ASSESSING THE IMPACT OF BANKING EFFICIENCY, OPERATIONS AND REGULATION ON BANKING PERFORMANCE: FRESH INSIGHT USING DYNAMIC CORRELATED FRAMEWORK ON THE DATA SET OF RUSSIA AND UKRAINE

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ABSTRACT

The purpose of this study is to investigate how banking industry-specific variables like regulation, efficiency, and operations affected nonperforming loans (NPLs) in Ukraine and Russia from 1995 to 2019. This study has employed the robust unit root test and cross-sectional dependencies technique along with a new DCCE approach. The dynamic correlated method is employed as it provides the best results when data suffers from cross-sectional dependencies. The study concludes that loose credit policy and lower profitability help in rising NPLs. However, in the context of macroeconomic variables, volatile interest rates and exchange rate fluctuations are the main reason for NPLs in Russia and Ukraine.

The research work also highlights the issue of cross-sectional dependencies and provide substantial methods to resolve the problem of cross-sectional dependencies and provide robust results. Findings will help policymakers to recognize the relevance of industry-specific variables in managing NPLs along with other macroeconomic variables.

Keywords: nonperforming loans, banking, PMG, unit root, cross-section dependency

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INTRODUCTION

Banks play a prominent role in the economic development of a country by providing adequate investment and credit opportunities (Petkovski & Kjosevski, 2014). Banks of most countries are suffering from the issue of NPLs, which are those loans which fail to repay principal and interest. Higher portfolio of NPLs affects banking performance and credit disbursement, which leads to lower consumption and investment levels in the economy (Stiglitz 1981; Stijepović, 2014). The economic development of a country depends upon the stability and sustainability of the banking structure. However, increased competition and financial autonomy have created pressure on banking businesses. Target-based banking and the need for credit creation has resulted in bad management practices, leading to ineffective decisions, faulty customer documentation, and finally ending up with NPLs.

Banks in Russia and Ukraine are also facing the issue of NPLs. The average of problem loans in both the countries stands more than the world average of 6.88 percent (World Development Indicators (FB.AST.NPER.ZS), 2019). In both countries, the portion of the corporate loan is much higher than the retail loans, as reported by the Central Bank of Russia and the National Bank of Ukraine. To revive the banking system and economic fundamentals, since 2016 host of reforms were introduced by both countries, like exchange rate reforms, inflation targeting, banking mergers, infusion of capital, and revocation of banking license (Financial development report, International Monetary Fund, 2019; Kichurchak, M.,2019). The International Monetary Fund suggested that due to the COVID-19 pandemic, both countries will face a recession in the near future, coupled with lower employment and consumer demand, which will eventually create a negative effect on debt service capabilities and banking profitability. Thus, based on all the above reasons for banking and economic disturbance, Ukraine and Russia have been considered as the sample country to study.

Previous studies have highlighted that sometime NPLs rise because of poor management decisions, ineffective policies like loan waiver schemes, and excessive credit flow (Salas & Saurina, 2002; Berger & DeYoung, 1997). Based on the theoretical background of the 'bad management hypothesis' as suggested by previous work, this study focuses on investigating how banking activities like operations, efficiency, and regulation affect NPLs, so that findings can be used for framing a suitable strategy for the future.

This study is novel and will help researchers, academicians, and policymakers in the following ways: first, this study contributes to the previous work of 'bad management hypothesis' by empirically investigating how banking variables like efficiency, regulations, and operations affect banking NPLs in Ukraine and Russia. Second, this study uses the new theoretical DCCE approach, which considers cross-sectional dependency of time series data and provides robust results. Third, the sample countries used in the study are also unique as the banks in these countries share a considerable amount of nonperforming loans ratio out of their total loans. These countries will also add a new region to previous literature; last, the period of study is relevant because, as the world is facing the issue of coronavirus and banks are the only source that can help in easing out the slow growth, thus studying banking variables in the current situation will add substantially toward the previous literature on NPLs.

LITERATURE REVIEW

There are various studies on investigating the determinants of NPLs, but this section of the paper will only focus on analyzing the banking determinants of NPLs.

Berger and DeYoung (1997), and Keeton and Morris (1987), conducted some of the leading studies on bank-specific determinants of nonperforming loans. They concluded that the lack of sufficient capital, profit motives, and inefficient management strategies are the main reasons behind NPL's growth in the United States. A study on the Spanish banking sector conducted by (Jimenez and Saurina, 2003), also supported the findings of (Berge and DeYoung, 1997; Keeton and Morris, 1987). The study further concluded that loose credit policies during the expansionary phase of the economy resulted in higher NPLs.

Podpiera and Weill (2008) focused his study on the Czech banking sector from 1994-2005 and suggested that bad management is the main reason for NPLs in the Czech banking sector. Further, his study concluded that regulatory capital and cost efficiency help in reducing NPLs. Hu,, Li, and Chiu, (2004) conducted a similar study focusing on the Taiwan banking sector and concluded that the size of the banks and credit disbursement policies affect NPLs significantly. Rajan and Dhal (2003) further supported the same findings in the context of the Indian banking sector.

Using a dynamic approach Espinoza and Prasad (2010), explored banks of GCC countries from 1995-2008. The findings conclude that the rate of interest spread charged by banks and lenient credit policy affects banking NPLs significantly. A study conducted by Nkusu (2011) among 26 advanced countries using impulsive response techniques also supports the above findings. Nkusu (2011) further added that management efficient decision making helps in reducing nonperforming loans to an extent. Ozili (2018) performed a study focusing on the level of financial development and financial liberalization and assessing its impact on NPLs in six regions of the world, using sensitivity analysis. The findings of the study concluded that the level of financial development and the presence of foreign banks positively affect NPLs. Chaibi and Ftiti, (2015) supported the above findings besides adding that leverage and inefficiency are also important determinants of NPLs in the German and French banking industry.

Swamy (2012) investigated the role of bank-specific determinants in the Indian banking industry, covering the period from 1997-2009. Using the autoregressive distribution lag method study, he concluded that profitability and loans to deposit rates are positively related to NPLs, whereas bank size is negatively associated with problem loans. Castro (2013) further substantiated the above work in context to GIPSI countries. Other studies that have evaluated the bank-specific determinants of NPLs (Vovchak et.al., 2019; Sobolieva-Tereshchenko et.al., 2020). Most of the studies have concluded that bank poor management practices, lower management productivity, credit policies, and bank size have a significant impact on the NPLs.

The literature review section shows that although there are various studies on bank-specific determinants and NPLs, yet they suffer some of the other limitations. First, all the above studies were focused on the country or region-specific findings and have ignored the role of cross-sectional dependencies. Thus, this new correlated model will add substantially toward previous literature. Second, most of the above studies have taken all industry and economic variables together, therefore, making it necessary to study the impact of both the variables separately. Finally, there is no conclusive study in Russia and Ukraine that focuses on the broad parameters of regulation, efficiency, and operation, thus, providing a suitable literature gap.

Theoretical background

The literature review shows that previous studies have used various models and variables. In earlier studies, determinants of nonperforming loans are categorized into two broad categories-macroeconomic determinants and bank or industry-specific determinants. Therefore, to evaluate the bank-specific determinants of NPLs, this study has used the theoretical background of the bad management theorem and too big to fail syndrome. Both the models argued that lower-efficiency, poor business decisions, lower-cost efficiency, lower-income, and regulations are the key factors that impact organizational productivity as given by Berger and De-Young, (1997) and Ghosh (2015). Thus, to reconfirm both the above theories, this study has tried to check the role of banking efficiency, regulation, and operation on the banking performances concerning NPLs based on following hypothesis.

- H_0: Bank efficiency has a negative impact on NPLs
- H_1: Banking Regulation has a negative impact on NPLs
- H_2: Banking Operations has a positive impact on NPLs

RESEARCH METHODOLOGY AND ANALYSIS

To study how industry-specific variables affect banking performance in Ukraine and Russia, the annual percentage change data have been taken from 1995-2019, using the statistical database of the International Financial Statistic and World Bank indicators. Due to the lack of data constraints, other industries or bank-specific variables are not included. The following proxies are considered, based on the review of previous literature and, according to various government working papers. Return on assets for banking efficiency (Abdioglu & Aytekin, 2016), capital adequacy for measuring banking regulations (Boudriga et al., 2010), credit to deposit ratio for banking operation (Kjosevski & Petkovski, 2014) and for measuring banking performances, nonperforming loans as a proxy variable (Syed & Aidyngul, 2020). Interest rates and exchange rates are included in this study to make it more comprehensive (Tanasković & Jandrić, 2015). The below table shows the detail of the data source and variables.

Table 1: Variables Description

Variable	Variable description	Data Source
NPL	Nonperforming Loans	International Financial Statistic (IMF)
ROA	Return on Assets	WB indicators
CAR	Capital Adequacy Ratio	WB indicators
CDR	Credit Deposit Ratio	WB indicators
INT	Interest Rate	WB indicators
EXH	Exchange rate variation in terms of USD.	WB indicators

Unit root and cross-sectional dependency test

Most of the studies have suggested that panel data face the issue of cross-sectional dependency because of unobserved elements and different country-specific situations, which results in idiosyncratic dependencies. Earlier studies like Levin et al. (2002) and Pesaran (2007) have employed those methods which have either ignored the above issue or were based on cross-sectional homogeneity. Thus, to avoid this issue and to prevent rejection of the null hypothesis on homogeneity, this research work has employed the unit root test proposed by Pesaran (2004).

$$\alpha_{it} = \gamma_i + \beta_{it} c_{it} + \mu_{it} \quad (1)$$

Eq.1 is used to examine cross-sectional dependencies.

$$H_0 = s_{iz} = s_{zi} = Cor\ (\mu_{it,} \mu_{it,})=0 \text{ for } i \neq z \quad (2)$$

$$H_1 = s_{iz} = s_{zi} = Cor\ (\mu_{it,} \mu_{it,}) \neq 0 \text{ for some } i \neq z (3)$$

H_0 =No Cross-sectional dependencies, H_1 = Data suffers from Cross-sectional dependencies.

Testing of Cointegration

Previous studies have suggested that for empirical or statistical analysis, numerous cointegration techniques are available. Researchers have always scrutinized cointegration techniques based on the duration of the data (Perron, 1991). To avoid the issue of structural break and to evaluate the long term association, this paper has used the bootstrap cointegration model, as proposed by Westerlund and Edgerton (2007). This model is appropriate for a short duration of data as it observes the lead-lag length. This feature is not available in other standard cointegration techniques like Hansen. The following equation represents the bootstrap cointegration model (Westerlund & Edgerton, 2008).

$$\Delta y_{it} = \delta e_t + \alpha_i (y_{i,t-1} - \beta i'^{x_{i,t-1}}) + \sum_{j=-qi}^{qi} a_{ij}\, \Delta y_{i,t-1} + \sum_{j=-qi}^{qi} \gamma_{ij}\, \Delta x_{i,t-1} + e_{i,t} \quad (4)$$

The stated Eq4. represents endogenous variables relationship for the different datasets and subscripts t and i depicts time and cross-section.

Dynamic Correlated Effect approach

A review of previous literature shows that most studies have given much importance to homogenous slopes rather than cross-sectional effects. Most of the panel data analysis tools like generalized methods of moments, random, and fixed effect, give misleading results because they ignore homogeneity and consider only intercept changes. Therefore, heterogeneous coefficient with cross-sectional units has become a point of discussion among many scholars.

Various studies have given relevance to cross-sectional dependencies among the data (Meo et al., 2020). Due to the issue of cross-sectional dependency, Chudik and Pesaran (2015b) introduced a new DCCE model. In this model 4 principles are used that are MG estimation, PMG estimation, CCE estimation, given by Shin et al. (1999); Pesaran and Smith (1995); and Pesaran (2006), along with using the estimation technique of Chudik and Pesaran (2015a). This model is more robust as it considers both cross-sectional dependencies along with heterogenous and homogenous coefficients by considering the means and lag of cross-sectional data. This approach is also suitable for data that suffers from the issue of structural break and has a small sample size with an unbalanced panel. This study has used the equation given by Chudik and Pesaran (2015b).

$$NPL_{it} = \partial_i NPL_{it-1} + \delta x_{it} + \sum_{p=0}^{p_t} \gamma_{xip} X_{t-p} + \sum_{p=0}^{p_t} \gamma_{yip} Y_{t-s} + \mu_{it}$$

NPL represents nonperforming loans, δx_{it} represents independent variables, p_t shows lag limit in the cross-sections, and $\partial_i NPL_{it-1}$ depicts the lag of NPL as an independent variable.

Table 2. Descriptive Statistics

	CAR	CDR	EXH	INT	NPL	ROA
Mean	16.07	108.02	20.69	2.81	16.45	.08
Median	15.8	108.37	16.85	1.63	13.14	1.70
Maximum	20.90	200.18	67.06	37.9	54.50	11.12
Minimum	11.20	20.20	1.47	-56.00	2.40	-22.03
Std. Dev	2.97	34.67	18.48	14.04	13.26	6.44
Skewness	-0.01	-0.17	1.08	-1.11	1.09	-2.45
Kurtosis	1.70	4.45	3.45	8.18	3.53	9.03
Jarque-Bera	3.36	4.48	9.84	7.32	10.10	12.13
Probability	0.186	.105	.074	.068	.0612	.0721

FINDINGS AND DATA ANALYSIS

Keeping into consideration the issue of cross-sectional dependencies and misleading results, this study has employed the cross-sectional dependency test, as given by Pesaran (2004), which focuses on the pertinent issue of cross-sectional dependency. By using the pairwise correlated Ordinary Least Square technique, this test helps in selecting the most significant generation of tests suitable in the case of cross-sectional dependencies (Syed, 2020). The below table 3 shows the results of the cross-sectional dependency test and descriptive analysis.

The findings of Table 3 clearly show that the data is suffering from the issue of cross-sectional dependency because the probability is less than five percent level of significance, meaning the null hypothesis needs to be rejected based on P-value. This study has used both first and second generations of the test, along with Augmented Dicky Fuller(ADF) test for robustness, attached as annexure 1, under which the first generation of the test assumes data homogeneity, and the other one considers cross-sectional dependency, to avoid misleading results (Chang, 2004 & Kahia et al., 2016). The below table shows the outcomes of the First Generation of the test

Table 3: Results of Cross-sectional Dependency test

	Cross-sectional Test	Probability value
NPL	5.21	0.0001*
ROA	7.13	0.0001*
CAR	5.34	0.0000*
CDR	9.14	0.0001*
INT	8.12	0.0000*
EXH	11.22	0.0000*

* at 1 percent significance level.

Table 4: Results of Levin and Shin test

	Levin Lin and Chu test				Pesaran Shin- Wat			
	(Levels)		(1st Difference)		(Levels)		(1st Difference)	
	Stats	P-value	Stats	P-value	Stats	P-value	Stats	P-value
NPL	-0.66	.25	-4.37	.0000*	-0.13	.4451	-3.14	.0008*
ROA	4.49	.07	-8.93	.0000*	2.11	.9826	-11.25	.0000*
CAR	-0.42	.33	-4.85	.0001*	-0.85	.1952	-4.45	.0000*
CDR	-2.60	.00*	-2.20	.0000*	-1.75	.0394	-2.05	.0000*
INT	-4.09	.00*	-5.60	.0000*	-4.40	.0742	-6.67	.0000*
EXH	2.28	.98	-4.75	.0001*	1.75	.9597	-4.35	.0000*

* at 1 percent significance level

The results of Table 4 show that except for credit deposit and interest rate, all variables are of the first order of integration. For reconfirmation of the findings, this research work has also used a 2nd generation test called a CIPS test (Pesaran 2007), which is appropriate for the issue of cross-sectional dependencies. Results of the CIPS test show interest rate is integrated at the level, whereas all others are of the first order of integration.

Table 5. Results of CIPS test

	Levels	1st Difference
NPL	.42	-3.14*
ROA	-1.13	-3.25*
CAR	-2.32	-3.13**
CDR	-3.18	-6.14*
INT	-1.06**	-2.48*
EXH	-1.12	-3.12**

* shows the different significance levels *1 percent, **5 percent

Unit root test findings show that the variables are of mixed order of integration, and none of the variables is of the second order of integration. Based on the favorable result of unit root, this study moves forward with checking the long-term association among the variables using the new dynamic correlated model. However, before using DCCE analysis, long-run cointegration is checked by using Pedroni and Westerlund Error Correction Model. Westerlund and Edgerton (2008) pointed out that most cointegration techniques like Hansen etc. ignore structural breaks, which often give spurious results; therefore, the ECM cointegration approach is employed as it considers the issue of heteroskedasticity, structural-breaks, serial correlation, and cross-sectional slopes. Table 6 and Table 7 shows the results of ECM cointegration techniques (Pedroni and Westerlund).

Table 6. Results of Pedroni Test of Cointegration

	t-statistic	Probability	Weight t-statistic	Probability
H_1: Within Dimension (Common Coefficient)				
V-Stats	-0.089	.53	-0.14	0.55
Rho-Stats	.66	.74	0.91	0.82
PP-Stats	-1.39	.08	-1.26	0.39
ADF- Stats	-1.47	.06	-0.44	0.02*
H1: Between Dimension(Individual Coefficients)				
Rho-stats	1.53	0.03		
ADF-stats	-0.11	0.45		
PP- Stats	-0.10	0.45		

* 5 percent Significance level

The Pedroni cointegration test results confirm that the null hypothesis of no cointegration cannot be rejected, as in six outcomes the probability value is more than a five percent significance level. Thus, to reconfirm the result of Pedroni, the Westerlund ECM cointegration test is also used. Table 7 describes the findings of ECM cointegration, which shows that banking regulation, operation, efficiency, and performance have a long-run relationship as in all cases, the probability value is less than 5 percent level of significance, meaning an alternative hypothesis to be accepted.

Table 7. Results of ECM Cointegration

	Value	**Robust P-value**
Gt	-4.1412	.0001*
Ga	-18.273	.0000*
Pt	-8.129	.0001*
Pa	-18.141	.0000*

* 1 percent level of significance

The results of the PMG model state that interest rate, exchange rate, returns on assets, and credit deposit ratio have a significant association with NPLs, as the probability value is less than 5 percent level of significance. Interest rates and credit deposits have a direct impact on NPLs, whereas the return on assets and exchange rates have an indirect impact on NPLs. Results of PMG estimates are re-checked by using the DCCE approach, as PMG ignores the issue of cross-sectional dependency. Table 9 shows the results of the DCCE model.

Table 8. PMG test result

Independent variable	**Coefficient**	**Probability-Value**
CDR	0.17	0.0000*
CAR	-0.13	0.0726
ROA	-0.24	0.0000*
INT	0.08	0.0513*
EXH	-0.20	0.0013*
C	22.12	0.0043*

* 5 percent significance level

The result of the dynamic correlated model confirms that the credit to deposit ratio (a proxy variable of operations), exchange rate, and interest rate have a direct and significant association with NPLs (as the coefficient shows a positive sign and the probability value is less than 5 percent). The return on assets (a proxy for efficiency) and capital adequacy ratio (a proxy for regulations) have an indirect and significant association with NPLs in the panel data of Russia and Ukraine (as the coefficient shows a negative sign and the probability value is less than 5 percent). In the case of Russia, data clearly show that over the years, the banking credit cycle witnessed considerable growth from 67 percent in 1995 to 112 percent in 2018. However, regulatory capital has shown a significant drop from 20.9 percent in 2009 to 12 percent in 2018, resulting in the growth of NPLs in Russia. Ukraine also shares a similar situation with a rise in the banking credit cycle over the years and subsequent drop in the regulatory capital and thus contributing toward NPLs. So, it can be concluded that the statistical analysis of the data fully supports the findings of this study.

Table 9. Findings of Dynamic Correlated Model

Independent variable	Coefficient	Probability-Value
NPL(-1)	-0.05	0.0320**
CDR	0.33	0.0001**
CAR	-.15	0.0010*
ROA	-0.28	0.0001**
INT	0.12	0.0200**
EXH	0.21	0.0040**

* 1 percent significance level, ** 5 percent significance level

The Findings of the DCCE model will be considered for final results, as the coefficient value is more than the PMG estimate. Additionally, the DCCE model is more robust in the case of cross-sectional dependency. The findings of the study also strengthen the work of Ozili (2018) and Beck et.al (2015).

CONCLUSION AND DISCUSSION

This research work focuses on investigating the impact of various banking parameters like regulation, efficiency, and operation on banking performance in Ukraine and Russia by employing a new DCCE framework. This study significantly contributes toward the theoretical literature by discussing the cross-sectional dependency issue of time series panel data, besides highlighting the role of three significant parameters of the banking industry.

The result of the study shows that lenient credit policy, inadequate regulatory capital, lower profitability, exchange rate disturbances, and abrupt interest rate fluctuation are the main reasons that result in increasing banking NPLs. Therefore, it can be concluded that poor credit disbursement policies, lower profitability due to inefficient operations, and the lack of sufficient regulatory capital that provide stability are the crucial reasons affecting banking performance in Ukraine and Russia.

The findings suggest that the banking industry of Russia and Ukraine should pay more attention to non-interest income and promote the profitability of banks through effective banking strategies and also by scrutinizing loan quality and recovery mechanisms. Banks having lower profits resort to excessive credit distribution without proper documentation of borrowers' creditworthiness, which often results in loan defaults. The banking system in Ukraine and Russia also lacks an effective credit recovery mechanism, leading to higher loan default. Therefore, based on the findings, the banking industry of Ukraine and Russia should focus more on other banking businesses like underwriting, share market operations, digitalized payment portals avenues, financial instrument trading, and other financial services instead of relying only on credit deposit spread. Based on reports from the World Bank and the International Monetary Fund, public sector banks constitute roughly 60 percent of the banking industry in Ukraine and Russia, which shows their disproportionate dependence on public sector organizations. Scrutiny of corporate lending also seems imperative for a healthier and more profitable banking sector to discourage bank owners and corporations from using loans for personal gains.

According to a report by the World Bank, the COVID-19 situation could plunge the Central and Eastern European region into a dire economic recession. Banks should, therefore, proactively focus on tackling the impending economic turbulence and the likely surge of loan defaults resulting from high unemployment rates and persistent lockdown. The government should also focus on other macroeconomic determinants like interest rate and exchange rate as they also substantially contribute to NPLs in Russia and Ukraine. The use of artificial intelligence (AI) and machine learning approach in keeping a watch on the frequent defaulter will also help in reducing NPLs. Digitalization and techniques of artificial intelligence can help in the preparation of early warning techniques and loan workout strategies. Banks can use automated systems for tracking small loans and industrial expert opinions for large loans. One of the surveys conducted by AI Opportunity Landscape research shows that around 15 percent of venture funding in banking-related artificial intelligence is for finding lending solutions Allen et al.,(2020). So the bank in Russia and Ukraine can also use the same AI and machine learning approach in reducing and tracking NPLs.

Last, based on the findings, it can also be concluded that the results of this study fully support the theoretical background of bad management and too big to fail syndrome.

LIMITATIONS AND IMPLICATIONS

Since only two countries are from Central and Eastern Europe, hence it serves as a limitation. This study also suggests that scholars may also consider other variables like the level of financial intermediation and development for studying their impact on NPLs in the coming future. Apart from focusing on accessing the role of banking and macroeconomic determinants, this study also emphasizes the issue of cross-sectional dependency along with providing suggestive methods to tackle such issues while dealing with time-series data.

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Annexure 1: Augmented Dicky Fuller test result.

	Levels		1st Difference	
	Stats	**P-value**	**Stats**	**P-value**
NPL	-0.25	.08	-2.14	.0000*
ROA	1.26	.03*	-4.15	.0000*
CAR	-0.12	.13	-3.16	.0000*
CDR	-1.25	.02*	1.13	.0000*
INT	-2.19	.01*	-2.15	.0000*
EXH	1.13	.16	-1.67	.0000*

* 5 percent level of significance.

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