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Mutual Causal Effects Between Bank Stability and Profitability in SSA Banking System

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Abstract

This paper intends to assess the interaction between stability factors and profitability proxies with macroeconomic factors as controllable variables. The analysis used bank risk metrics (LLRs, Credit Growth, and NPLs) and bank performance proxies (NIM, ROE, and ROA) with a dataset from 40 countries with 350 active commercial banks. The study uses Autoregressive Distributed Lags estimation with Dynamic Fixed Effect method (ARDL-DFE) to assess both short and long-run interaction effects. The analysis finds that both are interesting for a better sustainable banking system: the results evidenced a causal interdependence effect between bank profitability ratios and bank stability proxies. Furthermore, three causality tests and cointegration analyses were significant enough, which allowed us to conclude that caring for bank risk is caring for bank performance. This study recommends regulators (central banks and the Basel Committee) to enforce the bank profitability to mitigate related bank risks. The study also suggests (especially Basel Committee) a regulator tool called Bank Performance/Profit Requirement Ratio (BPRR).

JEL classification numbers: P430, G4, E510.
Keywords: Bank, Risk, Performance, Stability, Profitability, Interdependence, DFE, SSA, Africa.

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1. Introduction

The latest financial crisis of 2008 has increased the necessity of expanding the research on bank risk from a simple individualized and micro-based method to a complex and holistic approach to understand the origin, causes, and consequences of bank risk on the global economy. The intermediation institutions are the bridges on which borrowers and lenders pass to meet and satisfy their financial needs. These intermediaries use credits to expand their operations in their market shares filled with default risks. Lending operations are central key binders for all three partners (banks, investors, and borrowers) and bring another interesting factor in these business relationships: the benefit. The profit becomes the motivation in that partnership, even though it is not always assured to get it due to its association with default risk. Bank Credit is assumed to be an essential driver of external finance to economic operators in northern countries and southern countries.

Then, bank sensitivity towards failure recalls global sensitivity towards global financial crises. Bank risk cautions have become a concern for bank managers, governments, and policymakers, as evidenced by the 2008 crisis (Aisen and Franken 2010; Ivashina and Scharfstein 2010). Bank risk and stability have become a major concern in recent literature for those reasons. However, different researchers have developed other points of view about the real source and factor determining risks in the banking system since the 90s'.

In these recent decades, the recurrent finance instability has been debated in conferences, policymakers' speeches, and literature reviews (Galati and Moessner 2013). Considered financial intermediaries, banks firms played an important role in economies and consequently shared the pros and cons of the systemic risks with the global economy (Adrian and Shin 2008)

These concepts brought back the idea of interactions and interdependencies in banking and financial industries (Allen and Babus 2009). However, these concepts were not new. Only researchers were paying less attention to them before the recent financial crisis (Jarrow and Turnbull 2000; Alessandrini 1999). They have been qualified as systemic and contagion effects (Anderson, et al. 2002). Later, some other authors worked on this related topic to check whether bankruptcy has a characteristic of dependency or systemic risk (Altman and Hotchkiss 1993; Dichev 1998). The bank's systematic risk has generally been theorized as a situation in which many banks or financial institutions fail because of shared stock or due to a contagion process (Acharya, et al. 2011). Some other studies used the concept of networks in finance to describe the linkage between banks and mutual exposure risks accumulated at the interbank market (Allen and Babus 2009).

Previous research primarily concentrated on assessing the factors determining bank-specific risks one by one, for instance, non-performing loans (Nadham and Nahid 2015; Saba, et al. 2012; Škarica 2014; Umar and Sun 2018). For loan loss reserves(Wang, et al. 2019) ; credit growth (Gbenga, et al. 2019; Ivanović 2016; Önder and Özyıldırım 2013; Ahmad, et al. 2008; Moussa 2015). Likewise, the factors determining bank performance proxies (ROAE, ROAE) have been studied apart one by one (Sari, et al. 2020; Dang 2019; Anggono 2017; Ichsan, et al. 2021; Owusu-Antwi, et al. 2015) and in the same way net interest margin (Angori, et al. 2019; Sari, et al. 2020). However, some other studies used the capital market approach and equity returns of banks while supposing that the stock market captures banks' risk (Atindéhou and Gueyie 2001; Sukcharoensin 2013; Choi, et al. 1992).

All those mentioned bank risk and performance metrics used a single-factor approach explaining how more determinant variables (mainly macroeconomics) affect one bank risk ratio or performance ratios. They forgot, if not ignored, to evaluate the long-run interaction effects that could exist among them. As shown by some short-run tentative studies, these factors are more interconnected and interdependent (Noman et al. 2015; Agrawal and Sehgal 2018; Wong and Hui 2009).

The previous studies tried to determine the bank risk and performance as a single aspect apart from the entire banking system and neglected the interdependence aspects of bank factors -which made- bank systemic risk (Laeven, et al. 2016; Kaufman and Scott 2003; Adachi-Sato and Vithessonthi 2017; Allen, et al. 2010). The study which analyzed the interaction among bank factors used other factors such as credit, liquidity, and interest-related risk (Muhmad and Hashim 2017).

However, two groups of bank risks are formed in this study with six models as a holistic approach: one group for bank risk evaluation (credit growth, NPLs, and LLRs) and another group for bank performance ratios assessment (ROAA, ROAE, and NIM). Each ratio has plaid a dependent variable's role. In contrast, other remaining variables were taken as independent variables to evaluate how each dependent variable is affected by other independent variables using the same controllable variables and macroeconomic factors. The previous studies analyzed either one ratio or one variable separately against many different determinants, neglecting the aspect of bank ratios' connectivity.

This study assumes that bank risk factors are directly and indirectly related to the bank performance metrics and have interdependence effects. It proves that the factors influencing one of the risks proxies, directly and indirectly, affect others. When bank risk ratios are impacted, they directly influence the bank performance metrics and vice versa in dynamic ways (Agrawal and Sehgal 2018). A simple decrease or failure in real production (GDP) directly affects the expected loan performance, net interest margin, and finally, the return on equity. The implications become consecutively gradual.

Hence, the study brings new contributions to the literature:

1) While many studies analyzed each bank risk or performance factor apart from others, this analysis studies the interaction between two groups of bank ratios: stability ratios group on one side and profitability performance ratios group on another side.
2) Beyond the models limited for the analysis of the short-run relationship (Căpraru and Ihnatov 2014); this study uses the ARDL-DFE model to capture the long-run mutual causal effects within and between bank risk metrics and bank performance proxies.

3) Moreover, it demonstrates how different ratios from two groups are influenced by the same macroeconomic factors (GDPGR and TGE).
4) Proved a cointegration and causality between bank risk factors and bank performance proxies.
5) Furthermore, this analysis is more holistic and fills the scope gap from one country analysis to 40 countries with 350 banks.
6) Having explained this, it proves finally how caring for bank risk is caring for bank performance, and this is the main research objective of this study.

Some questions:
Do the same macroeconomic factors affecting bank risks influence profitability?
Is there any mutual causality between bank risk ratios and bank performance ratios?

From those questions, the hypotheses of this study were stated as follow:
H1: Macroeconomic factors affect both bank risk factors and performance proxies
H2: There are mutual causal effects between bank performance proxies and bank risk factors in the long run
H3: There is long run cointegration among bank risk and performance proxies.

After this introductory part, the second part is the literature review. The third part consists of preliminary statistic results, main findings for the long and short-run, plus discussions. The last part will be the conclusion and policy implications.

2. Literature review

Financial uncertainty could be understood and viewed in two main ways: its endogeneity cantered point of view and risk in an economic system based on non-linear build-up models (Galati and Moessner 2013). When analyzing the structure and the size of big banks as the sources of financial risk ("Too-big-to-fail" and too-central-to-fail), the author confirmed that centralization is a source of financial risks too (Battiston et al. 2012). in a contagion risk analysis, one financial institution's failure provokes the default of others via a domino effect (Allen, et al. 2010; Allen and Babus 2009).
However, information is also a source of contagion risks in the banking system via illiquidity assets' sale of distressed banks (fire sales) or banks that run at the same time for safety (Liedorp and van Lelyveld 2006), while other authors found the connectivity in asset portfolios is the major source of contagion risk (Elsinger, et al. 2006).
A study associated bank riskiness with external economic factors and the business cycle (Mpofu and Nikolaidou 2019) , while others have demonstrated that internal bank factors are a source of bank risk and finance crisis (Kaufman and Scott 2003). Recent studies on the 2008 finance crisis evidenced that abnormal credit growth that emerged from the USA was the source of bank risk and finance crisis (Vithessonthi 2016).

The same consideration is given in a study that concluded that bank health matters due to the growth credit from worldwide and domestic financing (Stepanyan and Guo 2011). NPLs have been found correlated with the credit growth later before the financial crisis (Adachi-Sato and Vithessonthi 2017). Discretionary credit and loan loss reserves have no significant influence on loan fluctuation, while non-discretionary credit and loan loss reserves could augment credit fluctuation and strengthen banks' pro-cyclical risk-taking behavior (Wang, et al. 2019). Bank risk is associated with capital ratio, and asset risk (Fahlenbrach, et al. 2018; Sobarsyah et al. 2020). It has been proved that credit growth increases bank risks (Foos, et al. 2010; Amador, et al. 2013). While other studies associate loan growth with loan loss (Keeton 1999), other researchers in the field stress the connection between loan growth and both loan quality and bank supervision (Curry, et al. 2008; Jin et al. 2019; Kupiec, et al. 2017).

Lending increases loan loss reserves and decreases the capital ratio the following year, while banks' profit is positively associated with loan growth for the long and short term (Dang 2019). Empirical results confirmed that higher credit growth intensifies credit risk for highly capitalized Islamic banks (Sobarsyah et al. 2020). More profound research highlights that this evidence was more noticeable after the crisis of 2008 (Ivashina and Scharfstein 2010; Aisen and Franken 2010; Murphy 2008).

One analysis discovered an association between bank-specific variables and past loan growth: these authors pointed out that a decline in loan loss provision, capital adequacy, and interest income is caused by the loan growth three years later while loan growth and risk-adjusted interest income negatively influence one another (Daniel and Jones 2007). CDs, asset size, and GDP growth rates positively affect credit growth (Sharma and Gounder 2012). This finding converges with some authors' conclusions (Castro 2013; De Bock and Demyanets 2012; Ivanović 2016). The impact of concentration on loan growth and overseas capital depends on the size of credit volume and the kind of credits (Georgios and Elvis 2019). An abnormal situation characterized by weak and sluggish credit growth during the liquidity excess period was noticed (Tan 2012).

While studying the relationship between credit growth and non-performing loans, one study discovers a positive association and finds a contagion effect on another bank factor and then alerted that this effect could restrain the economic activities (Tracey and Leon 2011). A credit growth raises non-performing loans and reduces the solvency of banks (Kashif, et al. 2016). Larger banks experience a minimum credit loss if compared to companies with smaller sizes (Ekanayake and Azeez 2015).

A long time atypical credit growth intensifies banks' riskiness, along with a decrease in bank solvency and a boost in non-performing credits to gross loans (Amador, et al. 2013). These findings converged with Matthias' study, confirming that a high loan growth rate increases bank riskiness and affects other banks' finance rates (Köhler 2012). High inflation is associated with a negative effect on real credit growth (Stepanyan and Guo 2011).

In investigating macroeconomic determinants of loan risk in the African banking system, a positive correlation has been found between NPLs and domestic credit (Mpofu and Nikolaidou 2018). One study has underlined that loan loss provisions for non-performing loans are lessened in the bank system during a booming period while the loan growth augments the loan loss reserves (Fahlenbrach, et al. 2018). One proof showed that balance sheets of the banks that are weak are negatively influencing bank credit, especially when there is an excellent relation to solvency ratio and non-performing loans (Tanasković and Jandrić 2015).

A study reveals that banks' profit and loan growth negatively affect NPLs, and banks with higher gain have lesser NPLs as they can properly manage loans loss with better loan management systems (Rachman et al. 2018). The cyclical nature of dynamic reserves augments individual banks' resilience and the entire banking system (Saurina 2009). Bank-specific variables, including liquidity, are significantly related to bank performance, especially when the interaction is with the third factor, corporate governance (Muhmad and Hashim 2017). Bank profit significantly declines the level of loans and liquidity risks for both separate or interacting effects (Abdelaziz, et al. 2020); likewise, loan growth is positively linked with bank profit (Dang 2019).

While analyzing the relationship between loan growth, non-performing credit, and bank profitability, a positive association between non-performing loans and loan growth was found in Japan and concluded that the rise in bank credits intensifies NPLs and does not lead to considerable gain (Vithessonthi 2016). A negative association has been found between ROAAE, ROAE, and NPLs, and an increase in NPLs reduces the bank profit (Jolevski 2017). These findings converge with Farooq's study (Farooq et al. 2019) and some other authors' findings (Salvi et al. 2018; Yap, et al. 2020). A study found that in financial crisis, systematic risks were significantly receptive/sensitive to provisions and performances (Floreani et al. 2015).

Other results showed a positive influence of NPLs on bank profits (ul Mustafa, et al. 2012). Bank size and credit growth had a statistical significance and adverse effect on credit risk, on the one hand, while two other variables (ownership and inefficiency) are positively and statistically affecting credit risk on the other hand. The same author further found that liquidity, capital adequacy, and profitability were associated negatively with credit risk but were also insignificant statistically (Tehulu and Olana 2014). A study discovered that loan growth and risk-adjusted interest income negatively influence one another (Daniel and Jones 2007); while liquidity risk exhibits a robust negative and statistically significant effect on financial performance (Adusei 2021).

3. Material and Methodology

3.1 Materials: data and variables

3.1.1 Data source and sample size

Table1 is a short panel data (larger N and small T) covering ten years from 2010 to

2019, and this panel is a cross-sectional and times series combination. In this study, 40 countries are concerned as sample size, with 350 banks operating in the SSA region. The study covers ten years and uses 3480 observations from 350 banks. Figure4 represents the region that encompasses three central communities: EAC (East African Community), SADC (South African development community), and ECOWAS (economic community of West African countries). The ECOWAS region is the first with 15 states (43% of the coverage sample). The SADC is second with 16 states (34% of the total sample size). The EAC comes in the third position with six countries (22% of the sample size). The other countries represent 1.15%, with three states. The calculated ratios were downloaded from the two abovementioned sources that we organized, cured, and uploaded for model and test analysis in the Stata system.

Table 1: Study scope and bank shares in SSA regions

SSA Regions	State members	No	Obs.	%
EAC	Burundi, Kenya, Tanzania, Rwanda, Uganda and South Soudan	6	770	22.13
ECOWAS	Benin, Burkina Faso, Cap Verda, Ivory Coast, Gambia, Ghana, Guinea Republic, Guinea Bissau, Liberia, Mali, Niger, Nigeria, Sierra Leone, Senegal and Togo.	15	1,490	42.82
SADC	Angola, Botswana, Comoros, Democratic Republic of Congo, Eswatini, Lesotho, Madagascar-car, Malawi, Mauritius, Mozambique, Namibia, Sey-Chelles, South Africa, Tanzania, Zambia, and Zimbabwe	16	1,180	33.91
Other	Ethiopia, Somalia and Djibouti	3	40	1.15
Total		40	3,480	100

3.1.2 Variable source and descriptions

Data covered ten years from 2010 to 2019 and were collected from two different sources, the world bank database, and Bureau Van Dijk. The natural logarithm was used in all the models, specifically in summarizing the descriptive statistics but not when running the model in the system. The macroeconomic variables are TGE and DGPGR, representing the total government expenses, respectively. The DGPGR denotes the growth of gross domestic product and the CPSB, which is the bank's credit to the private sector. All these three variables have been downloaded from the world bank database.

The remaining variables were taken from bank Focus, Bureau Van Dijk, a Moody's Analytics Company (www.oldorbis.bvdinfo.com), and are as follows: NIM represents the net interest margin, the ROAE and ROAA characterize the return on average equity and return on average asset, respectively. The LLR is the loan loss reserves, and the NPLs represent non-performing loans. Two groups were formed, and those macroeconomic were used for each model to assess their effect on both groups. For bank risk metrics, LLRs, CPSB, and NPL sewer used, while ROAA, ROAE, and NIM are for bank performance metrics. Each variable will be the dependent variable, while the remaining variables will account for bank risk, performance, and macroeconomic factors.

Table 2 presents the descriptive statistics of the variables used. The mean varies from 2.291 up to 1.568. The highest mean number is for TGE, as it is concerned with the government budget, which does not change much, and consecutively, it is the one with the lowest standard deviation (.064).

Table 2: Descriptive statistics

Variables	***Observ***	***Mean***	***Std. Dev.***	***Min***	***Max***
LLRs	1441	1.568	1.328	-7.844	7.612
ROAE	1952	2.286	1.492	-3.353	8.449
ROAA	1914	1.688	1.84	-5.077	6.599
NIM	1622	1.525	1.399	-7.336	8.1
NPLs	1340	2.113	1.335	-5.739	8.332
CPSB	3051	2.9	.748	1.308	10.602
GDPGR	1902	2.082	3.024	-.919	19.012
TGE	3480	2.991	.064	2.81	3.036

The lowest mean number is for NIM, around 1.525. The standard deviation of all variables is around one, unless for TGE and CPSB, respectively (.064 and.748). It can be explained that these variables do not vary much across the year, especially for the government expenses, while for CPSB, it reflects that the banks in SSA do not change much the annual volume offered to the customers. It can also signify that the credit growth rate is not too high. Oppositely, the standard deviation for the GDPGR is the highest in this region, implying that the country's policy and investment in gross domestic product vary much with time.

3.2 Methodology

3.2.1 Preliminary tests: correlation test and unit-roots test.

The preliminary correlation test among variables is conducted with the Pearson correlation matrix to verify the preliminary assumptions (see tables 1 to 3 for correlation and table 4 for Optimal lags in the Appendix). These correlations matrix evidences the linear relationship between the variables in the used model. The following test is unit-roots to check for non-stationary. There are many tests for panel data (Im, Pesaran, and Shin 2003; Levin, Lin, and Chu 2002; M. H. Pesaran, Shin, and Smith 1999). For simplicity, we performed only the IPS test (which assumes that the slopes are heterogeneous) and the ADF-Fisher test, which work well with the unbalanced panel data. Fisher-type unit-root test also includes AR parameter, panel means, and time trends. This test generates four statistics results for units test, P, Z, T, and PM (Harris and Tzavalis 1999). Generally, the unit-roots model is parametrized as follow:

$$\Delta Y_{it} = \emptyset Y_{it-1} + Y_{t-1} + \mu_{it} \qquad (1)$$

3.2.2 General ARDL model

The ARDL model, called the autoregressive distributed lag model, is an OLS (ordinary least square). This model is appropriate for the time-series dataset and has different advantages. The model is broadly recognized for the cointegration analysis in the time series dataset. As in our case study, the ARDL model is mainly efficient for a small sample size. Another key benefit of this ARDL modelling method is that it does not care whether the regressors are (0) or I (1). Once again, ARDL allows a considerable number of lags. Moreover, it will expand a dynamic error correction model that organizes short and long-run effects with unbiased estimates, as it considers all long-run data.
The generalized form of the ARDL (p, q) model is specified as follow:

$$Y_t = \gamma oi + Y_{t-1} + X_{t-1} + \varepsilon it \qquad (2)$$

In this model, Y_t represents the independent variable and is explained by its own lags $Y_{t-1.}$ δ and β are the coefficients to be estimated. X_{t-1} represents the repressors. It is as well defined by the current and lag values of the repressors. The p is related to the lag of the dependent variable. The q is associated with the lag of the repressors, which cannot necessarily have equal lag numbers. The γ is the intercept of the constant in the model, while εit represents the error term vector.

3.2.3 The ARDL- Dynamic Fixed Effect models

The ARDL method uses different techniques such as pooled mean group (PMG), mean group (MG), or dynamic fixed effect (DFE). These techniques are appropriate based on the aim of this research and are suitable for a small panel data set, where T<N (with 40 countries for ten years). ARDL-PMG estimators are flexible whether

variables exhibit I(0), I(1), or a mixture of both (Garratt et al. 1998) and can take care of such heterogeneity with DFE techniques. Additionally, this method has the power to capture the interesting variable dynamic in both the long and short-run (H. H. Pesaran and Shin 1998).

The pooled mean group method uses the averaged and pooled coefficients of cross-sectional units. It allows the long-run effects' restriction to be the same across all the panels. However, it permits the short-run effects across panels to be country-specific (heterogonous) as caused by differences in country-specific issues.
Contrary to the MG method allowing heterogeneity in both long and short-run relationships, the DFE (Dynamic Two-Way Fixed Effect) technique allows homogenous in both long and short-run relationships. We decided then to use DFE after comparing the best estimations results using Hausman tests selection between PMG, MG, and DFE (Pesaran, et al. 1999; Pesaran and Smith 1995). Furthermore, the slope, speed of adjustment, and short-run coefficient are restricted with DFE methods to exhibit homogeneity across countries.
Then, the ARDL-DFE error correction model for long run is re-parameterized as follow:

$$\Delta Yit = \Theta_i\, [Y_{i,t-1} - \delta_i X_{i,t}] + \Delta Y_{i,t-j} + {}_{ij}\, \Delta X_{i,t-j} + \varphi_i + \varepsilon_{it} \qquad (3)$$

$\Theta_{i=}$ -(1-δi), represents the speed's adjustment coefficient, is expected to be negative. δ_i is a long-run relationship vector. ECT = $[Y_{i,t-1} - \delta_i X_{i,t}]$; is representing the error correction term and ij represent the short-run dynamic coefficients.
From equations (3), then we can obtain DFE models specified as follows:

$$\Delta Yt = ɣoj + \Delta Y_{(t-1)} -1 + \Delta X_{1(j-1)} + \Delta X_{2(j-1)} + \Delta X_{2(j-1)} + \boldsymbol{\lambda} ECT_{(t-1)} + \varepsilon it \qquad (4)$$

Where Δ denote the variation, $X_{1(j-1)}$ represents the bank-specific variables as risk proxies, $X_{2(j-1)}$ bank-specific variables as performance proxies and $X_{3(j-1)}$ represents the macroeconomic variables and Y_t is a vector, The coefficients are β, β_1 and β_2, as slope to determine and ɣ represents the constant. J=1, k, p, and q are the optimal lags orders. And finally, εit is the vector of the error time. $\boldsymbol{\lambda} ECT_{(t-1)}$ captures the long-run coefficients. The variables of interest are in groups $X_{1(j-1)}$ and $X_{2(j-1)}$, and we are interested in how they influence each other in the long run.
By parameterizing model (4), the three models for three different dependent variables to assess the effect of bank performance proxies on bank risk factors are as follow:

$$\Delta \mathbf{NPLs_t} = \beta_1 + (\Delta NPLs)_{(t-1)} + (\Delta CPSB)_{(t-1)} + (\Delta LLRs)_{(t-1)} + (\Delta ROAA)_{(t-1)} + (\Delta ROAE)_{(t-1)} + (\Delta NIM)_{(t-1)} + GDPGR + TGE + \mathbf{(\lambda ECT_1)_{(t-1)}} + \varepsilon it_1 \quad (5)$$

$$\Delta \mathbf{LLRs_t} = \beta_2 + (\Delta LLRs)_{(t-1)} + (\Delta CPSB)_{(t-1)} + (\Delta NPLs)_{(t-1)} + (\Delta ROAA)_{(t-1)} + (\Delta ROAE)_{(t-1)} + (\Delta NIM)_{(t-1)} + GDPGR + TGE + \mathbf{(\lambda ECT_2)_{(t-1)}} + \varepsilon it_2 \quad (6)$$

$$\Delta \mathbf{CPSBs_t} = \beta_3 + (\Delta CPSBs)_{(t-1)} + (\Delta NPLs)_{(t-1)} + (\Delta LLRs)_{(t-1)} + (\Delta ROAA)_{(t-1)} + (\Delta ROAE)_{(t-1)} + \mathbf{(\Delta NIM)_{(t-1)}} + GDPGR + TGE + \mathbf{(\lambda ECT_3)_{(t-1)}} + \varepsilon it_3 \quad (7)$$

The three models for three different dependent variables assessing the effect of bank risk on bank performance are as follow:

$$\Delta \mathbf{ROAA_t} = \beta_4 + (\Delta ROAA)_{(t-1)} + (\Delta ROAE)_{(t-1)} + (\Delta NIM)_{(t-1)} + (\Delta NPLs)_{(t-1)} + (\Delta CPSB)_{(t-1)} + (\Delta LLRs)_{(t-1)} + GDPGR + TGE + \mathbf{(\lambda ECT_4)_{(t-1)}} + \varepsilon it_4 \quad (8)$$

$$\Delta \mathbf{ROAE_t} = \beta_5 + (\Delta ROAE)_{(t-1)} + (\Delta ROAA)_{(t-1)} + (\Delta NIM)_{(t-1)} + (\Delta NPLs)_{(t-1)} + (\Delta LLRs)_{(t-1)} + (\Delta CPSB)_{(t-1)} + GDPGR + TGE + \mathbf{(\lambda ECT_5)_{(t-1)}} + \varepsilon it_5 \quad (9)$$

$$\Delta \mathbf{NIM_t} = \beta_6 + (\Delta NIM)_{(t-1)} + (\Delta ROAA)_{(t-1)} + (\Delta ROAE)_{(t-1)} + (\Delta NPLs)_{(t-1)} + (\Delta LLRs)_{(t-1)} + (\Delta CPSB)_{(t-1)} + GDPGR + TGE + \mathbf{(\lambda ECT_6)_{(t-1)}} + \varepsilon it_6 \quad (10)$$

Each variable among the six of interest (three for bank risk and three for bank performance) will play the role of the dependent variable. Their coefficients comparison will evaluate the long-run influence and interdependence between them for the long run as it is the main purpose of this study. Three additional regressions (OLS, RE, and FE models) were independently run to check how much consistency are the results. These results served as robustness for our findings and are consistent with the main findings (see details in Appendix B, table 5 and 6).

4. Empirical results and discussions

4.1 Unit roots and correlation matrix results

Table 3 presents the unit-roots results for the variables while the correlation matrixes are presented in the appendix A1, A2, and A3. At level, four variables are only significant for the IPS test, while at the first difference, all variables are significant. For the ADF-Fisher test, which summarizes all the tests, the variables are significant at the first difference.

Table 3: Unit roots results

Tests	unit-root tests			
	Im-Pesaran-Shin test (IPS)		ADF-Fisher Test	
I(0)/I(1)	At level	At 1st difference	At level	At 1st difference
CPSB	-26.420	-10.357***	-7.1436	-7.143***
GDPGR	1.601***	-38.480***	.4967	.169***
ROAE	-6.220 **	-1.816***	-15.468***	-19.614***
NPLs	-1.065	3.1463***	-5.5628	-6.628***
LLR	-2.447***	9.0540 ***	-1.449***	-13.971***
TGE	- 6.063	.55***	-16.453***	-18.654***
RAOE	2.01***	-3.68***	-8.132***	-14.515***
ROAA	2.51***	-3.68***	-11.132***	-22.515***
NIM	-.29	-40.775***	-30.326***	-7.371***

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

The overall results imply that the series are all stationary at first difference. Nevertheless, Cointegration analysis was done through the figures. Correlation analysis was also done to check whether there is no linear dependency among the independent variables. Details on correlation analysis results can be contained in Tables 1, 2, and 3 of appendix A.

4.2 ARDL-DFE Results and discussions

4.2.1 Discussion 1: Bank risk metrics/ratios as dependent variables

Table 4 presents the results of the bank risk metrics as dependent variables in two compartments; one for short-run and another one for long-run. First, we interpret the shirt run and then the long run results later, and then a summary will be deducted for a decision. But as the first thing first, the ECM results for all models show that there will be a long run as its values are negative for all models. In the short run, the ROAE impacts the two bank risk proxies (CPSB and LLRs). Its effect for CPSB is positive and significant at a 1% significant level, ceteris paribus, while it is negative and significant for LLRs at a 1% significant level, too, ceteris paribus. The LLRs and NPLs have negative effects, but NPLs are not statically significant. However, when using OLS and Random effect models, the results of NPLs were significant. The ROAA has a negative impact and is statistically significant on CPSB at a 1% significance level, ceteris paribus.

NIM affects LLRs at a 1% significant level, ceteris paribus. The NPLs negatively influence both CPSB and LLRs at a 5% and a 1% significant level, respectively. Likewise, LLRs affect NPLs negatively and significantly at a 1% significant level, while LLRs affect positively and significantly at a 5% significant level CPSB. CPSB influence only the LLRs at a 5% significant level. Moreover, the macroeconomic variables GDPGR and TGE also have a negative and significant level on CPSB at a 1% and 5% significance level. In comparison, the influence on NPLs is positive and statistically significant at a 1% significant level. Hence, from these results, we can observe that the bank performance proxies have a short-run (either negative or positive) relationship with the bank risk proxies (at least with two) in the short run.

For the long run results of dynamic fixed effect with error correction model, first of all, we observe that the speed of adjustment for all the three models is all negative and significant at a 1% significance level for CPSB, LLRs, and NPLs, respectively at -.559, -.836, and -1.14. These results confirm that these proxies exhibit a long-run conversation with the independents (bank performance metrics) for the long run. Furthermore, the same situation was found when regressing the bank performance proxies as dependent variables. The ROAE exhibits a negative and statistically significant effect on both CPSB and LLRs at a 1% significance level in the long run for the repressors. The ROAA affects all the bank risk factors - negatively and statistically significant to LLRs and NPLs at a 1% and a 5% significant level, respectively.

In comparison, it is positively and statistically significant the CPSB is at a 1% significant level in the long run. NIM has a positive and high impact on the NPLs at a 1% significant level in the long run. NPLs have a positive and significant effect on CPBS and LLRs at a 1% significance level. The NPLs are negatively and significantly affected in the long run by the three repressors (LLRS, CPSD, and GDPGR), at a 1% for LLRs and a 5% significance level for CPSB and GDP. Tis later, affect also CPSB at a 5% significance level in the long run.

Table 4: Bank risk metrics/ratios as dependent variables

Bank risk metrics/ratios as dependent variables							
Models		**Model 1: CPSB**		**Model 2: LLRs**		**Model 3: NPLs**	
Periods	Variables	Coefficient	Z-stat.	Coefficient	Z-stat.	Coefficient	Z-stat.
Short run results	D1.ROAE	.014*** (.005)	2.44	-.086*** (.014)	-5.84	-.002* (.025)	-.10
	D1.ROAA	-.285*** (.062)	-4.56	.186 (.133)	1.40	-.035 (.323)	-.11
	D1.NIM	-.060 (.083)	-.73	.570*** (.144)	3.96	-2.276 (1.660)	-1.37
	D1.NPLs	-.037** (.017)	-2.57	-.082*** (.022)	-3.70	-	-
	D1.LLRs	.032*** (.017)	1.86	-	-	-.401*** (.151)	-2.64
	D1.CPSB	-	-	-.235*** (128)	-1.84	-.056 (.279)	-.20
	D1.GDP	-.097** (.040)	-2.40	-.030 (053)	-.57	2.694*** (.939)	2.87
	D1.TGE	-24.7*** (6.782)	-2.94	.118 (.076)	1.55	-3.114 (5.878)	-1.03
	DFE Error Correction Model						
Long run results	Speed of Adjust.	-.559*** (.056)	-9.90	-.836*** (.068)	1.97	-1.14*** (.059)	-1.05
	ROAE	-.030*** (.012)	-2.46	.064*** (.032)	2.61	-.020 (.034)	-.59
	ROAA	.579*** (.118)	4.87	-.646*** (.247)	-0.47	-.745** (.363)	-2.05
	NIM	.104 (.188)	.55	-.100 (.212)	5.88	7.804*** (1.749)	4.46
	NPLs	.073** (.035)	2.08	.201*** (.034)	-025	-	-
	LLRs	-.026 (.047)	-.56	-	-	-.086*** (.260)	-.33
	CPSB	-	-	-.031 (125)	1.08	-2.975** (1.33)	-2.22
	GDP	.294** (.124)	2.36	.115 (106)	0.20	3.271** (2.32)	1.33
	TGE	-2.540 (2.919)	-.97	.023 (121)	-2.13	-.020 (.034)	-.59

*,**, and*** denote significance at 10, 5, and 1%, respectively. Standards errors are between parentheses.

In the table 4, three models were regressed with three bank risk factors as dependent variables to assess the impact of bank performance proxies (along with macroeconomic factors) on bank risk factors. CPSB, LLR, and NPLs were used.

In the long run, the non-performing loans are negatively associated with the two returns because the more the bank experience more loans defaults loans, the more its returns decrease for the short and long term. However, these effects are more significant in the long-run periods.

Net interest margin is positively affecting loan loss reserves and non-performing loans. The high is the margin, the high is expected for the non-performing loans, and then consequently, the high becomes the loan loss reserves used to cover the defaulted loans for the long run, but that was positively kept for short-term security. In the long term, the net interest margin is positively associated with GDP growth and non-performing loans: the more GDP growth increases, the more the people tend to have the surplus production and tend to save more money in banks or make more transactions and then give the bank the ability to have more cash flows and high lending rate. Then the high it lends, the high the loans default rate becomes, especially in the long run (Vithessonthi 2016).

4.2.2 Discussion 2: Bank Performance metrics as dependent variables

Table 5 presents the results of the bank performance proxies as dependent variables in two compartments; one for the short-run and another one for the long run. Likewise, first, we interpret the short run and then the long run results after, and then a summary will be deducted for a decision. The NPLs positively affect the ROAE at a one % significant level in the short run. The CPSB also influences NIM at a 5% significant level, while this NIM affects the ROAE considerably at a 1% significant level. GDP negatively affects the ROAE, while it influences NIM positively at a 5% significance level.

Table 5: Bank Performance proxies as dependent variables

Bank Performance ratios as dependent variables							
Models		**Model 1: ROAE**		**Model 2: ROAA**		**Model 3: NIM**	
Periods	Variables	Coefficient	Z-stat.	Coefficient	Z-stat.	Coefficient	Z-stat.
Short run results	D1. NPLs	.157* (.132)	1.19	.002 (.011)	.20	-.002 (.002)	-1.28
	D1. LLRs	.438 (.336)	1.30	.025 (.029)	.86	.007 (.005)	1.37
	D1. CPSB	-.164 (.614)	-.27	-.040 (.054)	-.74	.018** (.009)	1.84
	D1. ROAE	-	-	.006 (.004)	1.37	000 (000)	.74
	D1.ROAA	.596 (.710)	.84	-	-	-.014 (.011)	-1.28
	D1. NIM	-12.4*** (3.581)	-3.47	-.528 (322)	-1.64	-	-
	D1.GDP	-.405** (2.094)	-.19	-.084 (185)	.46	.071** (.033)	2.12
	D1. TGE	-3.609 (18.942)	-.05	1.177 (3.986)	.25	.847 (1.279)	0.66
	PMG-DFE Error Correction Model						
Long run results	Speed of Adjust.	-1.09*** (.054)	-20.05	-.836*** (.068)	13.94	-.772*** (.057)	-13.38
	NPLs	-.256 (.182)	-1.41	-.041*** (.020)	-2.04	.014*** (.004)	3.36
	LLRs	-2.43*** (360)	-6.76	082*** (.042)	.195	.016 (.008)	1.93
	CPSB	1.123*** (.595)	1.89	-.057 (.066)	-0.87	-.21 (.013)	-1.60
	ROAE	-	-	.057*** (.006)	4.54	-.000 (001)	-.16
	ROAA	-7.17*** (.649)	-9.04	-	-	-.079*** (.019)	-4.15
	NIM	12.79*** (4.159)	3.07	1.001*** (.454)	2.20	-	-
	GDP	3.450 (3.138)	1.10	-.598** (.349)	-1.71	-.068 (5.878)	-.072
	TGE	16.659 (8.595)	1.11	.2.192 (3.244)	0.35	-2.172** (1.283)	1.69

*,**, and*** denote significance at 10, 5, and 1%, respectively. Standards errors in parentheses.

In the table 5, three models were regressed with three bank performance proxies as dependent variables to evaluate the influence of bank risk factors (along with macroeconomic) on bank performance proxies. ROAE, ROAA, and NIM were used.

When it comes to the long run results of dynamic fixed effect with error correction model, results showed that the speed of adjustment for all the three models are all negative and significant at a 1% significance level for ROAE, ROAA, and NIM, respectively, at a -1.09, -.836, and -.772. Surprisingly, the adjustment speed of the ROAA and LLRs, when they are each playing the role of the dependent variable, remains the same for both models (-.836).

In the long run, the NPLs affect the ROAA and NIM differently. ROAA is negatively and significantly affected by the NPLs, while the NIM is positively and significantly affected by the NPLs, both at a 1% significant level. Likewise, the LLRs influence differently the ROAE and ROAE (Noman et al. 2015). ROAE is negatively and significantly affected by the LLRs at a 1% significant level, while ROAE is positively and significantly affected by the LLRs at a 1% significant level. However, the effect of the LLRs on ROAE (-2.43) is considerably high (Căpraru and Ihnatov 2014). CPSB has a considerable impact on ROAE (1.123) at a 1% significant level, while the effect of ROAE on ROAA is positive at a 1% significant level. However, ROAA impacts ROAE (-7.17) considerably in the long run at a 1% significance level, while NIM affects ROAE (12.79) mainly in the long run (Noman et al. 2015). It also affects ROAA positively and significantly at a 1% significance level. In the long run, GDPGR affects positively and significantly ROAA, and TGE affects negatively and significantly NIM, both at a 1% significant level.

For the short and long run, the non-performing loans affect the bank performance (through returns) directly because a defaulted loan will affect the bank return directly for short as well as for the long run on one side and then impacts the loan loss reserves as these later will be used to cover the defaults loans. If this situation is repeated many times and in the long run, it will consequently affect the ROAA as the bank will not be earning enough to invest in long-term assets such as real state and long-term assets. Thus, it will negatively and significantly impact the ROAA and reduce the asset return for the long run (Thornton and Di Tommaso 2021). Credit and GDP growth positively influence the return on equity in regular times in the long run. In a favorable and growing business environment, the high the credit growth and GDP, the high the business activities, and the high should be the return on equity. Net interest margin is negatively associated with the credit and GDP growth for the long run and consequently negatively affects the returns on equity and returns on assets for the long run.

4.3 Causality effects analysis: Three tests for causality analysis

Table 6 shows three causality tests to assess the direction of the effect on each other.

Table 6: Results of causality between bank risk and bank performance proxies

Equation	No Test	Stat. Val.	P. V	No of Sig tests	Causality direction	Causality Type
NPLs ⇔LLRs	3	2.30	0.021	3 times	NPLs granger-causes LLRs	Bidirectional
LLR⇔ROAA	3	-2.69	0.007	3 times	LLR granger-causes ROAA	Bidirectional
ROAE⇔ROAA	3	11.01	0.004	3 times	ROAE granger-causes ROAA	Bidirectional
NIM⇔CPSB	3	4.803	0.002	3 times	NIM granger-causes CPSB	Bidirectional
NPLs ⇒ROAA	3	7.37	0.006	3 times	NPLs granger-causes ROAA	Unidirectional
NPLs ⇒ROAE	3	2.72	0.007	3 times	NPLs granger-causes ROAE	Unidirectional
GDPGR⇒ROAE	3	6.31	0.000	2 times	GDPGR granger-causes ROAE	Unidirectional
GDPGR⇒NPLs	3	6.31	0.000	3 times	ROAA granger-causes NPLs	Unidirectional
ROAA⇒CPSB	2	4.9285	0.008	2 times	ROAA granger-causes CPSB	Unidirectional
ROAE⇒LLRs	3	29.624	0.000	3 times	ROAE granger-causes LLRs	Unidirectional
ROAA⇒LLRs	3	29.624	0.000	3 times	ROAA granger-causes LLRs	Unidirectional
ROAA ⇒ NIM	2	4.803	0.002	2 times	ROAA granger-causes NIM	Unidirectional
TGE⇒ROAE	3	1.78	0.075	3 times	TGE granger-causes ROAE	Unidirectional
TGE⇒ LLRs	2	6.21	0.013	2 times	TGE granger-causes LLRs	Unidirectional

Note: "⇒"indicates the causality and the direction from one variable towards another while sign "⇔" indicates the bidirectional causality.

Table 6 displays the results from three causality tests: Z-statistics Test (VAR Causality), Granger and Wald Test for causality direction, and WALD coefficient test for causality. These tests were used to check for the causality and direction between two groups of bank risks. The first one is T-statistics Test. This causality test was obtained while running the vector auto-regression with two lags minimum. The second one is G Granger and Wald Test for causality direction. This second test is run after running a simple VAR regression and uses each variable as a dependent variable in the equation and excludes other remaining variables. It checks the causality direction between the two concerned variables. The third and last test is the WALD coefficient test for causality, which checks for causes between every couple of variables taken separately. The results from the tables present four bidirectional causes. On one the side between bank risk factors and bank performance proxies (LLR⇔ROAA and NIM⇔CPSB); on the other hand, bidirectional causality among bank risk proxies only (NPLs ⇔LLRs) and then among bank performance proxies aside (ROAE⇔ROAA). Moreover, the unidirectional causality exhibit, on one side, the causal effect of bank risk metrics on the bank performance (NPLs ⇒ROAA and NPLs ⇒ROAE). And on the other side, the unidirectional causalities exhibit a causal impact of bank performance on bank risk (ROAA⇒CPSB, ROAA⇒LLRs, ROAE⇒LLRs).

4.4 Cointegration analysis through figures

The following figures (from 1-4) corroborate the results presented in tables 4 and 5. Moreover, they justify three causality test results and match the two preliminary tests in the table 2. They also match the expectation economic theories in that the non-performing loans affect the returns on equity, and the return on equity also affects the loan loss reserves and vice versa.

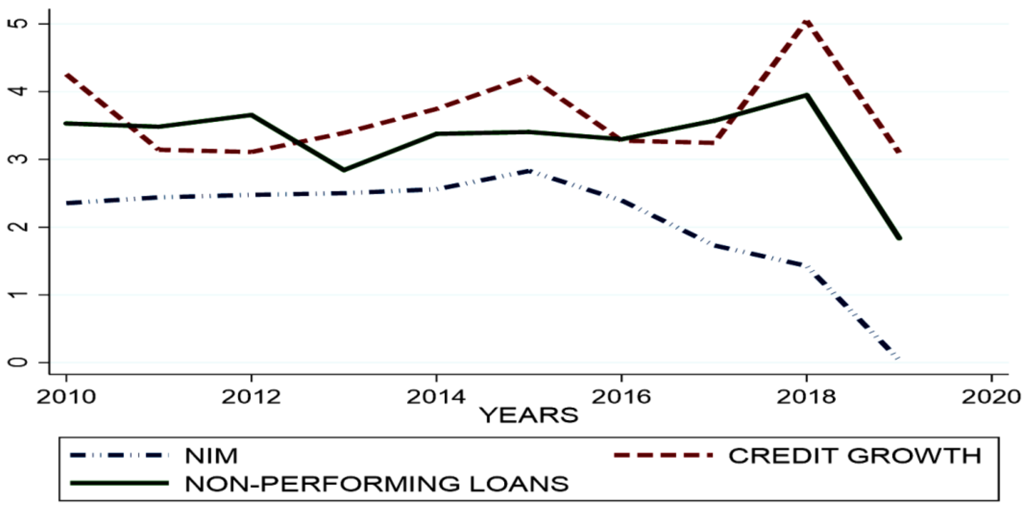

Figure 1: Cointegration trends between bank risk and bank performance factors

Figure 1 represents the perfect cointegration movements between bank risk factors (NPLs and CPSB) and bank performance proxies (NIM). The more the bank lands, the more the non-performing loans increase, and the higher the net interest margin.

These cointegration analyses validate the main empirical results.

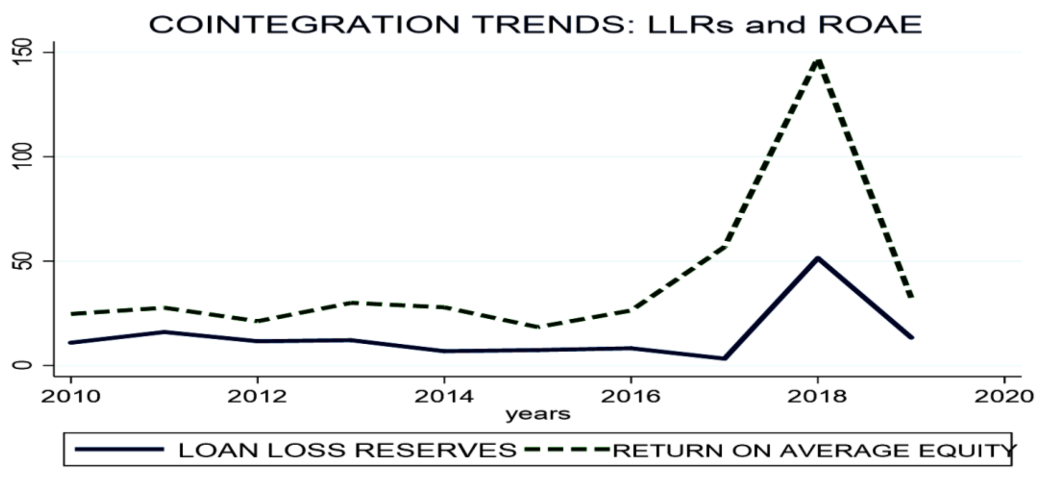

Figure 2: Cointegration movements between Ratio of NPLs to LLRs & Loans

Figure 2 shows the perfect comovements between loan loss reserves as bank risk factors and return on average equity as a bank performance proxy.

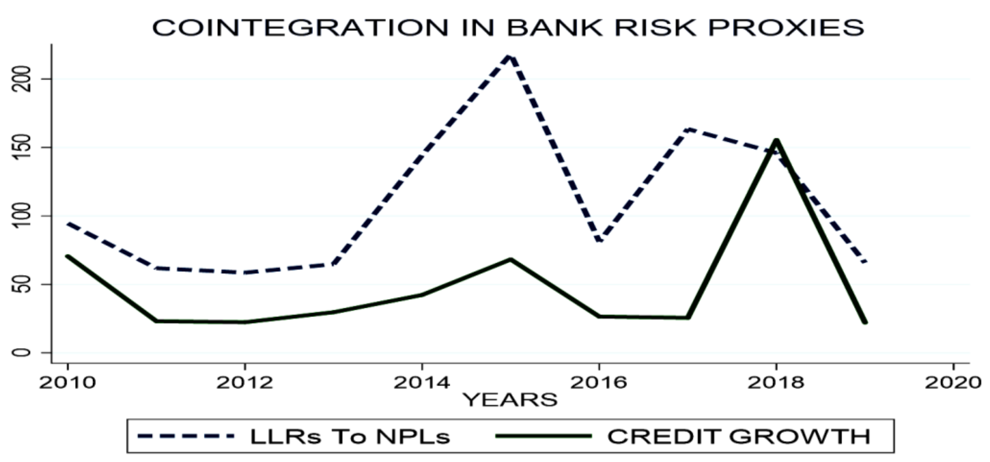

Figure 3: Cointegration movements between Ratio of NPLs to LLRs & Loans

Figure 3 presents the cointegrations between the ratio of loan loss reserves to no-performing loans on the bank credit growth. This figure also confirms the results and hypotheses on the effect between bank risk proxies.

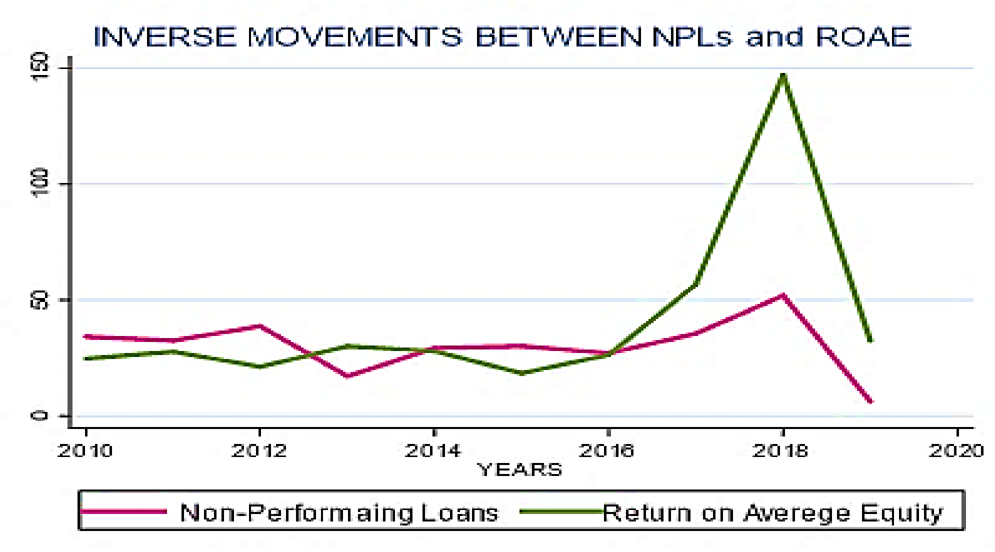

Figure 4: Cointegration movements between NPLs Versus ROE

Figure 4 reflects the inverse movement (negative correlation) between bank risk (NPLs) and bank performance (ROAE). It corroborates the signs and findings presented in tables 4 and 5.

4.5 Conclusion, further research, and policy implications

This research aimed to analyze the interdependency between bank risk factors and bank performance proxies and assess whether caring for bank risk is caring for bank performance. The study hypothesized that bank riskiness and performance are, on the one hand, the result of the same macroeconomic factors (GDP and TGE) and, on the other hand, the result of their interactional effects. Thus, based on the regressions outputs obtained from different results and figures, the general hypothesis has been confirmed by the correlation and causation between bank risk and bank profit. Hence, the study concluded that in the banking sector, caring for bank risk is caring for bank performance on one side, and caring for bank performance is caring for bank risk on the other side in the short and long run.

This study recommends that policymakers, especially the Basel committee - besides bank liquidity risks regulations and measures - consider the bank performance as a crucial tool to judge the bank riskiness. For central banks, to regularly evaluate bank performance as a metric of bank risks and set an additional tool called "bank's performance requirement ratios (PRR)." This new tool can be considered as a judge for non-performing banks as bank liquidity requirements and capital adequacy ratios. The study recommends the Basel committee sets performance requirement ratios for banks to ensure permanent performance to mitigate risk related to bank failure. Suppose the Basel committee and central banks together elaborate such policies thus. In that case, it can encourage the banks to focus more attention on performance rather than investing in activities with high risk (Delis, Tran, and

Tsionas 2012). Further research can explore the short and long-run interdependence effects between and within bank risk metrics and bank operational factors or with non-bank sectors such as insurance companies and other financial institutions.

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References

[1] Abdelaziz, Hakimi, Boussaada Rim, and Hamdi Helmi (2020). "The Interactional Relationships between Credit Risk, Liquidity Risk and Bank Profitability in MENA Region." Global Business Review, 0972150919879304.

[2] Acharya, Viral V, Yakov Amihud, and Lubomir Litov (2011). "Creditor Rights and Corporate Risk-Taking." Journal of Financial Economics 102 (1): 150–66.

[3] Adachi-Sato, Meg, and Chaiporn Vithessonthi (2017). "Bank Systemic Risk and Corporate Investment: Cross-Country Evidence." Available at SSRN 2629897.

[4] Adrian, Tobias, and Hyun Song Shin (2008). "Financial Intermediaries, Financial Stability, and Monetary Policy." FRB of New York Staff Report, no. 346.

[5] Adusei, Michael (2021). "The Liquidity Risk–Financial Performance Nexus: Evidence from Hybrid Financial Institutions." Managerial and Decision Economics.

[6] Agrawal, Tarunika Jain, and Sanjay Sehgal (2018). "Dynamic Interaction of Bank Risk Exposures: An Empirical Study for the Indian Banking Industry." IIM Kozhikode Society & Management Review 7 (2): 132–53.

[7] Ahmad, Rubi, Mohamed Ariff, and Michael J Skully (2008). "The Determinants of Bank Capital Ratios in a Developing Economy." Asia-Pacific Financial Markets 15 (3–4): 255–72.

[8] Aisen, Mr Ari, and Michael Franken (2010). Bank Credit during the 2008 Financial Crisis: A Cross-Country Comparison. International Monetary Fund.

[9] Alessandrini, Fabio (1999). "Credit Risk, Interest Rate Risk, and the Business Cycle." The Journal of Fixed Income 9 (2): 42–53.

[10] Allen, Franklin, and Ana Babus (2009). "Networks in Finance." The Network Challenge: Strategy, Profit, and Risk in an Interlinked World 367.

[11] Allen, Franklin, Ana Babus, and Elena Carletti (2010). "Financial Connections and Systemic Risk." National Bureau of Economic Research.

[12] Altman, Edward I, and Edith Hotchkiss (1993). "Corporate Financial Distress and Bankruptcy."

[13] Amador, Juan Sebastián, José E Gómez-González, and Andrés Murcia Pabón (2013). "Loan Growth and Bank Risk: New Evidence." Financial Markets and Portfolio Management 27 (4): 365–79.

[14] Anderson, Anne M, William Maxwell, and Theodore M Barnhill (2002). "Contingent Claims Analysis Applied in Credit Risk Modeling." The Journal of Fixed Income 12 (3): 24–31.
[15] Anggono, Herlanto (2017). "The Determinant Factors of Asset and Liability Management and the Bank Performance: Empirical Study on Foreign Exchange Commercial Banks in Indonesia from 2008 to 2013." International Journal of Business and Globalisation 19 (4): 512–27.
[16] Angori, Gabriele, David Aristei, and Manuela Gallo (2019). "Determinants of Banks' Net Interest Margin: Evidence from the Euro Area during the Crisis and Post-Crisis Period." Sustainability 11 (14): 3785.
[17] Atindéhou, Roger B, and Jean-Pierre Gueyie (2001). "Canadian Chartered Banks' Stock Returns and Exchange Rate Risk." Management Decision.
[18] Battiston, Stefano, Michelangelo Puliga, Rahul Kaushik, Paolo Tasca, and Guido Caldarelli (2012). "Debtrank: Too Central to Fail? Financial Networks, the Fed and Systemic Risk." Scientific Reports 2 (1): 1–6.
[19] Bock, Mr Reinout De, and Mr Alexander Demyanets (2012). Bank Asset Quality in Emerging Markets: Determinants and Spillovers. International Monetary Fund.
[20] Căpraru, Bogdan, and Iulian Ihnatov (2014). "Banks' Profitability in Selected Central and Eastern European Countries." Procedia Economics and Finance 16: 587–91.
[21] Castro, Vítor (2013). "Macroeconomic Determinants of the Credit Risk in the Banking System: The Case of the GIPSI." Economic Modelling 31: 672–83.
[22] Choi, Jongmoo Jay, Elyas Elyasiani, and Kenneth J Kopecky. (1992). "The Sensitivity of Bank Stock Returns to Market, Interest and Exchange Rate Risks." Journal of Banking & Finance 16 (5): 983–1004.
[23] Curry, Timothy J, Gary S Fissel, and Carlos D Ramirez (2008). "The Impact of Bank Supervision on Loan Growth." The North American Journal of Economics and Finance 19 (2): 113–34.
[24] Dang, V. (2019). "The Effects of Loan Growth on Bank Performance: Evidence from Vietnam." Management Science Letters 9 (6): 899–910.
[25] Daniel, Betty C, and John Bailey Jones (2007). "Financial Liberalization and Banking Crises in Emerging Economies." Journal of International Economics 72 (1): 202–21.
[26] Delis, Manthos D, Kien C Tran, and Efthymios G Tsionas (2012). "Quantifying and Explaining Parameter Heterogeneity in the Capital Regulation-Bank Risk Nexus." Journal of Financial Stability 8 (2): 57–68.
[27] Dichev, Ilia D. (1998). "Is the Risk of Bankruptcy a Systematic Risk?" The Journal of Finance 53 (3): 1131–47.
[28] Ekanayake, EMNN, and Athambawa Abdul Azeez (2015). "Determinants of Non-Performing Loans in Licensed Commercial Banks: Evidence from Sri Lanka." Asian Economic and Financial Review 5 (6): 868.
[29] Elsinger, Helmut, Alfred Lehar, and Martin Summer (2006). "Risk Assessment for Banking Systems." Management Science 52 (9): 1301–14.

[30] Fahlenbrach, Rüdiger, Robert Prilmeier, and René M Stulz (2018). "Why Does Fast Loan Growth Predict Poor Performance for Banks?" The Review of Financial Studies 31 (3): 1014–63.
[31] Farooq, Mohammad Omar, Mohammed Elseoud, Seref Turen, and Mohamed Abdulla (2019). "Causes of Non-Performing Loans: The Experience of Gulf Cooperation Council Countries." Entrepreneurship and Sustainability Issues 6 (4): 1955–74.
[32] Floreani, Josanco, Maurizio Polato, Andrea Paltrinieri, and Flavio Pichler (2015). "Credit Quality, Bank Provisioning and Systematic Risk in Banking Business." In Bank Risk, Governance and Regulation, 1–34. Springer.
[33] Foos, Daniel, Lars Norden, and Martin Weber (2010). "Loan Growth and Riskiness of Banks." Journal of Banking & Finance 34 (12): 2929–40.
[34] Galati, Gabriele, and Richhild Moessner (2013). "Macroprudential Policy–a Literature Review." Journal of Economic Surveys 27 (5): 846–78.
[35] Garratt, Anthony, Kevin Lee, M Hashem Pesaran, and Yongcheol Shin (1998). A Structural Cointegrating VAR Approach to Macroeconometric Modelling. Department of applied economics, University of Cambridge.
[36] Gbenga, Olorunmade, Samuel Olusegun James, and Adewole Joseph Adeyinka (2019). "Determinant of Private Sector Credit and Its Implication on Economic Growth in Nigeria: 2000-2017." American Economic & Social Review 5 (1): 10–20.
[37] Georgios, Kyriazopoulos, and Kondili Elvis (2019). "Bank Value Using Camels Model Evidence from Balkans Banking System." International Research Journal of Finance and Economics 176.
[38] Harris, Richard D F, and Elias Tzavalis (1999). "Inference for Unit Roots in Dynamic Panels Where the Time Dimension Is Fixed." Journal of Econometrics 91 (2): 201–26.
[39] Ichsan, Reza Nurul, Sudirman Suparmin, Mohammad Yusuf, Rifki Ismal, and Saleh Sitompul (2021). "Determinant of Sharia Bank's Financial Performance during the Covid-19 Pandemic." Budapest International Research and Critics Institute (BIRCI-Journal): Humanities and Social Sciences 4 (1): 298–309.
[40] Im, Kyung So, M Hashem Pesaran, and Yongcheol Shin (2003). "Testing for Unit Roots in Heterogeneous Panels." Journal of Econometrics 115 (1): 53–74.
[41] Ivanović, Maja (2016). "Determinants of Credit Growth: The Case of Montenegro." Journal of Central Banking Theory and Practice 5 (2): 101–18.
[42] Ivashina, Victoria, and David Scharfstein (2010). "Bank Lending during the Financial Crisis of 2008." Journal of Financial Economics 97 (3): 319–38.
[43] Jarrow, Robert A. and Stuart, M. Turnbull (2000). "The Intersection of Market and Credit Risk." Journal of Banking & Finance 24 (1–2): 271–99.
[44] Jin, Justin Yiqiang, Kiridaran Kanagaretnam, Yi Liu, and Ning Liu (2019). "Banks' Loan Growth, Loan Quality, and Social Capital." Journal of Behavioral and Experimental Finance 21: 83–102.

[45] Jolevski, Ljube (2017). "Non-Performing Loans and Profitability Indicators: The Case of the Republic of Macednia." Journal Of Contemporary Economic And Business Issues 4 (2): 5–20.
[46] Kashif, Muhammad, Syed Faizan Iftikhar, and Khurram Iftikhar (2016). "Loan Growth and Bank Solvency: Evidence from the Pakistani Banking Sector." Financial Innovation 2 (1): 1–13.
[47] Kaufman, George G, and Kenneth E Scott (2003). "What Is Systemic Risk, and Do Bank Regulators Retard or Contribute to It?" The Independent Review 7 (3): 371–91.
[48] Keeton, William R (1999). "Does Faster Loan Growth Lead to Higher Loan Losses?" Economic Review-Federal Reserve Bank of Kansas City 84 (2): 57.
[49] Köhler, Matthias (2012). "Which Banks Are More Risky? The Impact of Loan Growth and Business Model on Bank Risk-Taking."
[50] Kupiec, Paul, Yan Lee, and Claire Rosenfeld (2017). "Does Bank Supervision Impact Bank Loan Growth?" Journal of Financial Stability 28: 29–48.
[51] Laeven, Luc, Lev Ratnovski, and Hui Tong (2016). "Bank Size, Capital, and Systemic Risk: Some International Evidence." Journal of Banking & Finance 69: S25–34.
[52] Levin, Andrew, Chien-Fu Lin, and Chia-Shang James Chu (2002). "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties." Journal of Econometrics 108 (1): 1–24.
[53] Liedorp, Franka R, and Iman van Lelyveld (2006). "Interbank Contagion in the Dutch Banking Sector." International Journal of Central Banking 2: 99–132.
[54] Moussa, Mohamed Aymen Ben (2015). "The Determinants of Bank Liquidity: Case of Tunisia." International Journal of Economics and Financial Issues 5 (1): 249.
[55] Mpofu Trust and Eftychia Nikolaidou (2018). "Determinants of Credit Risk in the Banking System in Sub-Saharan Africa." Review of Development Finance 8 (2): 141–53.
[56] Mpofu Trust and Eftychia Nikolaidou (2019). "Macroeconomic and Bank-Specific Determinants of Non-Performing Loans in Sub-Saharan Africa." School of Economics Macroeconomic Discussion Paper Series.
[57] Muhmad, Siti Nurain, and Hafiza Aishah Hashim (2017). "The Interaction Effect of Corporate Governance and CAMEL Framework on Bank Performance in Malaysia." Afro-Asian Journal of Finance and Accounting 7 (4): 317–36.
[58] Murphy, Austin (2008). "An Analysis of the Financial Crisis of 2008: Causes and Solutions." An Analysis of the Financial Crisis Of.
[59] Nadham, Viswa, and B Nahid (2015). "Determinants of Non Performing Loans in Commercial Banks: A Study of NBC Bank Dodoma Tanzania." International Journal of Finance & Banking Studies (2147-4486) 4 (1): 70–94.
[60] Noman, Abu Hanifa Md, Sajeda Pervin, Mustofa Manir Chowdhury, and Hasanul Banna (2015). "The Effect of Credit Risk on the Banking Profitability:

A Case on Bangladesh." Global Journal of Management and Business Research.
[61] Önder, Zeynep, and Süheyla Özyıldırım (2013). "Role of Bank Credit on Local Growth: Do Politics and Crisis Matter?" Journal of Financial Stability 9 (1): 13–25.
[62] Owusu-Antwi, George, Lord Mensah, Margret Crabbe, and James Antwi (2015). "Determinants of Bank Performance in Ghana, the Economic Value Added (EVA) Approach." International Journal of Economics and Finance 7 (1): 204–15.
[63] Pesaran, H Hashem, and Yongcheol Shin (1998). "Generalized Impulse Response Analysis in Linear Multivariate Models." Economics Letters 58 (1): 17–29.
[64] Pesaran, M Hashem, Yongcheol Shin, and Ron P Smith (1999). "Pooled Mean Group Estimation of Dynamic Heterogeneous Panels." Journal of the American Statistical Association 94 (446): 621–34.
[65] Pesaran, M Hashem, and Ron Smith (1995). "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels." Journal of Econometrics 68 (1): 79–113.
[66] Rachman, Rathria Arrina, Yohanes Berenika Kadarusman, Kevin Anggriono, and Robertus Setiadi (2018). "Bank-Specific Factors Affecting Non-Performing Loans in Developing Countries: Case Study of Indonesia." The Journal of Asian Finance, Economics, and Business 5 (2): 35–42.
[67] Saba, Irum, Rehana Kouser, and Muhammad Azeem (2012). "Determinants of Non Performing Loans: Case of US Banking Sector." The Romanian Economic Journal 44 (6): 125–36.
[68] Salvi, Antonio, Candida Bussoli, Lavinia Conca, and Marisa Gigante (2018). "Determinants of Non-Performing Loans: Evidence from Europe." International Journal of Business and Management 13 (10).
[69] Sari, Laynita, Nandan Limakrisna, and Renil Septiano (2020). "Determinant Of Government Bank Performance Through Nim As Intervening." Dinasti International Journal of Economics, Finance & Accounting 1 (4): 619–28.
[70] Saurina, Jesús (2009). "Loan Loss Provisions in Spain. A Working Macroprudential Tool." Revista de Estabilidad Financiera 17: 11–26.
[71] Sharma, Parmendra, and Neelesh Gounder (2012). "Determinants of Bank Credit in Small Open Economies: The Case of Six Pacific Island Countries." Available at SSRN 2187772.
[72] Škarica, Bruna (2014). "Determinants of Non-Performing Loans in Central and Eastern European Countries." Financial Theory and Practice 38 (1): 37–59.
[73] Sobarsyah, Muhammad, Wahyoe Soedarmono, Wahdi Salasi Apri Yudhi, Irwan Trinugroho, Ari Warokka, and Sigid Eko Pramono (2020). "Loan Growth, Capitalization, and Credit Risk in Islamic Banking." International Economics 163: 155–62.

[74] Stepanyan, Vahram, and Kai Guo (2011). Determinants of Bank Credit in Emerging Market Economies. International Monetary Fund.
[75] Sukcharoensin, Pariyada (2013). "Time-Varying Market, Interest Rate and Exchange Rate Risks of Thai Commercial Banks." Asian Academy of Management Journal of Accounting and Finance 9 (1): 25–45.
[76] Tan, Ms Tatum Blaise Pua (2012). Determinants of Credit Growth and Interest Margins in the Philippines and Asia. International Monetary Fund.
[77] Tanasković, Svetozar, and Maja Jandrić (2015). "Macroeconomic and Institutional Determinants of Non-Performing Loans." Journal of Central Banking Theory and Practice 4 (1): 47–62.
[78] Tehulu, Tilahun Aemiro, and Dugasa Rafisa Olana (2014). "Bank-Specific Determinants of Credit Risk: Empirical Evidence from Ethiopian Banks." Research Journal of Finance and Accounting 5 (7): 80–85.
[79] Thornton, John, and Caterina Di Tommaso (2021). "The Effect of Non-performing Loans on Credit Expansion: Do Capital and Profitability Matter? Evidence from European Banks." International Journal of Finance & Economics 26 (3): 4822–39.
[80] Tracey, Mark, and Hyginus Leon (2011). "The Impact of Non Performing Loans on Loan Growth." IMF Working Papers.
[81] ul Mustafa, Ahmed Raza, Riaz Hussain Ansari, and Muhammad Umair Younis (2012). "Does the Loan Loss Provision Affect the Banking Profitability in Case of Pakistan?" Asian Economic and Financial Review 2 (7): 772.
[82] Umar, Muhammad, and Gang Sun (2018). "Determinants of Non-Performing Loans in Chinese Banks." Journal of Asia Business Studies.
[83] Vithessonthi, Chaiporn (2016). "Deflation, Bank Credit Growth, and Non-Performing Loans: Evidence from Japan." International Review of Financial Analysis 45: 295–305.
[84] Wang, Zongrun, Nan Xie, and Yanbo Jin (2019). "Do Loan Loss Provisions Affect the Credit Fluctuations in China's Banking System?" Emerging Markets Finance and Trade 55 (11): 2425–36.
[85] Wong, T C, and Cho-Hoi Hui (2009). "A Liquidity Risk Stress-Testing Framework with Interaction between Market and Credit Risks." Available at SSRN 1370826.
[86] Yap, Woon Kan, Siong Hook Law, and Judhiana Abdul-Ghani (2020). "Effects of Economic Freedom on Bank Profit Beta-Convergence in ASEAN-5 Banking Sectors." Journal of Economic Integration 35 (3): 479–502.

APPENDIX A:
Tables for matrix of correlations among studied variables

Table A1: Pearson correlation coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1) LLRs	1.000							
2) ROAE	-0.311	1.000						
3) ROAA	-0.162	0.686	1.000					
4) NIM	-0.109	0.312	0.121	1.000				
5) NPLs	0.664	-0.366	-0.218	-0.049	1.000			
6) CPSB	0.037	0.019	0.018	0.114	-0.029	1.000		
7) GDPGR	-0.022	-0.009	0.139	0.032	0.095	-0.013	1.000	
8) TGE	0.078	-0.138	-0.140	-0.058	0.102	-0.030	0.125	1.000

Table A2: Pearson correlation coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1) NPLs	1.000							
2) LLRs	0.664	1.000						
3) ROAE	-0.366	-0.311	1.000					
4) ROAA	-0.218	-0.162	0.686	1.000				
5) NIM	-0.049	-0.109	0.312	0.121	1.000			
6) CPSB	-0.029	0.037	0.019	0.018	0.114	1.000		
7) CPSB	0.095	-0.022	-0.009	0.139	0.032	-0.013	1.000	
8) TGE	0.102	0.078	-0.138	-0.140	-0.058	-0.030	0.125	1.000

Table A3: Pearson correlation coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1) CPSB	1.000							
2) NPLs	-0.029	1.000						
3) LLRs	0.037	0.664	1.000					
4) ROAE	0.019	-0.366	-0.311	1.000				
5) ROAA	0.018	-0.218	-0.162	0.686	1.000			
6) NIM	0.114	-0.049	-0.109	0.312	0.121	1.000		
7) CPSB	-0.013	0.095	-0.022	-0.009	0.139	0.032	1.000	
8) TGE	-0.030	0.102	0.078	-0.138	-0.140	-0.058	0.125	1.000

Table A4 : Selection criteria for optimal lags

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-5968.58	-	-	-	7.30	3.43	3.44	3.45
1	62015.6	1.45*	49	0.000	7.82*	-35.64*	-35.61*	-35.55*
2	62015.700	0.132	49	1.000	0.000	-35.62	-35.55	-35.43
3	62015.700	0.132	49	1.000	0.000	-35.59	-35.49	-35.32
4	62015.800	0.133	49	1.000	0.000	-35.56	-35.43	-35.20

This table presents the information criteria that serve as the lags in the following regressions. Across all criterion specifications, all the tests selected one lag from FPE, AIC, HQIC, and SBIC. Then, one lag is the optimal lag for all proceeding regressions.

APPENDIX B: Robustness checks using OLS, RE, and FE model

Table B5: Bank risk metrics/ratios as dependent variables

Bank risk		OLS		GLS		FE	
Dep. Var	Indep. var	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Model 4 NLPs as dependent variable	lnroae	-1.515*** (.303)	-4.98	-1.621*** (.367)	-4.42	-1.621 (.367)	-4.42
	ROAA	.029 (.025)	1.10	.036 (.042)	0.84	.036 (.042)	0.84
	NIM	-.273*** (.088)	-3.07	-.301** (.135)	-2.23	-.301 (.135)	-2.23
	LLR	.219*** (.038)	5.71	.183*** (.042)	4.38	.183 (.042)	4.38
	GDGGR	.029 (.018)	1.55	.036 (1.13)	1.13	.036 (.032)	1.13
	CPSB	1.480*** (6.760)	5.11	1.470*** (3.01)	13.01	-.097 (.115)	13.01
	LNTGE	3.671*** (8.531)	-4.98	7.353*** (5.95)	3.60	57.353 (8.545)	3.60
Model 5 LLRs as dependent variable	NPL	.3*** (.023)	13.71	.183*** (.018)	10.16	.159*** (.019)	8.25
	ROAE	-.012** (004)	-2.80	-.117*** (.016)	-7.20	-.122*** (.018)	-6.73
	lnROAA	.083* (044)	2.11	-.277 (.206)	-1.35	-.507*** (.24)	-2.11
	lnNIM	-.098*** (.062)	-1.76	.646 (.416)	1.55	1.799*** (.762)	2.36
	GDGGR	.001 (0.14)	0.02	.013** (.016)	0.84	-.049 (.041)	-0.75
	CPSB	-.634*** (.209)	-3.72	-7.89* (3.45)	-2.29	.11*** (.054)	2.67
	TGE	.033 (.034)	1.13	.033 (.034)	0.25	.056 (.048)	1.05
Model 6 CPSB as dependent variable	LLR	.002 (.003)	0.72	-.023*** (.004)	0.72	-.044 (.04)	-1.10
	NPL	.006** (.002)	2.52	.004*** (.001)	2.52	-.021 (.016)	-1.37
	ROAE	-.001**	-2.41	.005*** (.002)	-2.41	.021 (.011)	1.95
	ROAA	.006*** (.002)	3.37	.009** (.004)	3.37	-.26 (.08)	-3.24
	NIM	.023*** (.006)	3.61	0 (.003)	3.61	-.198 (.085)	-2.33
	ED	1.57*** (0)	-3.13	-2.19** (.02)	-1.19	-.038 (.224)	-0.17
	lnTGE	-3.147** (1.416)	-2.22	-.039 (.712)	-2.22	-.058 (.05)	-1.16

Table B6: Bank Performance metrics/ratios as dependent variables

Bank Performance		OLS		GLS		FE	
Dep. Var	Indep. var	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Model 1 ROAE as dependent variable	NPLs	-.744*** (.091)	-8.19	-.629*** (.093)	-6.79	-.019 (.084)	-0.22
	ROAA	.801*** (.134)	5.97	1.083*** (.155)	7.01	4.829 (.33)	14.62
	lnNIM	6.95*** (1.424)	4.88	9.867*** (1.771)	5.57	3.822 (2.243)	1.70
	LLRs	-.211 (.166)	-1.27	-.569*** (.183)	-3.11	-.861 (.195)	-4.41
	CPSB	-.044** (.044)	-1.01	-.068 (.069)	-0.99	.433 (.278)	1.56
	lnGDPGR	1.543 (.786)	1.96	1.406** (.801)	1.76	2.118 (1.12)	1.89
	lnTGE	-49.26 (3.373)	-0.98	-26.147 (4.423)	-0.62	-.071 (.247)	-0.29
Model 2 ROAA as dependent variable	NPLs	.073*** (.012)	5.97	.059*** (.004)	4.09	.004*** (.002)	2.81
	ROAE	.191*** (.028)	6.85	-.01 (.011)	-0.86	-.047*** (.015)	-3.09
	lnNIM	-3.958*** (.408)	-9.71	-.597** (.279)	-2.14	-.362 (.083)	-4.39
	LLRs	-.572*** (.044)	-2.91	.003 (.024)	0.11	-.033* (.019)	-1.77
	CPSB	.031** (.013)	2.34	.01*** (.027)	0.37	.344*** (.053)	6.54
	lnGDPGR	.43** (.238)	1.81	.17 (.152)	1.12	-.654** (.26)	-2.52
	lnTGE	-8.132 (5.263)	-0.53	.314 (4.284)	0.07	7.633 (7.269)	1.05

Model 3 NIM as dependent variable	ROAA	-.036*** (.004)	-9.71	-.023*** (.004)	-5.25	.054*** (.009)	2.66
	ROAE	.006*** (.001)	4.88	.004*** (.001)	5.79	0** (.001)	1.70
	NPLs	-.002 (.003)	-0.76	.005*** (.002)	2.92	.008*** (.002)	4.76
	LLRs	-.005 (.005)	-1.08	.009** (.004)	2.29	.008** (.004)	1.60
	CPSB	.004*** (.001)	3.44	0 (.003)	0.15	-.002 (.006)	-1.41
	lnGDPGR	.049** (.023)	2.15	-.033** (.02)	-1.67	-.013 (.028)	-0.96
	lnTGE	-1.267 (1.453)	-0.87	-.039 (.712)	-0.05	-.409 (.725)	1.42