bank categories (independent variables) is modelled as follows:

$$NPLsRtP_{it} = X_{it}^{T} \beta + \xi_{it} = \beta_0 + \beta_1 CE_{it} + \beta_2 TeCRS_{it} + \beta_3 TeVRS_{it} + \beta_4 SE_{it} + \beta_5 NCCBs1_{it} + \beta_6 NCCBs2_{it} + \xi_{it} \quad \ldots\ldots(6)$$

Where $X_{it}^{T} = (1X_{it}, X_{2it}, \ldots, X_{kit})$, a 1xK row vector of independent variables for observation i over time t. Note that, with more than one dummy variables, we introduce (m-1) dummy variables to avoid the "dummy variable trap" that may lead to perfect collinearity problem (Gujarati, 2012). Since three dummies were involved, only two dummies were thus introduced in equation 6. The category for which no dummy variable was introduced, the CCBs, was thus referred to as the reference category. Table 1 provides definitions and details of the variables in the model, and a priori expectation of the relationships between variables.

Table 1: Variables and variable definitions in Probit regression model

Variable	Definition	Unit of measurement	*A priori* expectation
NPLsRtP*	Binary dependent variable	NPLs ratio≤IANPLsRt =1, 0 otherwise	-
CE	Cost efficiency Score relative to the best bank in the year	Ratio score	Not clear
TeCRS	Technical efficiency under constant return to scale (independent)	Ratio score	(+)
TeVRS	Technical efficiency under variable return to scale (independent)	Ratio score	(+/-)
SE	Scale efficiency (independent)	Ratio score	(-)
CCBs	Independent variable proxing Cooperative Community Banks (reference category)	CCBs=1(factor variable)	-
NCCBs1	Independent variable proxing Non-Cooperative Community Banks that existed before second financial reforms	NCCBs1=2(factor variable)	(+)
NCCBs2	Independent variable proxing Non-Cooperative Community Banks that existed after the second financial reforms	NCCBs2=3(factor variable)	(+)

4.0 EMPIRICAL FINDINGS AND DISCUSSION

4.1 Descriptive Statistics for Efficiency Measures and Categorical Variables

Tables 2 and 3 provide descriptive statistics for continuous and categorical variables respectively. The dependent variable ($NPLsRtP_{it}$) is binary taking the value 0 and 1 with a mean of 0.423913. This implies that a larger proportion of bank NPLs ratios were above the NPLs threshold, which is a typical characteristic of CBs in Tanzania during the study period. The standard deviation is 0.4968847 reflecting a deviation between 0 and 1 for a binary variable.

Table 2: Descriptive statistics for continuous variables

Variable	Mean	Standard Deviation	Min.	Max.
NPLsRtP	0.423913	0.4968847	0	1
CE	0.355	0.2319036	0.00171	1
TeCRS	0.634	0.2116916	0.002366	1
TeVRS	0.698	0.2163532	0.002519	1
SE	0.919	0.1413259	0.183567	1

The means of TeCRS and TeVRS of 63.4% and 69.80% respectively are above average, reflecting moderate technical efficiency status of CBs in Tanzania. The standard deviations are as high as 23.20% and 21.17% for TeCRS and TeVRs respectively, indicating substantial dispersions of technical efficiency across CBs in Tanzania. However, the mean of SE of 91.9% is relatively high, implying that CBs in Tanzania have been using effectively the production opportunities to generate scale advantages. In respect of categorical variables as presented in Table 3, observations for CCBs were 33 which constitute 27.11% of all CBs observations. Observations for NCCBs1 were 61 which represent 51.70% while observations for NCCBs2 were 25 constituting 21.19% of total observations in categorical variables for all CBs.

Table 3: Bank Categories observation summary

Category	Frequency	Percent	Cumulative
CCBs	32	27.11	27.11
NCCBs1	61	51.70	78.81
NCCBs2	25	21.19	100.00
Total	118	100.00	100.00

4.2 Model Fit

The likelihood ratio Chi-square of 35.5 (6 degrees of freedom) with P= 0.000 indicates that the model was statistically significant, that is, the model fitted significantly better than a model with no predictors. The McFadden's pseudo R-squared was 28.31%. It should be note; however, that the R-squared in binary models does not correspond with that in OLS, and its interpretation has remained open to discussions (Zhou, Kuttal and Ahmed, 2018)

4.3 Effects of Efficiency Measures on NPLs Threshold

Table 4 presents preliminary results showing statistical significance and the direction of the relationships of the efficiency measures on the NPLs threshold. As it is indicated in Table 4, cost efficiency is neither significant at 10, 5 nor 1% levels, indicating its limited role in driving CBs to NPLs threshold. However, the rest of the variables are statistically significant, albeit at various statistical levels, thus rejecting the first null hypothesis in section 2.1 that bank efficiency measures do not significantly impact NPLs threshold in CBs.

Table 4: Probit results for (continuous) efficiency variables

Variable	Coefficient	Standard error
Cost efficiency (CE)	0.4879136	1.023797
Scale efficiency (SE)	-24.45126**	11.87875
Technical efficiency VRT (TeVRS)	-22.52574**	11.43266
Technical efficiency CRS (TeCRS)	23.09209*	12.23525

, ** and * denote 10 and 5 and 1% level of significance.*

4.4 Graphical Representation of Adjusted Predictions at Representative Values (APRs)

In Probit, the coefficients of the continuous independent variables in Table 4 do not provide useful information (Breen, Karlson and Holm, 2018) even though they serve to show the significance and direction of the relationship between variables. Thus, the Adjusted Predictions at Representative values (APRs) had to be estimated to allow graphical presentation of the results for meaningful interpretations. In order to explore the effect of efficiency measures on NPLs threshold, some levels of efficiency measures were identified to represent lower, middle and high levels. The following levels of efficiency measures were selected: 10, 30, 50, 70, 90 and 99%. These efficiency levels chosen are thought to be empirically relevant as they represented lower, middle and higher levels of efficiency (Breen, Karlson and Holm, 2018; William, 2013). Using margin command in Stata software, Adjusted Predictions at Representative Values (APRs) were generated for Scale Efficiency (SE), Technical efficiency under Variable Returns to Scale (TeVRS) and Technical efficiency under Constant Returns to Scale (TeCRS)).

Figure 2 depicts the relationship between statistically significant continuous independent variable and NPLs threshold.

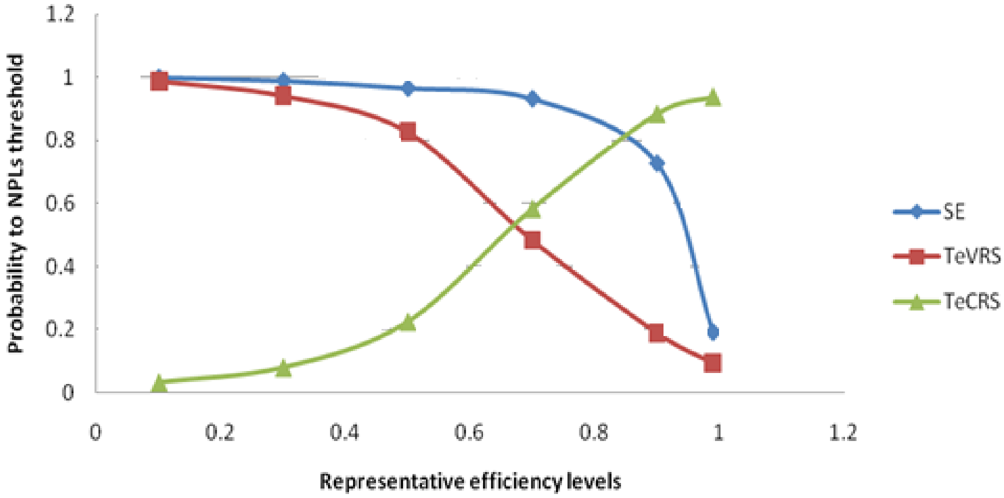

Figure 2: Graphical Presentation of Adjusted Predictions at Representative Values (APRs) against probability to NPLs threshold

SE and TeVRS were negative and statistically significant at 5% level (P=0.04, and P=0.049 respectively). As TeVRS increases, it decreases the probability of CBs to operate within NPLs threshold. This might be explained by the skimping hypothesis as per Berger and DeYoung (1997) that, as banks gain management efficiency by economizing on the operational costs, some functions including screening and monitoring are compromised, which increases the probability to operate above the NPLs threshold. The effect of SE to NPLs threshold in CBs may also be conveniently explained. As Community Banks (CBs) strive to optimize on their resources capacity, notably through increased registration of more borrowers, they decrease their probability to NPLs threshold. This may be due to low institutional capacity to deal with a large mass of borrowers. Currently, the ratio of borrowers to credit personnel in Tanzanian CBs is highly overstretched. While the industry standard caseload of loan officer to active borrowers is at an average ratio of 1:250-300, some CBs in Tanzania had an adverse ratio of 1:400-500 during the study period. Of course, many CBs (including some other rural financial institutions) in Tanzania were using group lending methodology thus benefiting from joint liability lending (Magumula and Ndiege, 2019; Sarker, 2013). This, in a way, provided some relief to the already overloaded loan officers. This finding was also validated through interviews with some key informants:

> "*…It is true that our credit department is overstretched. The number of borrowers has been increasing each month while our credit staffs have remained the same. Just recently, we employed three credit officers to help with the situation of increasing borrowers even though the number is not sufficient to match with load…*" (Interview field data, Mufindi).

As it can be noted in the quotes, increasing scale in terms of borrowers without improving on the production capacity in terms of number of loan officers and working facilities have negatively impacted CBs' abilities to manage increasing borrowers resulting in increasing NPLs, which decreases the probability for CBs to operate within the NPLs threshold. On the hand, Technical efficiency under Constant Returns to Scale (TeCRS) was positive and statistically significant at 10% level (P=0.059). The implication is that increasing TeCRS improves on the probability to NPLs threshold. This is also consistent with the general knowledge that, even with an adverse ratio of loan borrowers to loan officers, CBs could increase the probability to NPLs threshold by improving efficient utilization of the available loan officers, possibly through applying group lending methodology (BOTandFSDT, 2016).

4.5 Effect of Categorical Variables on NPLs Threshold

Table 5 presents the coefficients and standard errors for the categorical variables, that is, NCCBs 1 and NCCBs 2 relative to the reference category. The coefficients were positive and statistically significant at 5 and 1% (P=0.041 and P=0.000 respectively), thus rejecting the second null hypothesis in section 2.2 that bank categories do not impact on NPLs threshold.

Table 5: Probit results for categorical variables

Category	Coefficient	Standard error
NCCBs 1(category 2)	0.7667433**	0.3754081
NCCBs 2 (category 3)	2.239321***	0.5585922

* , ** and *** denote 10 and 5 and 1% level of significance

To explore the effect of categorical variables (relative to the reference category) on NPLs threshold, Marginal Effects at Representative Values (MERs) was applied as a superior approach to computing marginal effects (see William, 2013). To apply MERs, various levels of efficiency measures under study (SE, TeVRS and TeCRS) were identified and then MERs were estimated using margin command (dydx) in Stata.

Tables 6 present the Marginal Effects at Representative Values (MERs) for SE, TeVRS and TeCRS. Holding SE at 10%, the probability to be within the NPLs threshold was greater by 0.044% for Non-Cooperative Community Banks initiated during the first financial banking reforms (NCCBs1) relative to the reference category i.e. the Co-operative Community Banks (CCBs), while the probability was greater by 0.052% for Non-Co-operative Community Banks initiated during the second financial reforms (NCCBs2) relative to the reference category.

Likewise, holding SE at 50%, the probability to be in the NPLs threshold was greater by 0.42% for NCCBs1, while the probability was greater by 1.134% for NCCBs2 relative to the reference category. On the other hand, when SE was set at 99%, the probability to be in the NPLs threshold was greater by 11.00% for NCCBs1, while the probability was greater by 51.57% for NCCBs2 relative to the reference category. These findings indicate that the probability to be within the NPLs threshold was higher for both NCCBs1 and NCCBs2 categories than CCBs (the reference category) at all levels of Scale Efficiency (SE).

Table 6: Marginal Effects for categories at various levels of SE, TeVRS and TeCRS

	CB Type at:	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.99**
SE	NCCBs1	0.000444	0.001313	0.004273	0.0036142	0.184745	0.110044
	NCCBs2	0.000526	0.00335	0.011341	0.014674	0.334704	0.51571
TEVRS	NCCBs1	0.003453	0.009866	0.040305	0.0713371	0.027613	0.045097
	NCCBs2	0.011062	0.03111	0.100383	0.225162	0.092497	0.123249
TECRS	NCCBs1	0.0042	0.01134	0.03115	0.8447	0.01694	0.02111
	NCCBs2	0.0138	0.04089	0.10336	0.23598	0.03991	0.07451

The MERs at various levels of Technical efficiency under Variable Return to Scale (TeVRS) are also presented in Table 6. Setting TeVRS at 10%, the probability to be in the NPLs threshold was greater by 0.035% for NCCBs1 than for CCBs, while the probability was greater by 1.106% for NCCBs2 than the reference category. Again, when TeVRS was set at 50% the probability was greater by 4.03% for NCCBs1 and 10.03% for NCCBs2 than the reference category. When the TeVRS was set at the highest level, i.e. at 99%, the probability was greater by 4.51% for NCCBs1 and 12.32% for NCCBs2, implying again that, at low, middle and high TeVRS levels the probability for Non-Co-operative Community Bank categories to be in the NPLs threshold was higher than the reference category at all levels of TeVRS.

Similarly, Table 6 presents MEs when TeCRS are set at various levels. The probability was greater by 0.42% for NCCBs1 and greater by 1.40% for NCCBs2 when TeCRS was held at 10%; was greater by 3.11% and 10.34% when TECRS was at 50%; and grater by 2.11% and 7.41% when TeCRS was held at 99%, implying again that at low, middle and high TeCRS levels the probability to be in the NPLs threshold was higher for Non-Co-operative Community Bank categories than for the reference category.

The overall implications from these findings are that, various categories of community banks react differently to NPLs threshold at various levels of efficiency measures. Generally, the Non-Co-operative Community Banks that were initiated after the second financial reform generation (NCCBs2 category) had the highest probability of being in the NPLs threshold at all levels of efficiency measures, followed by Non-Co-operative Community Banks that were initiated during the first financial reform generation (NCCBs1 category). The Co-operative Community Banks (CCBs), which played the role of the reference category, had the lowest chances to NPLs threshold compared to both NCCBs categories. These findings are consistent with moral hazard hypothesis that, banks with lower capitalization ratio have higher incentive to undertake excessive risks leading to higher NPLs which in turn drives them to operate above NPLs threshold.

4.6 Consistency of Empirical Results with Theories and Hypotheses

This study was guided by the theory of information asymmetry. One of the implications of the theory is that banks with lower capital adequacy ratio are prone to taking excessive risks in loan issuance, which lead to higher NPLs. The empirical findings attest to this theory as Co-operative Community Banks (CCBs), which exhibited lower capitalization ratios had higher chances to operate above the NPLs ratio threshold than the Non-Co-operative-based CBs (NCCBs). The findings lead to the rejection of the null hypothesis in section 2.2 that community bank categories do not significantly influence NPLs ratio threshold and confirms the predictions of the moral hazard hypothesis that lower capitalized banks are likely to exhibit higher NPLs ratio. Similarly, the results reject the null hypothesis in section 2.1 that bank efficiency measures do not significantly impact NPLs threshold. The fact is that SE, TeCRS and TeVR have significant influence on NPLs threshold.

5.0 CONCLUSION ANDRECOMMENDATIONS

On the effect of efficiency measures on NPLs threshold it is concluded that increasing scale in terms of borrowers without improving on the production capacity has negatively impacted CBs' abilities to manage increasing borrowers resulting in increasing NPLs. It is therefore recommended that bank managers should restrain from excessive expansion without regard to the increased facilities and loan officers to match the number of borrowers. It is further recommended that, CBs should restrain from excessive skimping so that sufficient resources are availed for loan management and monitoring efforts. Furthermore, CBs should intensify the use of group lending methodologies to help dealing with increasing customers. On the influence of bank categories to NPLs, it is concluded that low capitalized co-operative community banks (CCBs) have been undertaking excessive risks in terms of loan issuance leading to higher NPLs. It is thus recommended that, bank regulators should strictly require CCBs to adhere to capital adequacy regulations. Regulators should control excessive loan issuance to reduce incidence of high NPLs ratio in CBS.

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[i] The Bank of Tanzania (BOT), through its Banking and Financial Institutions (Capital Adequacy) Regulations 2014, defines a community bank as a financial institution serving a defined geographical area and whose primary activities are restricted to acceptance of deposits from the public and lending and such other activities as may be specified by BOT. The amendment of 2015 to the Principal Regulations of 2014 provides a separate classification where the regional co-operative banks are distinguished from the other community banks in terms of minimum capital requirements. The Regional Co-operative Banks (RCBs) are required to have a minimum capital of TZS 5 billion while the other CBs have to have a minimum capital of TZS 2 billion by March, 2018.

[ii] By 2018 there were about 11 community banks in Tanzania. However, the number has decreased to five only as the licenses of rest were revoked by BOT for failure to comply with the Capital Adequacy Regulations and Minimum Capital Requirements of 2014.