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Macroeconomic Determinants Of Credit Risks: The Case Of Low-And Lower-Middle Income Countries

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Abstract – The financial system of low- and middle-income countries is characterized by the difficulty of credit risk management. This study aims to create an effective risk management framework by studying the impacts of the macroeconomic environment on credit risk. It applies the GMM system model in the context of the unbalanced panel data of 43 countries over the period from 2005 to 2021. The results indicated that economic activity variables do not have a significant effect on credit risk, unlike monetary variables.

Keywords – credit risk, systemic risk, non-performing loans, low-income countries, system-GMM

Introduction

Despite its 5,000 years history and researches around it, our current financial system still struggle in finding the right way to hedge against credit risk without harming global economies. These last decades showed that credit risk is an important issue banks and financial institutions, and even the broader economy needs to manage. In fact, between 2008 and 2023, there were three important events related to debt management which had bigger impact on the economy, starting from the great financial crisis where we saw the collapse of a systemic bank, then the European debt crisis which mostly affected the Greek economy and finally the Evergrande incident on the Chinese financial market which lead to a negative rating on the Chinese credit outlook, and ended with the retreat of massive american fund from the Chinese stock in the end of 2023. Several works on the determinants of credit risk exists, especially in advanced economies and on European financial systems. Studies on macroeconomic factors of credit risk try to identify the variables that can affect the general level of risk, commonly known as systemic risks. It is undisputed in the literature that the bank credit risk, measured by Nonperforming loans (NPL) is a dynamic variable. Each studies found that the coefficient of previous nonperforming loan on the current nonperforming loan is both positive and significant, suggesting that credit risk is both self-sustaining and self-cumulative. Apart from that, studies demonstrated that other macroeconomic variables have an impact on NPL. It is a common knowledge that situation that reduces income or increase expenditure are more incline to increase payment default. It is therefore suggested that period of growth can encourage risks as banks are willing to take more risk (Bonfim, 2008;) as it can be a factor of risk reduction (). Also, conditions on financial market, such as the credit growth and interest rate raises can determine the level of risk. Finally, inflation and exchange rate have mixed behavior, according to the position of the economic agents and the use of credits. Despite the interest on credit risk, researches on developing economies is insufficient. However, due to the lack of techniques related to risk management and the nonexistence of direct finance and some market, least developed markets rely mostly on credits to fund its growth. The developing markets have their own particularities. Some studies identify exchange rate, interest rate and diversification of economic activity as key determinants of credit risk (Fofack, 2005; Warue, 2014). Other authors found the importance of remittance and secondary income (Nikolaidou and Vogiazas, 2017). The following adds up

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the existing studies on credit risk, using the case of low income economies where literature is scarce. Most articles have used static panel model. Others used differenced-GMM which does not consider underlying heteroskedasticity. Using system-GMM model on an unbalanced data composed by 47 countries and 5 to 17 time periods, we will try to identify the key determinants of credit risk in developing economies. Then, we will check for the robustness of our model. The paper is structured as follow: in section 2, we will look back at existing literature. Then, in section 3, we will describe the data used to perform the analysis and the methodology. Next, in section 4, we will display and discuss the results and finally in section 5, we will conclude the article by emphasizing on the policy implications of the findings.

Literature review

The impact of macroeconomic environment on credit risk have been studied previously and mostly in developed economies. These researches can be classified as ones that are purely related to the understanding of the relationship between macroeconomic environment and credit risk (Castro, 2013; Koju et al., 2019) and others which aims at stress-testing the soundness of financial system (). Few are the articles which focuses on low- and lower-middle income countries but in the current section, we will look at all of the existing literature.

Cases of advanced economies

It is clear that there are differences in advanced and in developing economies. Here, we will take both perspective separately. There are few variables that are often taken into account when studying the determinants of systemic credit risk. The first among them is productivity. Often using GDP growth as proxy, this variable is always significant when it comes to determining credit risk. It is said that productivity has two distinct effects on credit risk. On the one hand and where most economists agree is the fact that a growing economy helps reduce credit risk. This effect has been supported by Jiménez and Saurina (2006), Koju et al. (2019) using GMM following Arellano-Bond (1991) specifications. On the other hand, the increase of income in time of growth boosts bank's confidence in the economy and therefore increase risk-taking which leads them to funding low and nonperforming projects. The period of recession which follows just shed light on the excessive risk-taking in time of growth (Bonfim, 2008;). Another variable that has always been present is unemployment. Alongside productivity related variables, this variable is closely related to the income of economic agents. It is a common knowledge that an increase in unemployment rate means that households are looking for more to cover their needs; which in turn, will increase their probability of default and leads to the formation of credit risk. Following this logic, we found in all studies related to developed markets that unemployment affects positively credit risk (Nkusu, 2011; Yurdakul, 2014). Louzis et al. (2012) go further by suggesting that in time of difficulty, businesses reduce their labor cost to pay off their debt. Inflation is also an important variable. It is a common knowledge that inflation have two opposite effect. The first effect is that it affects income by reducing purchasing power if there is no increase of revenue at the same pace. Having an inflation rate that runs faster than the growth of income will lead to an increase in cost of living and bring the difficulty to reimburse their loans. However, there is a second perspective where inflation tend to reduce the cost of debts by reducing the real interest rate. Empirical studies suggest that inflation does not have significant effect on credit risk, despite the variable being considered so often (Otasević, 2015;). There is a way for us to say that both effects of inflation cancel each other out. Apart from traditional macroeconomic variables, other variables related to banking are also used. Among them is interest rate. Considered to be the cost of funding, this variable is therefore directly related to the funding issue. Often used as a way to push "bad" loans out of the market, empirical studies suggest that interest rate is often found to take the same direction as does credit risk (Jiménez and Saurina, 2006; Koju et al., 2019). In addition to interest rate, the annual growth of credit is also a bank-related variable which is used often to proxy risk-taking by banks. Theories suggest that an increase in the amount of loan granted increase credit risk. This assumption is always verified empirically (Kattai, 2011; Castro, 2013). Finally, empirical researches often include foreign variables in their analysis. The first variable where authors are often on agreement is exchange rate. Studies often use real effective exchange rate to measure the impact of exchange rate on credit risk and found a positive effect of exchange rate on credit risk (Castro, 2013; Yurdakul, 2014) for the case of the countries in the GIPSI (Greece, Italy, Portugal, Spain, Ireland) and Turkey respectively whereas Otasević (2013) suggests a positive relationship for the case of Serbia. Also, other variables related to trade are often used, for instance, exports (Koju et al., 2019), terms of trade (Castro, 2013), oil price (Yurdakul, 2014). If we've discussed about the main variables found in most analysis, other variables are also considered by these paper, for example: confidence level (Bonfim, 2008;

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). While most studies have used GMM models in their analysis (Jiménez and Saurina, 2006; Louzis et al., 2012; Castro, 2013; Otasević, 2015), others use VAR related models to obtain results(Fainstein and Novikov, 2011; Kattai, 2011). There is however small minority use both model (Nkusu, 2011). How far off are the results in developing economies compared to those of more advanced ones?

Case of developing economies

As we have already mentioned, the analysis on credit risk in developing economy are scarce. Here, we will look at how these papers compare to the previous ones. There are three notable articles which studied the relationship between credit risk and macroeconomic variables: Fofack (2005) on countries from Sub-Saharan Africa, using correlation and causality analysis on pseudo-panel; Warue (2013) on the case of Kenya using fixed- and pooled-effect model; and Nikolaidou and Vogiazas (2017) on a panel data composed by five countries from Sub-Saharan Africa: Kenya, Uganda, Zambia, Namibia and South Africa using ARDL model. The first study (Fofack, 2005) was important in a way that it performed a sub-panel analysis on the data, by analyzing separately data from CFA countries and non-CFA countries on a yearly basis. Using GDP per capita, inflation, interest rate, effective exchange rate, money supply, interest rate margin, interbank loan and other banking variables, the study suggests that an economic decline is determinant in the formation of credit risk. In addition to that, real interest rate, money supply and change in real exchange rate have positive effect on interest rate. The most important and unique finding form this finding is however the fact that exchange rate does not have significant effect for the non-CFA sub panel, suggesting the effect of the adjustment of exchange rate. The second paper by Beatrice Njeru Warue (2013) analyzed the relation of macroeconomic variable and credit risk for the case of Kenya. Using almost the same variables as used by Fofack, and using pooled and fixed-effect regression, the study found similar results as the previous article. The most important part of this paper is however the fact that it took into consideration the governance and the size of banks and studied the relationship between size, governance and return on credit risk. Finally, the third article by Nikolaidou and Vogiazas (2017) is a panel analysis on five countries from Subsaharan Africa: two upper-middle income countries (South Africa and Namibia), one lower-middle income country (Kenya) and two low-income countries (Uganda and Zambia). The paper aims at identifying the determinants of credit risk in Subsaharan Africa. Using ARDL regression with almost similar variables compared to the previous papers on developing countries, the analysis included the effect of the financial crisis and the remittance on credit risk; with the latter being characteristic of developing countries. The study found that NPL are in the long run, in all countries except Uganda, determined by macroeconomic variables. In the short run however, money supply is a key factor of credit risk and bank-specific variables are also determinant in the case of South Africa. Remittance has negative effect on credit risk in the case of Kenya. To sum up, using smaller sample of lower income markets, the empirical evidence from developing and developed countries were quite similar. However, there were times where the variable used were different.

Data and methodology

In the following section, we are going to look at the data and distribution and present the methodology used.

The data

In this paper, we are aiming at identifying the macroeconomic determinant of credit risk in low- and lower-middle income countries, following the classification from the World Development Indicator of the World Bank. We will use the data extracted from WDI package in R. Following this choice, we have a data set composed by 72 countries in six regions (see Appendix 1). We have decided to remove some countries which have unique characteristics such as countries involved in notable conflicts. The variation of NPL in the remaining countries is plotted following Figure 1.

Plotted here (Figure 1) is the distribution of NPL by countries, and colored according to their income group. Judging from this figure, we can see that the value of credit risk vary according to the country and the value are disparate between countries. However, we see that the income group classification does not have significant variation on credit risk as both median can be as high and as low as each could be.

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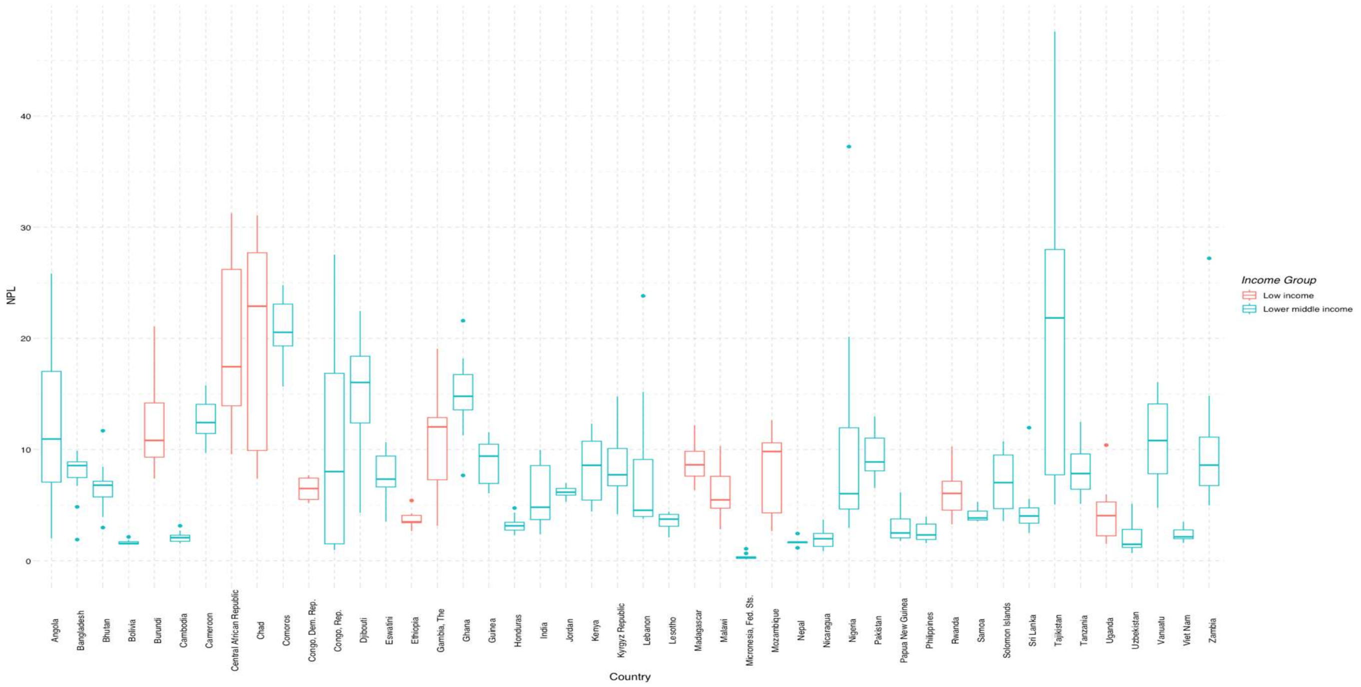

Figure 1 : NPL distribution per country

In the present paper, we will analyze the effect of macroeconomic variables on credit risk. To achieve our goal, we choose the following variables:

- Nonperforming loans as a proxy of credit risk (Fainstein and Novikov, 2011; Nkusu, 2011)
- The economic activity using annual real GDP growth per capita (Jiménez and Saurina, 2006; Festić and Beko, 2018)
- The unemployment using unemployment rate (Otasević, 2015, Castro, 2013)
- Price level using consumer price index (Fofack, 2005; Warue, 2013)
- Interest rate measured by the nominal lending rate (Castro, 2013)
- Bank risk-taking measured by domestic credit to private sector by bank growth (Bonfim, 2008; Kattai, 2011)
- Exchange rate using the yearly growth of the official value of the US dollar (Warue, 2013)
- Risk sharing between countries, using the net secondary income (Nikolaidou and Vogiazas, 2017)

After defining the metrics required for this analysis, we will dig deeper into the distribution of each variable and the relationship with credit risk.

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Table 1 : Variable distribution

Variables	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
Bank nonperforming loans to total gross loans (%)	0.128	3.296	6.385	8.052	10.478	47.596	0
GDP per capita growth (annual %)	-36.778	0.018	2.281	1.747	4.438	11.300	2
Unemployment, total (% of total labor force) (modeled ILO estimate)	0.120	2.945	4.700	6.806	8.065	37.852	9
Inflation, consumer prices (annual %)	-16.860	3.172	5.518	6.765	8.764	84.864	21
Lending interest rate (%)	5.176	10.096	13.845	15.914	18.531	60.000	142
Net secondary income (% of GDP)	-4.699	3.453	6.007	8.056	9.916	37.177	41
Credit to private sector by banks, real annual growth (%)	-36.454	0.597	6.839	7.301	12.62	52.057	74
Change of official exchange rate (%)	-15.390	0.000	2.372	5.081	7.505	72.460	59

Now that we have seen the distribution of each variable, we are going to look into the relationship between nonperforming loans and each individual variables following a linear regression.

In Figure 2, we plotted each variable against NPLs. Shown here are:

- ***Scatter plot*** which represents each observation. Using a lower value of alpha, we can see the difference between dense areas (with dark areas) and less dense area (brighter points)
- ***Linear smoothing*** in cyan: this is a simple linear regression. The goal is to show the individual effect of the variable.
- A ***loess smoothing*** in pink. This curve is displayed to confirm whether the variable has closer shape compared to the linear model or not.

Following the plots here, we can see that the behavior of the distribution is close to a linear path, suggesting that we can approximate the relationship between our variables and credit risk using a linear type of regression. It is a common knowledge that low- and lower-income countries are often prone to face instability. Following that perspective, we decided to perform a twoways regression instead of an individual effect only to capture the effect of each year on the model.

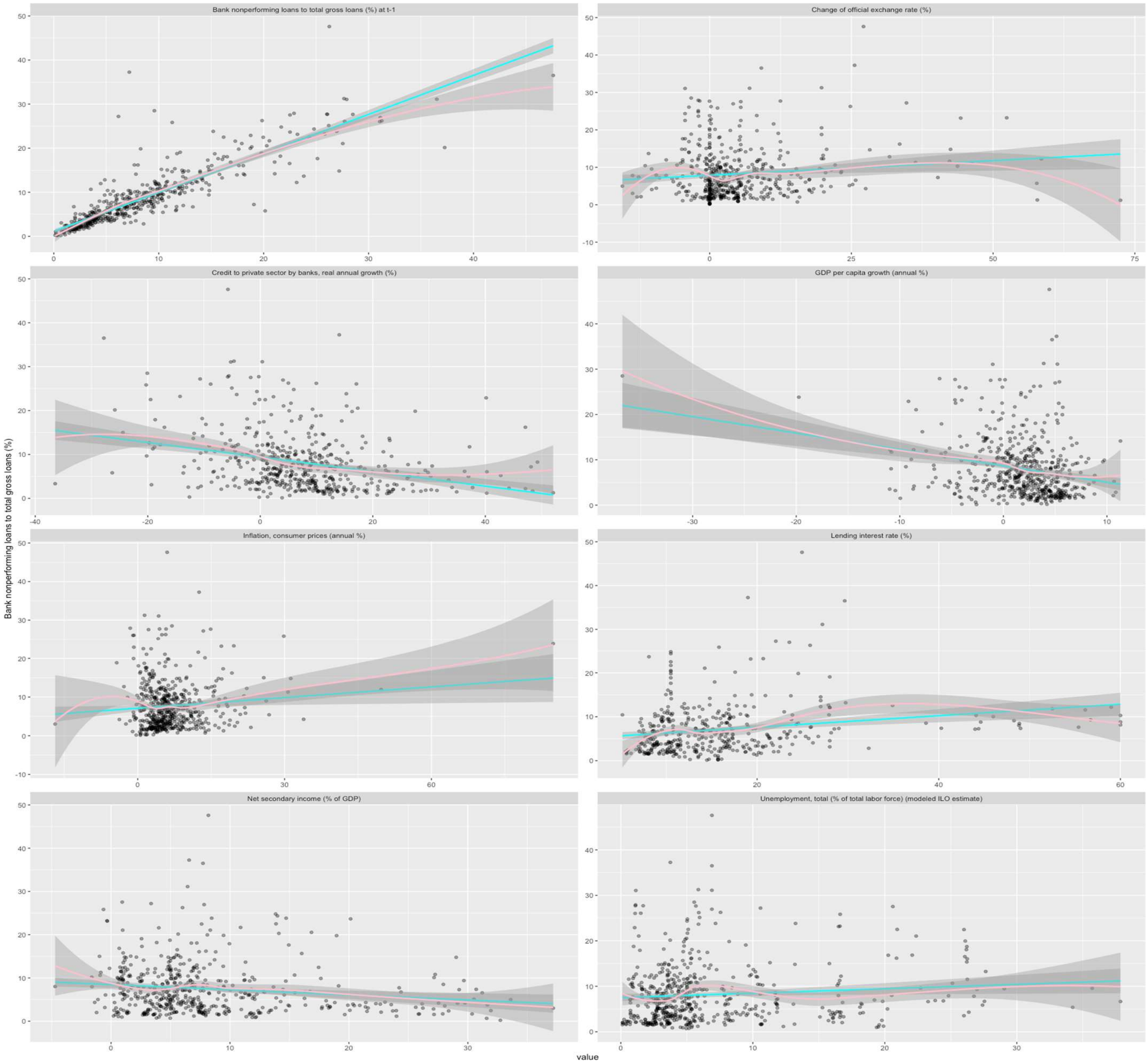

Figure 2: Variables over NPL trends

Now that we have fully identified the variables, we can look at the methodology.

Methodology

The present paper follows methodology on dynamic panel data analysis. Anderson and Hsiao (1981, 1982), and Griliches and Hausman (1986) exposed the limitation of classic panel data analysis (pooled, fixed and random effect) on dynamic panel data. They proposed therefore the use of instrument variable methods to solve the endogeneity problem from previous model. Following this study, Arellano and Bond (1991) proposed another type of specification that deals with dynamic panel data using Gneralized Method of Moments (GMM). The first model proposed was **differenced-GMM** which differentiate variables and use lagged variable to solve endogeneity. Later, Arellano and Bover (1995) and Blundell and Bond (1998) proposed another specification and technique to solve the deletion of information from differentiation and therefore created what we call now **system-GMM**. Later on, discussion emerged on the required steps for a system-GMM regression. The GMM regression is also the best call for us in this study given the fact that our data consist on large individual N and small time period T. Therefore, we will apply the methodology on system-GMM to determine the determinants of credit risk. It is best to consider two estimations in a sense that we want to identify the degree of complexity at which the relationship exists between our variables. We will use one-step system-GMM and two-step system-GMM to test the following hypothesis:

H1. Credit risk in low- and lower-middle income countries are determined by household's income

H2. Credit risk in low- and lower-middle income countries are determined by the behavior of banks

We will also apply robustness and sensitivity check by removing some countries from our observations. We will show and discuss the results in the next section, while the results of robustness and sensitivity check will be displayed in the Appendix 2.

Following our data and the requirement relative to dynamic model data, here is a specification of the model used for the analysis:

$$NPL_{i,t} = \rho NPL_{i,t-1} + \alpha_1 GDPG_{i,t} + \alpha_2 UR_{i,t} + \alpha_3 Infl_{i,t} + \alpha_4 GCPS_{i,t} + \alpha_5 NIR_{i,t} + \alpha_6 Sec_{i,t} + \alpha_7 GNER_{i,t} | Z_{i,t}$$

Here, we have:

- **NPL** the value of NPL, which measures credit risk;
- **GDPG** the annual growth of GDP;
- **UR** a proxy for employment level;
- **Infl** the inflation level measured by consumer price index;
- **GCPS** the annual growth of credit to private sector by banks, measuring bank risk-taking level
- **NIR** the nominal lending rate
- **Sec** the net secondary income in % of GDP
- **GNER** the change of the value of US$ on a yearly basis
- ρ , α_1 , α_2 , α_3 , α_4 , α_5 , α_6 , and α_7: coefficients measuring the effect of each variables on credit risk
- **i and t** are indexes for individual and time.

The restriction $Z_{i,t}$ follows the specifications by Arellano and Bover (1995) which was also checked for robustness by Blundell and Bond(1998). These papers suggests a specification taking the lagged difference of endogenous variables as instruments. Given the fact that only the secondary income is not endogenous to the model. With the model clearly specified, we will move on to the discussion of results.

Results

Results (Table 2) show that:

- Both lagged dependent variable and unemployment rate are statistically significant on both regression;
- Interest rate is statistically significant on one-step system GMM only;
- All the remaining variables are not significant on both variables.

The results showed two different results, the second one being included in the first. The two-step GMM considered as more robust and more able to deal with endogeneity, added with the less complex one which is the one-step system GMM, has shown the importance of unemployment rate in determining credit risk. The effect of unemployment on credit risk can be seen from two distinct perspective: a direct one, part of the common knowledge is that it gets more difficult for households to pay off their debt when their income is low. Given the fact that a raise of unemployment reduces income inflows, therefore, an increase of unemployment rate leads to more payment default. Fisher's Deflation (Fisher, 1933) Theory also suggests that in times when debt bubble explodes debt payment leads to a contraction of deposits, which tend to reduce price level and therefore, place businesses in a situation of difficulty. In turn, businesses reduces their production, and the use of workforce. From this second perspective, it is also a fact that unemployment rate and credit risk have a deeper relationship. The current and all previous studies suggests the strength of this relationship. (Fainstein and Novikov, 2011; Koju et al. 2019).

Interest rate is, on the other hand, significant only on the one-step system-GMM regression. Castro (2013) supports the use of nominal interest rate in finding the key determinant of credit risk, as it is the rate relative to decision taking. Theories on credit risk also suggests the impact of interest rate on credit risk, as it is:

- A mean to hedge from risk: banks can use interest rate to cover from any losses caused by the default of their customer.
- Increase credit risk through the channel of anti-selection, as "lemon" businesses are the ones who are willing to accept high-interest loans.

Table 2: Regression estimates

Variable	One-step System-GMM	Two-step System-GMM
lag(npl, 1)	0.813	0.851
	(0.000***)	(0.000***)
gdpg	0.037	0.034
	(0.483)	(0.611)
ur	0.059	0.054
	(0.029**)	(0.079*)
infl	0.013	0.021
	(0.856)	(0.766)
gcps	-0.020	-0.020
	(0.365)	(0.373)
nir	0.040	0.029
	(0.038**)	(0.264)
sec	-0.011	-0.010
	(0.499)	(0.656)
gner	0.051	0.039
	(0.264)	(0.383)
gfc	4.286	2.75
	(0.162)	(0.441)
covid	0.226	0.557

Variable	One-step System-GMM	Two-step System-GMM
	(0.720)	(0.610)
Sargan Test	chisq(339) = 34 (p-value = 1)	chisq(339) = 26.11081 (p-value = 1)
AR test (1)	normal = -2.452118 (p-value = 0.014**)	normal = -2.298632 (p-value = 0.021**)
AR test (2)	normal = 0.5360149 (p-value = 0.592)	normal = 0.4496782 (p-value = 0.653)
Wald test	chisq(10) = 5720.244 (p-value = 0.000)	chisq(10) = 3400.672 (p-value = 0.000)

Here, we find that nominal interest rate has a positive but non significant relationship with credit risk on the two-step regression. This suggests that this variable did not pass the complexity offered by the regression. However, we can maintain the existence, even if it is in a small amount, of the impact of interest rate on credit risk. This variable is not used much in the literature, as authors tend to prefer real interest rate over nominal one.

Finally, credit risk is a self-sustaining variable. We can see from both model that past value of credit risk is significantly significant on determining the present value.

Conclusion

In this study on the impact of macroeconomic variables on credit risk, we used quantitative approaches to determine the key determinant of credit risk. The dynamic behavior of credit risk and the availability of data lead us to the use of one and two-step system-GMM.On an unbalanced panel data composed by 47 countries and 4 to 18 time periods, we used on one hand, as dependent variable the ratio of nonperforming loans to gross loan. The independent variables used, on the other hand, are the lagged dependent variable, the annual GDP growth, unemployment rate as estimated by the ILO model, inflation rate, the annual growth of credit to private sector, nominal interest rate, net secondary income as percent of GDP, the annual growth of the value of US dollar in local currency and dummies of the financial crisis and COVID-19 crisis. Finding suggests that credit risk is mostly determined by previous credit risk and unemployment rate. Interest rate is also a determinant of credit risk, though the relationship does not pass the complexity of the two-step GMM. Though the two-step system-GMM is considered as more efficient model, Hwang and Sun (2018) suggests that the further step is not always necessary. Following the findings, we can see from this study that unemployment rate should be considered as part of macroprudential tool to preserve financial stability, especially in the context of developing economies, where vulnerability reins and where there is not enough financial tools to absorb risk. Also, the developing character of the market restricts the ability of interest rate to manage risk to a certain extent. These findings suggest the importance of employment in financial stability, especially in developing market where financial inclusion is low which leads to a diminished role of financial institutions in terms of risk management. (Koju, Koju, & Wang, 2019).

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