The Effect of Bank Liquidity and Unemployment on Bank Credit Risk

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Abstract: The aim of this article is to investigate the impact of bank liquidity risk and unemployment on credit risk in the South African banking sector. The panel data analysis approach is used, primarily employing the dynamic generalized method of moments model to examine 12 Banks in South Africa from 2009 to 2019. The results showed that credit risk is positively related to unemployment while, the relationship between credit risk and bank liquidity is negative in line with theory. The findings in this article may enhance bank policy formulation. Since credit and liquidity risk are a major source of risk that banks face especially in terms of stringent regulatory oversight and policy debate, this paper contributes significantly in the methods that central banks need to undertake to monitor and supervise the banking sector on liquidity and credit risks in time of crisis. Furthermore, employment is one critical economic fundamental in developing or emerging markets, the analysis of the nexus between employment and credit risk likewise provided important insights especially in time were the world is facing the COVID-19 pandemic.

Keywords: Credit risk; liquidity risk; unemployment; panel data; GMM; bank liquidity

JEL Classification: G01; G18; G21; G32

1. Introduction

Although South Africa has one of the best-regulated financial systems in the world, it has experienced several bank failures in the recent past. These include the African Bank failure in 2013, VBS Mutual bank liquidation on 13 August 2019 and the recent downgrade of South African banks by Fitch. Fitch downgraded five of South Africa's banks (Absa, FirstRand Bank Limited, Investec, Nedbank and Standard Bank) to BB negative outlook. This is mainly due to the negative forecast in GDP growth emanating from the impact of COVID-19. This was exacerbated by the Moody's downgrading of South Africa's sovereign credit rating to "junk" status in March 2020.

Among these problems, credit risk is regarded as a devastating risk which may cause financial instability and threaten the survival of many financial institutions. Bank credit rating is mainly driven by its credit exposure, operational environment and efficiencies. Therefore, credit risk is an important component of bank performance and sustainability (Waemustafa & Sukri, 2015). Considering recent development in the South African banking sector, it is important to investigate the effects of liquidity risk and unemployment on bank credit risk. South Africa is facing unfavorable economic, financial outlook because of the impact of COVID-19 pandemic. Unemployment has increased in the first quarter of 2020 to 30.1%. However, bank liquidity was not significantly affected as the South African Reserve Bank in March 2020 put in new liquidity measures to support banks.

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According to Hund and Lesmond (2008), liquidity risk is an important component credit risk in emerging markets, and it explains about half as much of the yield spread and credit risk specific variables (see also, Hakimi & Zaghdoudi, 2017). On the other hand, credit risk is theoretically predicted to be caused by changes in unemployment (Abras & de Paula Rocha, 2020; Kharabsheh, 2019). Unemployment directly affects the ability of retail clients to pay their obligations when they are due. Yüksel (2017) argues that there is a linear linkage between non-performing loans and the rate of unemployment.

The article aims to contribute to the credit risk literature in two ways. Firstly, the effects of bank liquidity on credit risk is examined. In theory, the nexus between bank credit risk and liquidity risk is well established. However, there is contradicting evidence and perceptions on the effects of liquidity on credit risk in the empirical literature (Ericsson & Renault, 2006; Ponnala & Kasilingam, 2019; Ahmad, Salam, Ahmad & Abbas, 2019). The aim is to investigate the impact of liquidity risk amongst other critical factors on credit risk by looking backwards at the level of non-performing loans (NPLs) than expected default.

Different from all known studies, in this article, the liquidity measure used is the bank liquidity mismatch index (BLMI) (Marozva, 2017; Bai, Krishnamurthy and Weymuller, 2018; Marozva & Makina, 2020). The BLMI is examined as one of the determinants of credit risk because banks' business is centred on the management of assets and liabilities and any mismatch in asset and liability would contribute significantly to liquidity risk and credit risk.

Secondly, the nexus between employment and credit risk within the context of an emerging market is investigated. Unemployment remains critical in most of the developing countries, including South Africa. Moreover, in South Africa, the percentage of household debt to disposable income has been increasing over time and was standing at 72.8% as of December 2019. This justifies why it is necessary to understand the effects of unemployment on credit risk, especially in times when unemployment is at an all-time high in South Africa. Finally, banks have been found to be the major source of credit within the SA domestic market which has a total gross loan debt as a percentage of GDP of 63.4% as of March 2020.

Therefore, it is the aim of this study to investigate the impact of bank liquidity mismatch index and unemployment on banks' credit risk in South Africa. In line with theory and other empirical studies, the results showed that there is a negative relationship between bank liquidity mismatch index and credit risk. Results also indicate that in line with theory, credit risk is positively and significantly related to unemployment.

2. General Organization of the Paper

The rest of the paper is organised as follows: Section 3 presents the data and describes the methodological approach. Section 4 presents and discusses the empirical results. Section 5 concludes by presenting the main findings of the paper and the recommendations.

3. Data and Variables

This article employed monthly and annual financial and economic data drawn from the South African Reserve Bank (SARB), the iress INET BFA database and the Stats SA from 2009 to 2019. From a country population of 18 locally registered banks in South Africa, a sample of 12 banks were selected for this article. These banks were selected based on the availability of data on specific variables. Since the approach was both longitudinal and cross-sectional, a panel study using pooled time series and cross-sectional data was conducted on selected South African banks. This was an individual country study; therefore, the policy difference between countries was not a problem. The following section discusses the variables that were used in the analysis. This includes dependent and independent variables.

3.1. Dependent Variable: Non-Performing Loans

Non-performing loans are defined as bad debts where the borrowers fail to make scheduled payments for a specific period, usually, when payments are past due by more than 90 days (Dimitrios, Helen & Mike, 2016). According to Boumparis, Milas, and Panagiotidis (2019), non-performing loans can be used as a proxy for credit risk. A loan is classified as non-performing if the bank does not expect full or partial payment of the loan (Apostolik & Donohue, 2015:46). Since the accounting term for the non-performing loan is called impaired loans, this article uses these two terms to represent credit risk. The credit risk is used as the dependent variable, and it is measured as the ratio between the banks' NPLs to total gross loans. Figure 1 presents the exegesis of non-performing loans from 2008 to 2019.

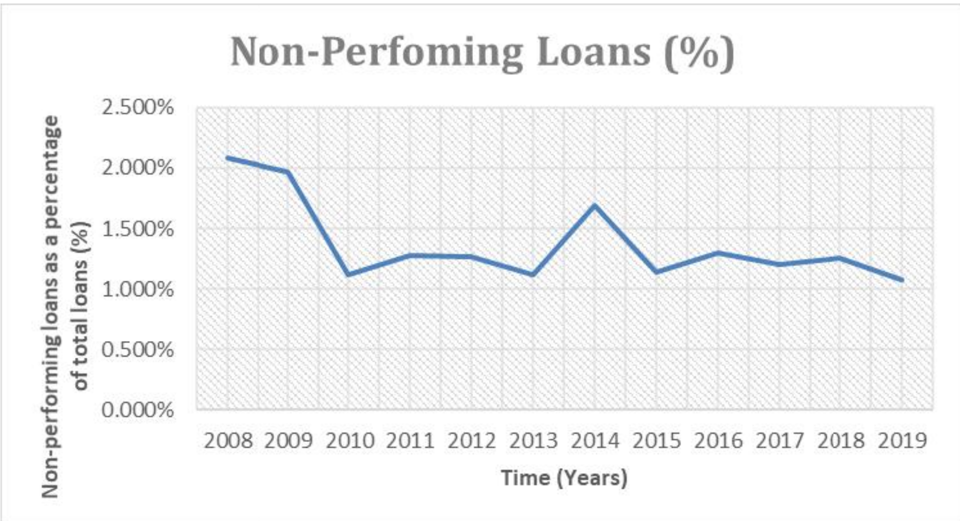

Figure 1. Non-performing Loans from 2005 to 2019

Source: Authors' Computations

Figure 1 shows that South African banks' non-performing loans were at their peak in 2008 and 2009. As expected, this period coincides with the hysteria of the global financial crises of 2007-2009. The non-performing loans significantly decreased in 2010 and remained stable until 2013 as banks employed some stringent measures when issuing loans. The non-performing loans spiked in 2014, followed by a huge decrease in 2015. Since 2016 non-performing loans were relatively stable until the end of 2019. However, another spike in 2020 is anticipated because of the COVID-19 pandemic.

3.2. Independent Variables

3.2.1. Liquidity

This article employed the bank liquidity mismatch index (BLMI) by Marozva (2017) as a measure for bank liquidity. Liquidity mismatch index is a ratio that has been used in other studies to capture the asset-liability mismatches of a bank (see Bai et al., 2018; Marozva & Makina, 2020). Thus, it gives information about the general liquidity shock absorption capacity of a bank (Berhanu, 2015). Therefore, the composition of the bank liquidity mismatch index depends on the value of assets, liabilities and the weight for both assets and liabilities. Following the approach of Bai et al. (2018), the original measure of LMI at bank-level calculated as follows:

$$BLMI_t^i = \sum_k \lambda_t\, A_k, X_t^i A_k + \sum_k \lambda_t\, L_k, X_t^i L_k \qquad (1)$$

where assets ($X_t^i A_k$) and liabilities ($X_t^i L_k$) are balance sheet components that vary over time depending on their asset or liability class (*k,k'*). The liquidity weights, $\lambda_t A_k > 0$ and $\lambda_t L_k < 0$, are key components that are computed and are time-varying. The detailed discussion on the derivation of the weight is contained in Marozva and Makina's (2020).

The higher the liquidity mismatch index, the higher the liquidity and the more stable is the financial institution in question. Bank liquidity is expected to be negatively related to credit risk. Naturally, short term liquid assets (loans or financial securities) have less credit risk, meaning that the higher the liquidity of an asset, the lower the probability that the customer will default. Therefore, there is a trade-off between credit risk and liquidity risk (Waemustafa & Sukri, 2015). However, Cardone-Riportella, Samaniego-Medina and Trujillo-Ponce (2010) argue against the trade-off as they indicate that banks have other ways of managing their liquidity positions. Banks improve their liquidity positions through securitisation instead of keeping some liquid asset buffers.

Theoretically, if a bank holds more liquid assets, this inevitably results in lower profitability, while on the other hand if a bank holds more illiquid loan portfolio, the loan default increases liquidity risk. Therefore, according to Dermine (1986), in theory, credit risk and liquidity risk are positively related, implying that bank liquidity is negatively related to credit risk. Iyer and Puri (2012) argue that risky bank assets, coupled with the country's uncertainty on liquidity need spark bank-runs. Bank-runs consequently lead to liquidity and credit spirals (Marozva, 2020). Based on the theoretical underpinnings discussed here, the liquidity mismatch indices are expected to be negatively related to credit risk. Gorton and Metrick (2011) also find that there is a positive relationship between credit risk and liquidity risk. However, they argue that it is not the actual liquidity risk that derives credit risk but the perceived liquidity risk.

3.2.2. Unemployment

The employment rate is calculated as the total of the employed population divided by the total population. Messai and Gallali (2019) argue that an increase in unemployment rate causes a deterioration in the consumer's ability to generate cash flow and service debt. For companies, an increase in unemployment results in lower consumption of goods and services, consequently leading to a decrease in the firm's cash flow and a weak position regarding debt. Therefore, the effect of unemployment on NPLs is expected to be positive. Hang, Trinh and Vy (2019) found a positive and significant relationship between the unemployment rate and credit risk.

In earlier studies, Castro (2013) found that credit risk is positively related to unemployment. Also, Berge and Boye (2007) found that NPLs are highly sensitive to unemployment for the Nordic banking system for the period 1993-2005. Higher unemployment is associated with debt service problems, as reflected in the rising NPLs (Nkusu, 2011:18). Higher unemployment leads to a decline in household incomes, which in turn increases the debt burden of households. Therefore, an increase in unemployment results in an increase in the rate of NPLs. Figure 3 shows the South African levels of unemployment.

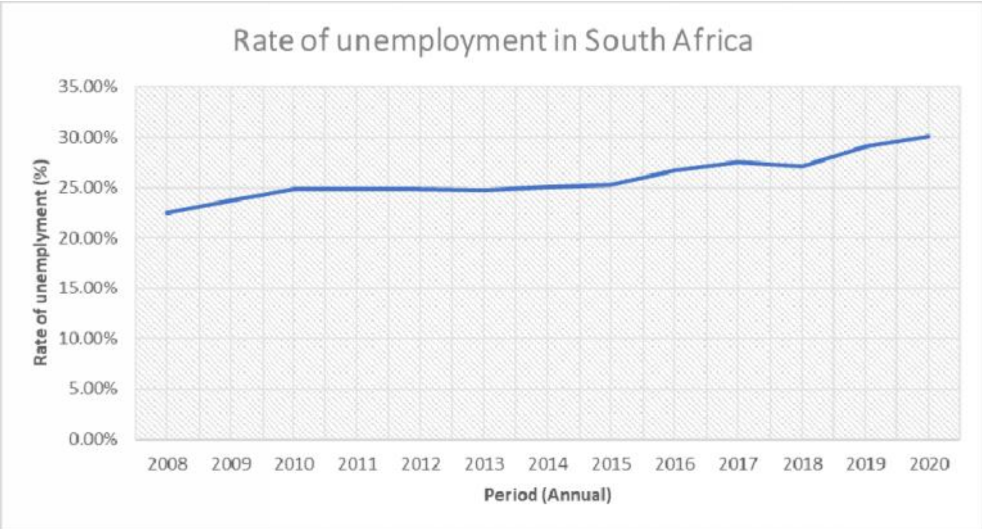

Figure 2. RSA Rate of Employment to the Population from 2008 to 2020
Source: Authors' computations

Figure 2 shows that South Africa's rate of employment has been on an upward spiral since the year 2008. Hodge (2009) argues that failure in macroeconomic policies did not contribute to an increase in unemployment; rather, the increase was a result of a very large increase in the labour force. Nonetheless, unemployment remains critical in most of the developing countries, including South Africa. This justifies why it is necessary to understand the effects of unemployment on credit risk considering that the ratio of household debt to disposable income remains very high and standing at 72.8% in the fourth quarter of 2019.

3.3. Econometric Model

Following other empirical literature in panel data studies (Louzis, Vouldis & Metaxas, 2012), the dynamic Generalised Method of Moments (GMM) model was adopted in order to account for the time persistence nature of the NPL. A dynamic panel data specification has the following form:

$$y_{i,t} = \alpha y_{i,t-1} + \beta x_{i,t} + \mu_i + \varepsilon_{i,t,} \quad (2)$$

where the variable $y_{i,t}$ represent the credit risk for bank i in time t; $x_{i,t}$ is a vector of independent variables for bank i in time t, to be more precise, they represent the bank-specific variable and macro-economic variables; α is the slope of the lagged liquidity variable; β is the elasticity of the explanatory variables, i.e. slope of variables; μ_i denotes fixed effects in bank *i*; $\varepsilon_{i,t}$ denotes the error term; the subscript *i* denotes the cross-section (i = 1,…,N); and *t* represents the time-series dimension (t = 1,…, T) According to earlier studies, to remove bank-specific effects, the first difference of the GMM model above is presented as follows:

$$\Delta y_{i,t} = (1-\alpha)\Delta y_{i,t-1} + \beta \Delta x_{i,t} + \Delta\varepsilon_{i,t} \quad (3)$$

Where Δ is the first difference operator. In equation (2) the lagged depended variable, $\Delta y_{i,t-1}$ is by nature correlated with the error term, $\Delta\varepsilon_{i,t}$. Thus, the differenced model is still not efficient as the correlation between the error component, the lagged variables remain correlated, and this imposes some bias in the estimation of the model (see Arellano & Bover, 1995). Consequently, the model using the GMM estimation technique with lagged values of the regressors as instruments were estimated. The Two-step GMM system estimation approach of Arellano and Bover (1995) and Blundell and Bond (1998) was employed with both level and lagged values of the variables being used as instruments. Two-step GMM system estimation approach is assumed an improvement from Arellano and Bond's (1991) GMM estimation technique.

For the empirical estimation, the relationship between unemployment, bank liquidity and non-performing loans is captured in equation 4.

$$\Delta NPL_{i,t} = (\alpha-1)\Delta NPL_{i,t-1} + \beta_{i,1}\Delta UNEMPL_t + \beta_{i,2}\Delta BLMI_{it} + \beta_{i,3}Dummy_t + \varepsilon_{i,t} \quad (4)$$

where $NPL_{i,t}$ is the non-performing loans for bank i in time t, $UNEMPL_t$, is the rate of unemployment for South Africa at time t, $\Delta BLMI_{it}$ is the measure of liquidity for bank *i* at time *t*, α is an auto-regression coefficient, β is the coefficient which represents the sensitivity of independent variables, $\varepsilon_{i,t}$ is the error term. $Dummy_t$ denotes the dummy variable for the existence of a crisis.

4. Empirical Results and Analysis

The main objectives of this study were to determine the relationship between BLMI and bank credit risk and to examine the impact of the unemployment level on non-performing loans. Descriptive statistics to the data utilised in this study is presented in Table 1.

Table 1. Descriptive STATISTICS

Variable	Obs	Mean	Std.Dev	Min	Max
NPL	132	0.01	0.01	0.01	0.02
UNEMPL	132	0.26	0.06	0.23	0.30
BLMI	132	0.15	0.11	-0.09	0.47

Source: Author's Computations

Results in Table 1 show that the average NPL was very low at 1% annually. The standard deviation of 0.01 is relatively tight signifying very low volatility of NPL over the period of analysis. The maximum NPL and minimum NPL were 2% and 1% respectively, indicating a narrow range of 1%. An average rate of unemployment to population ratio was 25.88%, indicating that a significant proportion of South Africans are unemployed. The bank liquidity mismatch index shows that an average bank's adjusted asset side out-way the adjusted liability side by close to 15%. The standard deviation of 11% indicates that bank liquidity positions fluctuated considerably under the period of analysis. Minimum of -0.09 on BLMI showed that some of the banks held more adjusted liabilities as compared to adjusted assets. However, on the other hand, banks held as high as 47% in liquidity as measured by BLMI.

The estimation results for the equation and the diagnostic statistics are presented in Table 2. The analysis is done on the estimation output from Two-step system GMM. The other estimation output results from the Pooled effects model, Generalised least square model, Fixed effects model and LSDVC model corrected for Kiviet bias are presented for robustness only.

Table 2. Dynamic Panel-Data Estimations the Determinates of NPL

Approaches	OLS - Robust	GLS	Fixed effect	LSDVC-Kiviet	Two-Step System GMM
Dependent Variable	NPL	NPL	NPL	NPL	NPL
L.NPL	0.953***	0.910***	0.250***	0.474***	0.639***
	(12.20)	(27.19)	(6.16)	(3.32)	(7.03)
UNEMPL	0.130*	0.114***	0.308	0.526	0.653***
	(0.72)	(9.50)	(0.77)	(0.78)	(0.04)
BLMI	-0.0208*	-0.015***	-0.0243***	0.0222	-0.0530**
	(-2.19)	(-5.64)	(-5.57)	(1.36)	(1.09)
DUMMY	0.00107	0.002***	0.000631	0.00143	0.00178**
	(0.63)	(3.71)	(0.77)	(0.35)	(0.12)
_cons	-0.0564	-0.049***	-0.00535		-0.00893
	(-1.78)	(-9.39)	(-0.31)		(-0.12)
N	132	132	132	132	132
Groups	12	12	12	12	12
F-stas/Wald chi2	78.63	1012.49	98.12***		37.96
Hausman Test			313.64***		
R-SQUARED	0.9371		0.9135		
Arellano-Bond AR(1)					-1.34
Arellano-Bond AR(2)					0.46
Sargan test of overid					5.92**
Hansen test of overid					2.05
Instruments					4

t-statistics in parentheses * p<0.05 ** p<0.01 *** p<0.001

Source: Author's compilation from Stata

Table 2 results confirm a negative and significant relationship between BLMI and bank credit risk. The results are in line with expectation, as banks which proportionally hold riskier and less liquid assets tend to be associated with higher default risk. Banks are, therefore, encouraged to strike a balance between liquid assets and illiquid assets. Liquid assets have lower credit risk and lower liquidity risk but have lower returns, while illiquid assets have higher credit risk and high liquidity risk but are associated with high return assets.

Furthermore, the results revealed a positive and significant relationship between unemployment and bank credit risk. These results confirm the fact that unemployment is positively related to bank credit risk. Firms and households find it difficult to pay their obligations during the recession and when the economy slows down. Banks are recommended to reduce their loan book and investments in securities with low credit ratings in periods associated with high unemployment. A flight towards risk-free securities, for example, government bonds and treasury bills are encouraged.

Finally, the dummy variable was found to be significant, indicating that the 2007-2009 global financial crisis influenced bank credit risk. This is expected as most of the companies and households were financially constrained. Banks are recommended to put in place mechanisms that help them to model, forecast and anticipate recessions and other financial crises so that they can reduce investments in less liquid assets. Alternatively, banks can hold more liquid buffers prior to crises and during crises because during crises bank stability and survival is more important than profitability.

Previous studies that attempted to analyse the nexus between credit risk and the micro-and macro-economic factors in relation to their conventional peers have often led to conflicting evidence due to different sample sizes, use of different methodologies and subjective credit risk proxies. The contribution of this research to the body of empirical research lies in that the BLMI liquidity measure and employment variables were included in the model. Though the relationship between liquidity and credit risk has strong theoretical underpinning, there is very little that has been done empirically. While on the other hand, the nexus between employment and credit risk has been thoroughly analysed empirically, most of the studies were done in developed markets where unemployment is very low. Furthermore, a dummy was used to capture the dynamics of what happened during the global financial crisis of 2007-2009. As per expectation, the system GMM shows that credit risk was rampant during the 2007-2009 financial crisis. Considering these findings, several conclusions can be drawn, and recommendations can be made, as discussed in the next section.

5. Conclusion

After the 2007-2009 global financial crisis, followed by the U.S. debt downgrade in 2011, then the Eurozone debt crisis and the recent COVID-19 pandemic, credit risk remains the banking sector's main risk. The aim of this research was to further investigate the effects of Unemployment and liquidity on bank credit risk during the periods of stability and periods of financial markets turmoil.

Using the panel data analysis approach primarily employing the dynamic generalised method of moments model, the tests suggest that bank liquidity and unemployment variables are determinants of NPL since together they account for a significant portion of the variations in credit risk as measured by non-performing loans. Results on the nexus between bank liquidity and credit risk were in line with theory as a negative relationship between liquidity as measured by BLMI and the credit risk was found. Unemployment was found to be positively and significantly related to bank credit risk in South Africa.

This research has contributed to the body of knowledge through mainly the investigation of the influence of employment and bank liquidity factors on credit risk. The impact of BLMI on credit risk provided important insight that BLMI is a good measure of liquidity in the banking sector as the results did not deviate from other studies. Furthermore, a dummy variable was included in the model to capture the dynamics of 2007-2009 global financial crises, and the results showed that indeed the financial crisis period had a significant influence on non-performing loans.

Based on the research outcome and discussions, it seems that determinants of credit risk require further analysis. The recent Basel III requirements have emphasised on liquidity risk and credit risk. Therefore, an analysis of the interaction between credit risk and the two Basel III liquidity ratios, the net stable funding ratio (NSFR) and Liquidity coverage ratios (LCR) may provide some important insights. Furthermore, there is a need to investigate the effects of the overall market liquidity as measured by aggregate liquidity mismatch index (ALMI) on bank credit risk.

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