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Impact of credit risk and profitability on liquidity shocks of Namibian banks: an application of the structural VAR model

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Abstract

The main purpose of this paper was to investigate the relationship between banks' credit risk and profitability on liquidity shocks in Namibia for the period 2009 to 2018 using the SVAR model. In estimating the SVAR regression model, Granger causality, impulse-response functions and forecast error variance decomposition were employed and evaluated. The sample consisted of Namibian commercial banks. By auditing liquidity data between 2009 and 2018, empirical results showed that liquidity risk is caused by a combination of structural shocks. The granger causality, impulse-response functions and forecast error variance decomposition analysis showed that credit risk (non-performing loans) is a key factor affecting liquidity conditions in Namibia in the medium to long run. In addition, the empirical results demonstrated that quality earnings (ROA) have minimal impact on liquidity conditions in the short run. Reforming assets quality policies and earnings quality policies can be valuable policy tools to minimize liquidity shortages and avoid insolvent banks in Namibia.

Keywords: *liquidity shocks, liquidity risk, camels, credit risk, namibian banking ındustry*

Jel codes: *E58, G21; G28, G32*

1. INTRODUCTION

One of the lessons learnt in the 2007 to 2009 global financial crisis was the shortage of liquidity in the market and its serious effects on the real economy (Casu, Pietro and Trujillo-Ponce, 2017; Kapan and Minoiu, 2017; Sironi, 2018). This led to bailouts and failures of several financial institutions globally. In banking, liquidity refers to the ability of a bank to meet obligations and unanticipated withdrawals from depositors (Le, 2017; Vousinas, 2018). Financial analysts consider the provision of liquidity as a central function of banks and also as an essential element of the functioning of the economy as a whole. Karri, Meghani and Mishra (2015) pointed out that liquidity is essential for any institutions working with money.

Liquidity creation refers to a situation where banks obtain liquid deposits on a short-term basis and offer them to borrowers on a long-term period (Angora and Roulett, 2011). Banks are intermediaries between those aiming to save their money and those aiming to borrow from the banks. The rationale of intermediation between savers and borrowers is necessitated by different needs in terms of liquidity, maturity and yield. In playing the intermediary role, banks are exposed to maturity transformation risks such as bank-run arising from the maturity mismatch of assets and liabilities from a balance sheet as discussed by Bonfim and Kim (2017). The maturity transformation risk refers to a situation in which banks are unable to meet the obligations and unexpected withdrawals from depo-

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sitors (Angora et al. 2011). "The fundamental role of banks in the maturity transformation of short-term deposits into long-term loans makes banks inherently vulnerable to liquidity risk both of an institution-specific nature and those which affect markets in general" (BCBS, 2008). Gobat, Yanase and Maloney (2014) stress that banks are exposed to maturity transformation risks because they are taking deposits from savers on short-term requirements and lend this liquidity on long term requirements such as residential mortgages. As a result, banks are inherently exposed to maturity transformation risks that derive from a maturity mismatch of assets and liabilities from a balance sheet.

However, higher non-performing loans (credit risk) and earnings quality in banks have been shown to be key factors affecting liquidity conditions in banks. For example, higher non-performing loans are found to be caused by lower liquidity and consequently liquidity risk in banks (Berrios, 2013; Hajja and Hussain, 2015; Nabilar and Khushiri, 2018). On the other hand, focusing maximizes earnings or profit could lower liquidity conditions of banks, while focusing on liquidity may also lower the earnings or profit of a bank (Panigrahi, 2014). The financial crisis revealed inadequate supervision, lack of sufficient capital reserves and insufficient liquidity buffers which appeared to have led to systemic risks to the banking systems in other parts of the world. Varotto (2011) and Giustiniani and Thornton (2011) cite the above-mentioned factors as the root causes of the crisis. The risk of liquidity could affect the image of a bank, consumers and the public at large (Gowri and Ramya, 2013; Gautam, Singh and Kumar, 2014). Thus, the maturity transformation risk could lead to higher bank distress. Notwithstanding the differing scales of impact on liquidity shocks, we underscore the importance of credit risk and profitability in understanding banking liquidity in Namibia. This study therefore lend support to liquidity risk management policies which are directed at credit risk and profitability as effective indicators for early intervention.

This study seeks to make contributions in several ways. First and foremost, this study contributes to financial risk management literature in the African context by exploring the nature of the impact of credit risk and profitability on liquidity shocks using the Namibian banking context and relatively recent data. As far as we know this aspect is missing from extant literature and hence a vital gap that the current study seeks to fill. Secondly, to the extent that the central issues in this study are relevant and generalizable beyond Namibia`s contextual settings, it is envisaged that the empirical findings and policy guidelines from this enquiry will contribute lessons for Africa and other developing economies. Thirdly, we believe that this study is particularly relevant considering the prevailing context of business failures, economic hardships and general economic contraction triggered by the Covid-19 pandemic. Due to national lockdowns that followed the onset of Covid-19 including extended stimulus and relief packages offered by many governments around the world, liquidity deteriorated in many financial markets in both low income and middle-income countries. Adrian and Natalucci (2020) claim that market liquidity deteriorated significantly even in markets traditionally considered deep such as the US Treasury market.

The remainder of this manuscript is organized as follows. Section 2 provides a review of the literature on liquidity shocks. Section 3 describes the methodology and structural VAR model for liquidity shocks in Namibia. Section 4 presents empirical results and discusses robustness checks. Section 5 provides a conclusion and offer policy recommendations to the study.

2. LITERATURE REVIEW

The literature on identifying financial shocks can be traced back as from the 1970s and 1980s through the works of several authors (e.g., Sinkey, 1975, Altman, 1977, Martin, 1977, Barth, Brumbaugh, Sauerhaft and Wang, 1985, Demirguc-Kunt, 1989). These works were in response to the 1930s and 1980s financial crises that led to the closure of 1,500 banks in the 1930s and 800 banks in the 1980s (Demirguc-Kunt, 1989). These studies applied several financial ratios consistent with the CAMELS rating and models in the determinant of the likelihood of financial constraints. The use of financial ratios was related to financial crises when most bank distress was common, to assess the performance between failed and non-failed banks. Consequently, in 1979 the CAMEL rating system came into effect, and financial ratios that were used by these researchers were consistent with the CAMEL rating (Angora et al., 2011:9). In the 1970s, 1980s and 1990s, numerous early warning indicator studies on bank performance were conducted to study the accuracy of various models and the CAMELS rating system in identifying shocks and banks distress. The CAMELS rating system is utilised for measuring capital adequacy, asset quality, management efficiency, earning quality, liquidity management and sensitivity to the market risks of banks. This trend has grown and become also common and relevant to the current decade by comparing various models and financial ratios in identifying shocks and predicting bank distress.

Assets quality refers to the risk associated with different assets such as loans and advances, investments, securities, off-balance sheets items, land, fixed assets and properties (Ishag, Karim, Zaheer and Ahmed, 2015). Asset quality is used to assess the repayment of loans and advances which are the main sources of bank incomes (Gowri and Ramya, 2013 and Vousinas, 2018). Mazreku and Morina (2016) stressed that the performance of loans is important because it represents around 50 percent of assets of a bank. Kowanda, Pasaribu and Firdaus (2014) utilized NPL to total assets ratio to measure asset quality on Indonesian banks and found it to be significantly positive in detecting bank financial shocks. Similarly, financial shocks probabilities were also revealed in the analysis presented in Majumder and Rahman (2016) for the period spanning between 2009 and 2013 of Bangladesh banks; Affes and Hentati-Kaffel (2017) for the period spanning between 2008 and 2013 of US banks, and Vousinas (2018) for the period spanning between 2007 and 2016 of Greek banks. In contrast, Sjahril, Priharta, Parewangi and Hermiyetti (2014) found that NPL does not affect on the bank's financial distress. Sjahril et al.'s (2014) study examined Indonesian banks over the 2002 to 2013 period. Thus, the results overall suggest that NPL proved significant in detecting the likelihood of bank financial shocks. On the other hand, Hajja and Hussain (2013) revealed the relationship between credit risk and liquidity risk. Hajja et al.'s (2013) study found that higher non-performing loans lower liquidity and consequently liquidity risk. Similarly, Berrios (2013) and Nibilah and Khushiri (2018) arrived at the same sentiment that credit risk that is measured by NPL also causes liquidity risk and subsequently financial distress.

Earning quality refers to the ability of a bank to generate profit compared to the expenses it incurred (Venkatesh et al. 2014). Earning quality ratios are used to measure the profit of a bank and also the ability of a bank to maintain consistent earnings (Tripathi, Meghani, Mahajan, 2014 and Gupta, 2014). From a profitability viewpoint, strong earnings from a bank side reflect a bank's ability to sustain itself in the present and future operations (Vousinas, 2018). Angora et al. (2011) analysed US and European banks over the 2005 to 2009 period, using ROA to measure earnings and profitability. The results indicated that the coefficient of ROA was significantly lower and contributed to bank financial shocks. Oliveira, Martins and Brandao (2015) scrutinised US banks over the 2000 to 2014 period, using ROA to measure earnings and profitability. The results also revealed that ROA was significantly lower and contributed to bank financial shocks. Kandrac (2014) found that ROA is a potential indicator of bank financial shocks, demonstrating lower income of US banks during the 2007 - 2009 global financial crisis. This result is also demonstrated in the analysis presented by Tatom and Hauston (2011) who analysed US banks over the 2006 to 2010 period; Kowanda et al. (2014) for a study period of 2009 to 2012 on Indonesian banks; Kumar et al. (2017) for a study period of 2012 to 2016 on Indian banks; and Affes et al. (2017) for a study period of 2008 to 2013 on US banks. Further to this, the works of Panigrahi (2014), Ghurtskaia and Lemonjava (2016), and Pradhan and Shrestha (2016) documented the relationship between ROA and banks' liquidity conditions. Pradhan and Shrestha (2016) argued that focusing on profit maximisation lowers liquidity on one hand, while focusing on liquidity lowers the profit on another hand.

Liquidity management refers to the ability of a bank to satisfy depositors' withdrawal and maintaining adequate capital (Isanzu, 2016). Liquidity ratios are used to measure the ability of a bank to meet its commitments whenever they come due, for example, the depositors' withdrawals demand (Gupta, 2014 and Le, 2017). Venkatesh et al. (2014) argue that the inability to satisfy these commitments will affect performance and lead to bank financial constraints. To avoid the liquidity shortfall, the bank is required to hold high liquid assets that can be easily changed into cash, forecast future cash inflow and outflow, and be able to obtain loans from the inter-bank market (Ishag, Karim, Zaheer and Ahmed, 2015). Majumder and Rahman (2016) scrutinised Bangladesh banks over the 2009 to 2013 period, using liquid assets to total assets ratio (LATA) to measure liquidity capability. The study found that LATA was significantly positive and is good in detecting the probability of bank financial shocks. Vousinas (2018) analysed Greek banks over the 2007 to 2016 period using LATA to measure the liquidity capability of banks. The results indicated that liquidity was improving in the last years of the reviewed period. Makinen and Solanko (2017) analysed Russian banks over the 2013 to 2017 period using LATA to measure the asset quality of banks. The results indicated that LATA is significantly correlated with bank financial shocks. Thus, the results demonstrated the significance of LATA in measuring liquidity.

Majumder et al. (2016) scrutinised Bangladesh banks over the 2009 to 2013 period using liquid assets to total customer deposits ratio (LADEPO) to measure liquidity capability. The study found that LADEPO is significant in detecting the probability of bank financial shocks. Kumar and Murty (2017) scrutinised Indian banks over the 2012 to 2016 period using LADEPO to measure liquidity capability. The results revealed the significance of LADEPO ratio in identifying bank financial shocks. The result is also demonstrated in the study of Affes et al. (2017) over the 2008 to 2013 period of US banks, and Lallour and Mio (2016) examined US and European banks over the 2010 to 2014 period. Overall, the results suggest the significance of LADEPO in determining the likelihood of bank financial shocks.

3. DATA AND ECONOMETRIC MODEL

3.1 Data and Variable Measurements

The data was sourced from Bank of Namibia and Namibia Statistics Agency (NSA). The data sources were existing banks' balance-sheets used to identify the sources of liquidity shocks in Namibia. Banks financial data includes balance sheets were taken from the Bank of Namibia, whilst economic performance data were taken from NSA. The sample period spans from 2009 to 2018, using quarterly data from the Namibian commercial banks. The study period covered the most recent financial crisis which took place in 2007-09 that was caused by shortage of liquidity among other root causes.

We collected data related to financial variables that used mostly for measuring asset quality (NPLs) and earnings (ROA) of banks. Most empirical studies (e.g. Sinkey, 1975, Altman, 1977, Martin, 1977, Demirguc-Kunt, 1989, Angora and Roulett, 2011, Distinguin, Roulet and Tarazi, 2013; Horvath, Seidler and Weill, 2014; and Kapan et al., 2017) found these variables useful and statistically significant in identifying financial shocks.

As regards to the quality of bank assets, the non-performing loans (NPL) is considered as a proxy and as an early warning indicator. NPL refers to the percentage of loans overdue for a particular year observed (Nurazi and Usman, 2016). The higher the NPL ratio is, the more risk a bank is facing (Kowanda et al. 2014). Credit risk measured by NPL is an essential factor of bank liquidity conditions due to non-repayment loans by borrowers as it increases liquidity risk that could lead to bank distress (Hajja et al. 2015). Prior works by Berrios (2013); Hajja and Hussain (2015); Nabilar et al. (2018) find a significant positive relationship between credit risk and liquidity risk.

As for the bank earnings quality, the study considered the return of assets (ROA) as a proxy in measuring the influence of profitability on liquidity conditions of banks. ROA shows the returns received on assets employed by a bank (Karri et al. 2015; Srinivasan and Saminathan, 2016). A higher return on assets means higher profit generated by a bank (Karri et al. 2015). Banking institutions with low levels of earnings also have a higher insolvency probability (Papanikolaou, 2017). Prior works find a positive correlation between ROA and liquidity conditions in banks (Panigrahi, 2014; Ghurtskaia et al., 2016; Pradhan and Shrestha, 2016). Consequently, a correlation between ROA and liquidity conditions is expected, and the influence of ROA on liquidity conditions could be one of the sources of liquidity shocks in Namibia.

With regards to liquidity ratios, these ratios determined the ability of the bank to meet its commitments resulting from depositors and investors demands. In the case of banking liquidity conditions, the study proxies' two liquidity ratios in measuring with other non-liquidity ratios, but all are part of CAMELS framework. The first liquidity ratio is Liquid assets to average total liabilities (LA_ATL). It measures the ability of a bank to meet minimum liquid assets requirements arising from funding obligations. The lower the ratio, the bank faces the risk of unexpected withdrawals from savers (Srinivasan et al. 2016). Prior studies find that LA_ATL could be affected by non-performing loans and sensitivity to market risk (Hajja et al., 2015; Nabilar and Khushiri, 2018; Distinguin et al., 2013; Casu et al., 2017; and Banti et al., 2019).

The second liquidity ratio is the liquid assets to total assets ratio (LA_TA). This ratio is imposed by the central banks on commercial banks (Saunders and Cornett, 2008). It measures the maturity transformation risk arising from the maturity mismatch of assets and liabilities from a balance sheet (Srinivasan, 2016). An increase of liquid assets to total assets ratio means a bank has higher liquidity and is unlikely to face a bank run (Shen and Chen, 2014). Prior studies find that LA_TA could be affected by non-performing loans ratio and earnings quality (Berrios, 2013; Hajja et al., 2015; Nabilar et al., 2018; Casu et al., 2017; Distinguin et al., 2013).

In addition to the mentioned variables, we add other explanatory variables as part of the control variables. From a literature perspective, bank size came into consideration as a result of the argument that is too-big-to-fail (e.g. refer to a bank). The natural logarithm of total bank assets less loan loss reserve (LNTA) is a proxy of the bank size and capital adequacy. A positive signal is the indication of bank probability of default (Angora et al. 2011). In addition, numerous researchers argued that economic downturn is also an important factor when studying bank liquidity shortages and financial distress. For example, when a country is experiencing an economic downturn, it could lead to the deterioration of banks' loans and losses (Angora et al. 2011). The annual growth rate of real Gross Domestic Product (GDP) is a proxy of macroeconomic conditions of a country that determine bank liquidity shortages and financial distress. A negative signal determines the bank liquidity risk and financial distress. Lastly, the higher demand for liquidity from the interbank market is also taken into consideration for liquidity shortages and subsequently financial distress. For example, the shortage of liquidity from the interbank is likely to affect banking daily operations (Angora et al. 2011; Bonfim et al. 2017). The spread of the one-month interbank rate and the central bank policy rate (SIB_CDR) are proxies of the demand for liquidity from the interbank market. The higher value of the spread of the one-month interbank rate and the central bank policy rate is likely to affect the bank in terms of accessing the liquidity from the interbank. A positive signal determines the bank financial distress. In data analysis, all variables have been converted into natural logs except GPD and SIB_CDR due to their lower values against the other ratios.

3.2. Econometric Model

Based on empirical literature and the nature of the data, the study adopted the SVAR to identify and establish sources of liquidity shocks in Namibia. A large body of empirical literature considered SVAR as a result of its appropriateness to display the interactions between sets of macroeconomic variables using panel data. With the help of granger causality, impulse response functions and variance decompositions part of SVAR, the structural shocks to liquidity conditions were identified and established. The focal area was the liquidity conditions of banks caused by other macroeconomic variables.

The SVAR model used is as following:

$$L_{it} + a_T T_t = B_L + B_{LT1} T_{it-1} + B_{LT2} T_{it-2} +$$

$$a_L L_{it} + T_{it} = B_T + B_{TT1} T_{it-1} + B_{TT2} T_{it-2} + e_{T \ldots 3.1}$$

$$B_{LL1} L_{it-1} + B_{LL2} L_{it-2} + C_L GDP_{it} + e_L$$

$$B_{TL1} L_{it-1} + B_{TL2} L_{it-2} + C_T GDP_{it} + \quad (1)$$

L_{it} = Current level of Liquidity conditions

T_{it} = Current level of T

T_{it-1} = T lagged once

T_{it-2} = T lagged twice

L_{it-1} = L lagged once

L_{it-2} = L lagged twice

GDP_{it} = current level of GDP

e_T white noise error term with zero mean and constant variance.

B_L = slope parameter for equation [1] variance intercept

B_T = vertical intercept for equation [2]

The granger causality provides causation links between variables in determining which variables are truly exogenous that can be used for data analysis (Amisano and Giannini, 1997; Gottschalk, 2001). The granger causality tool is a hypothesis that evaluates the usefulness of one variable on forecasting another variable (Wei, 2013). The granger causality test has been used to establish causality between banks' asset quality (NPL) and earnings quality (ROA) against liquidity conditions in Namibia.

The impulse response functions are a tool that displays the response of each variable to structural shocks derived from economic time series (Barnichon and Brownless, 2018). The impulse response functions were proposed by Sims (1980), they show the patterns of movement of a variable over time. Yu, Ju'e and Youmin (2008) point out that an impulse response function is a useful tool in showing the direction of an endogenous variable in identifying the shocks. The impulse function has been used to trace the response of liquidity conditions against banks' asset quality (NPL) and earnings quality (ROA).

4. EMPIRICAL RESULTS

In this paper, we identify the sources of liquidity shocks in Namibia for the period 2009 to 2018 using a liquidity ratio based upon the traditional CAMELS ratios. We test the relationships between asset quality and earning quality against the liquidity conditions of banks. Thus, we estimate a Structural VAR model by relating other CAMELS ratios against liquidity ratios, namely LA_ATL, and LA_TA to identify and establish the sources of liquidity shocks in Namibia. Firstly, we display descriptive statistics of the variables used in the SVAR model. Descriptive statistics attempt to describe the main characteristics of data used in this study. The descriptive statistics were measured as mean, median, maximum, minimum and standard deviation.

Table 1: Descriptive statistics of the variables understudy, for Namibian commercial banks, on average, from 2009 to 2018

Variables	Mean	Median	Max	Min	Std Dev	Obs
NPL	2	2	5	1	1	188
ROA	2	2	4	1	1	181
LA_TA	11	10	25	7	3	186
LA_ATL	12	12	20	10	2	188
GDP	3.6	4.3	15.34	-6.09	4.97	156
LNTA	16.66	16.67	17.5	15.57	0.48	144
SIBR_CDR	0	0	0	-1	1	124

Source: Authors' Own construction

Considering the NPL ratio, the variable has an average value of 2 with a standard deviation of 1 value. This means that sampled banks NPL ratio remained below the statutory maximum of 4% target or benchmark. However, minimum and maximum recorded 1 and 5 respectively. The 1 recorded standard deviation values highlight that there is little dispersion in terms of capital set aside to cover the non-performing loans. Over the 2009 to 2018 period, ROA on average stood at 2 values while standard deviation stood at 1 value. The minimum and maximum values stood at 1 and 4 respectively. The LA_TA shows an average value of 11% for the period from 2009 to 2018. However, the standard deviation value is 3 and minimum and maximum values stood at 7 and 25 respectively. The average mean for LA_ATL reported for sample banks over the period from 2009 to 2018 is 12 while standard deviation stood at 2 values. In addition, minimum and maximum stood at 10 and 20 respectively. The GPD has a mean value of 3.6 with a standard deviation standing at 4.97, whilst minimum and maximum values of -6.09 and 15.34 respectively. Considering LNTA, on average, the mean value stands at 16.66 while the standard deviation at 0.48 values. However, the reported minimum and maximum are 15.57 and 17.5 respectively. Lastly, the SIBR_CDR variable has an average value of 0 during the sample period. The minimum and maximum values are -1 and 0 respectively. The reported standard deviation value is 1%, which implies that there is small dispersion in terms of interbank rates over the sample period.

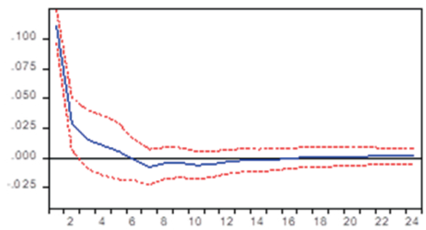
Considering the granger causality between asset quality and liquidity, the relation between NPL and LA_ATL shows that it is the strongest. NPL is granger causing the LA_ATL at a 1% level of statistical significance. This means that liquidity conditions in banks are influenced by NPL from the borrowers' side. Furthermore, ROA and LA_ATL show that there is weak causality at a 9% level of significance. This means that there is a granger causality between income and liquidity positions in banks. These results imply that NPL and ROA ratios have granger causality with the LA_ATL ratio (see Appendix 1). The results conclude that credit risk (non-performing loans) and poor earning could affect liquidity conditions in banks.

Figure 1 shows the impulse response of the Liquid assets to average total liabilities (LA_ATL) to a shock of non-performing loans and returns on assets. According to Panel (a) in Figure 1, it shows that LA_ATL positively responds to a positive availability of liquidity shocks. Thus, the availability of liquidity shock has an effect on the liquidity conditions of banks. Panel (b) in Figure 4.1 shows that liquidity conditions respond to positive non-performing loans shock in banks. Liquidity increases in the first two years then slightly remain constant. Thus, non-performing loans shocks have an effect on liquidity conditions in banks in the long run. From a lending perspective, the NPL ratio is determined by the lack of repayments of loans from the borrowers' side.

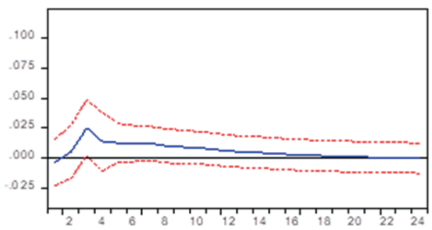
Panel (c) displays the impulse response functions of the LA_ATL to a shock of return on assets. The results show that liquidity conditions in banks were both increases and decreases in the first four years before they gradually decreased in the remaining year's understudy. Again, the effect is borderline significant in the long run. This means that profitability shocks measured by return on assets responded positively than negatively and have a favourable effect on liquidity positions in banks in the short run. A negative profitability shock may be caused by a declined economic performance by referring to Namibia performance over the last 4 years. For example, in Namibia GDP recorded 4.8% in 2015, 0.6% in 2016, -2.0% in 2017, and -1.7% in 2018 (Namibia Statistics Agency, 2019).

Figure 1: Response of LA_ATL to other CAMELS indicators

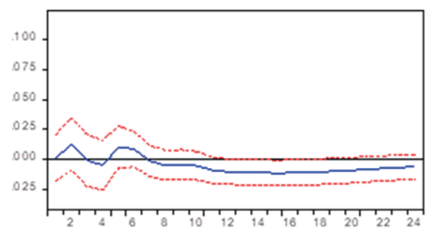
(a) Response of LNLA_ATL to LNLA_ATL



(b) Response of LNLA_ATL to LNNPL



(c) Response of LNLA_ATL to LNROA



Apart from impulse response, considering the forecast error variance decomposition of the variables understudy derived from Structural VAR, the results demonstrates that NPL shocks have the most important impact on the forecast error variance of the liquidity conditions (see Appendix 1). It shows that it has increased over time from 5% to 10%. The ROA shocks are another important dynamic for the forecast error variance of the liquidity conditions. They increased from 1% to 8% over time. In the long run, ROA is the second important factor of the forecast error variability of the liquidity conditions.

Considering the granger causality between LA_TA and other CAMELS variables, NPL is the granger causing the liquidity variable at a 0% level of significance. This implies that the causality between NPL and LA_TA is strong. Further to this, the causation between ROA and LA_TA is weak. This indicates that it is only NPL that has granger causality on LA_TA (see Appendix 1). As demonstrated in Figure 4.5, Panel (a) that LA_TA positively responds to availability liquidity impulses. This means that availability liquidity has an effect on the LA_TA and specifically liquidity conditions in Namibia. Panel (b) displays that LA_TA shocks respond positively to NPL ratio impulse. The results show that NPL shocks increases before it decreases for the remainder of the period. Thus, NPL impulses have an effect on LA_TA and particularly the liquidity conditions in banks.

Panel (c) displays that LA_TA responds positively to ROA impulses in the first 4 years. Then it responds negatively to ROA impulses for the remaining 6 years of understudy. This means that earnings within banks have an influence on LA_TA and particularly liquidity in banks. Considering the forecast error variance of the liquidity conditions, NPL ratio shocks have the most impact on liquidity conditions and stand at 40%, which increases from 4% from the beginning. Lastly, ROA shocks are the second largest part account for about 19%, which increase from 2% from the beginning.

Robustness checks

In this section, the study reveals the robustness checks in relation to the SVAR model and liquidity shocks. The summarised statistics are derived from the liquidity ratios indicated that both variables are normally distributed and this implies that the estimated model was normally distributed (See table 2 and 3).

Figure 2: Response of LA_TA to other CAMELS indicators

(a) Response of LNLA_TA to LNLA_TA (b) Response of LNLA_TA to LNNPL

(c) Response of LNLA_TA to LNROA

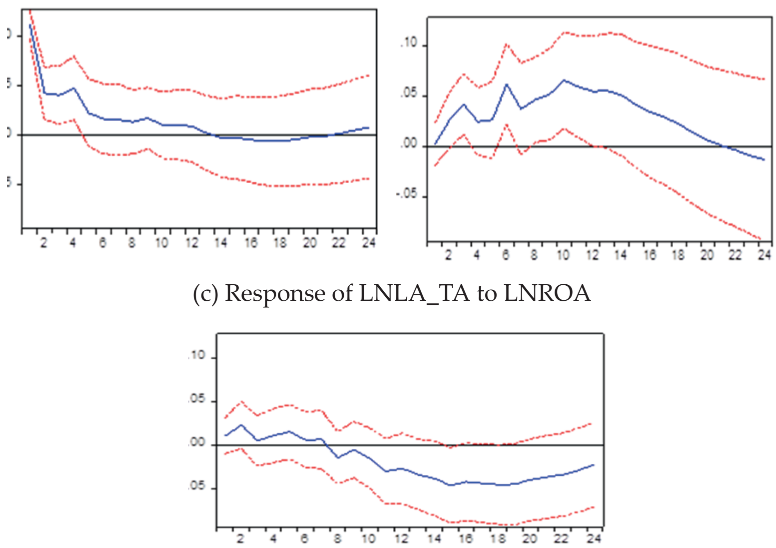


Table 2: LA_ATL Normality Test

Normality test results

Component	*Jarque-Bera*	*df*	*Prob.*
1	102.2671	2	0
2	1.657384	2	0.4366
3	0.996068	2	0.6077
4	0.473858	2	0.789
5	3733.912	2	0

Source: Authors' Own calculation from Eviews 8

Table 3: LA_TA Normality Test

Normality test results			
Component	*Jarque-Bera*	*df*	*Prob.*
1	57.09221	2	0
2	2.374059	2	0.3051
3	1.339835	2	0.5118
4	0.317627	2	0.8532
5	3055.604	2	0

Source: Authors' Own calculation from Eviews 8

Considering the autocorrelation, both LA_ATL and LA_TA results imply that they are free from autocorrelation (see Appendix 2). Additionally, the inverse roots of AR characteristics polynomial for showing stability, indicates that characteristics roots lie within the circle and concludes that the parameters used in the SVAR model are stable (see Appendix 3). Focusing on the heteroscedasticity test, the results imply that the residuals from the model are homoscedastic (see Appendix 4).

The diagnostic tests from the SVAR model show that the errors from the model are normally distributed. Furthermore, the tests show that the results do not suffer from autocorrelation. In addition, the tests are not suffering from heteroscedasticity and also that there is no parameter instability. Overall, the results obtained are reliable and valid for this study.

5. CONCLUSIONS AND POLICY RECOMMENDATIONS

The primary motivation of the paper has been to explore the nature of the impact of credit risk and profitability on liquidity shocks of Namibia`s commercial banking industry using a structural vector autoregressive model (SVAR). Firstly, the empirical evidence found in this paper showed that liquidity shocks are caused by a combination of shocks with credit risk (approximated by NPLs) being the dominant source of liquidity shocks in Namibia. This is in keeping with several studies (Berrios 2013; Hajja et al. 2015; Nabilar et al. 2018) which reached a similar conclusion that higher NPLs cause lower liquidity and consequently higher liquidity risk. Given this outcome, we recommend the adoption of a proactive and efficient credit risk management system. As opposed to reacting when customers default, proactive credit risk management would entail close monitoring of changes in relevant key indicator variables of clients to anticipate or detect timely those clients at high risk of defaulting and provide preventive interventions in advance.

Our empirical findings have also cast some light on the link between profitability and liquidity risk. Evidence in the study suggests that profitability (approximated by ROA) exert a minimal effect on liquidity conditions in Namibia. These findings align with those of Panigrahi (2014) Ghurtskaia et al. (2016) and Pradhan et al. (2016) who argue that maximising profit may result in lower liquidity conditions on one hand, while focusing on improving liquidity may deteriorate profitability of firms. Given this outcome, we recommend an optimal blend of both liquidity risk management and profitability. We suggest modestly that this can be done by calibrating the appropriate threshold level of non-performing loans/credit risk that simultaneously optimise banking liquidity and profitability. Lastly, promoting a well-regulated banking sector and sound macroeconomic policies is an important policy direction that the Bank of Namibia needs to support.

This study submits that policies that are focused on targeting credit risk and profitability of banks contribute positively towards enhancing liquidity conditions of the Namibian banking industry. In this regard, this study has contributed to African financial risk management literature by providing specific policy guidelines contextual to the Namibian banking industry and general policy directions for comparable low- and middle-income countries. In addition, we are modest to suggest that the current context of the prevailing pandemic crisis further sustain the grounds for this study. Owing to a contraction in both business and consumer activity particularly during the height of the pandemic, the financial sector liquidity outlook for many countries deteriorated significantly exacerbated by the pressure on the banking sector to provide paid holidays and other financial relief arrangements to affected businesses and households. These challenges are current and ongoing, warranting further research. A comparative study that involves more countries and banking sectors is vital for improvements in research. The findings call for more research on this topic concerning the fast-changing of the financial sector and financial regulations.

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Appendix 1

Variance decomposition of LA_ATL

Period	S.E.	LNLA_ATL	LNNPL	LNROA
1	0.110939	100.0000	0.000000	0.000000
2	0.116721	96.40850	0.422066	1.234705
3	0.122336	89.39358	5.433861	1.197484
4	0.124231	87.40831	6.381398	1.176012
5	0.126611	84.35517	7.257487	2.130428
6	0.128738	81.60288	8.046500	2.773933
7	0.129925	80.44017	8.816950	2.728646
8	0.130794	79.46795	9.237911	2.729502
9	0.131459	78.75200	9.596119	2.726021
10	0.132054	78.24332	9.918876	2.778180
11	0.132644	77.70960	10.09597	3.065149
12	0.133273	77.02938	10.14159	3.483545
13	0.133841	76.39589	10.16104	3.928399
14	0.134374	75.81131	10.16668	4.439520
15	0.134943	75.18153	10.13267	5.018787
16	0.135518	74.54450	10.07088	5.578951
17	0.136039	73.97677	10.00802	6.087983
18	0.136506	73.47489	9.949193	6.561782
19	0.136937	73.01839	9.890984	6.991715
20	0.137322	72.61907	9.836594	7.356265
21	0.137649	72.28746	9.790104	7.658006
22	0.137922	72.01361	9.751366	7.909981
23	0.138152	71.78620	9.719269	8.116493
24	0.138341	71.60181	9.693789	8.279101

Source: Authors' Own calculation from Eviews 8

Variance Decomposition of LA_TA

Period	S.E.	LNLA_TA	LNNPL	LNROA
1	0.112351	100.0000	0.000000	0.000000
2	0.128883	87.08697	4.686406	2.170941
3	0.142291	79.74774	12.79579	1.970138
4	0.153028	78.77596	13.15429	2.439808
5	0.158274	75.73597	15.26291	3.327466
6	0.171887	65.19726	25.19507	3.811083
7	0.176942	62.34574	28.07356	4.033943
8	0.185003	57.59244	31.36560	3.775778
9	0.194899	52.72838	35.26661	3.405900
10	0.207468	46.79205	40.89681	3.056338
11	0.218535	42.44392	43.82799	3.611025
12	0.228177	39.10282	45.57976	3.854486
13	0.237771	36.02109	47.09890	4.535766
14	0.246277	33.58484	47.92880	5.525831
15	0.253761	31.63937	47.47953	7.334765
16	0.259575	30.26417	46.88250	8.717892
17	0.264632	29.16506	46.13993	10.31972
18	0.269237	28.22170	45.12970	12.11671
19	0.273309	27.40440	43.95659	13.94275
20	0.276417	26.79342	42.99290	15.41808
21	0.279073	26.28610	42.18025	16.73617
22	0.281649	25.81371	41.45452	17.85014
23	0.284097	25.41024	40.90489	18.61825
24	0.286254	25.11921	40.56758	19.04972

Source: Authors' Own calculation from Eviews 8

Appendix 2

Dependent variable: LA_ATL

VAR Granger Causality/Block Exogeneity Wald Tests			
Sample: 2009Q1 2018Q3			
Included observations: 128			
Dependent variable: LNLA_ALTL			
Excluded	Chi-sq	df	Prob.

Depended variable: LA_TA

VAR Granger Causality/Block Exogeneity Wald Tests			
Sample: 2009Q1 2018Q3			
Included observations: 116			
Dependent variable: LNLA_TA			
Excluded	Chi-sq	df	Prob.
LNTIER1RWCR	10.86979	7	0.1444
LNNPL	26.14262	7	0.0005
LNROA	12.31972	7	0.0905
LNRSA_RSL	9.289951	7	0.2325
All	53.01680	28	0.0029

Appendix 3

LA_ATL autocorrelation

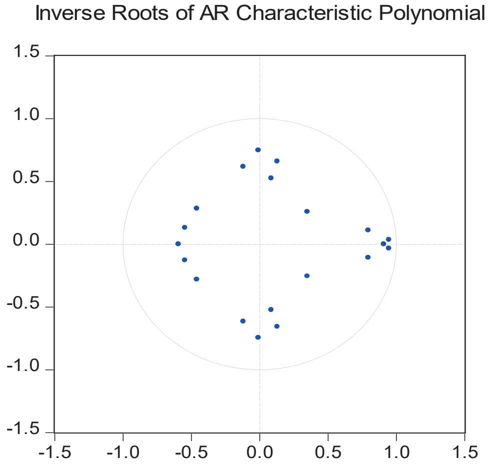
VAR Residual Serial Correlation LM Tests						
Sample: 2009Q1 2018Q3						
Included observations: 128						
Null hypothesis: No serial correlation at lag h						
Lag	**LRE* stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	43.42285	25	0.0126	1.785712	(25, 358.1)	0.0126
2	25.82792	25	0.4168	1.036775	(25, 358.1)	0.4173
3	25.08742	25	0.4575	1.006030	(25, 358.1)	0.4580
4	16.08131	25	0.9124	0.636996	(25, 358.1)	0.9125
5	30.04274	25	0.2227	1.212947	(25, 358.1)	0.2231

LA_TA autocorrelation

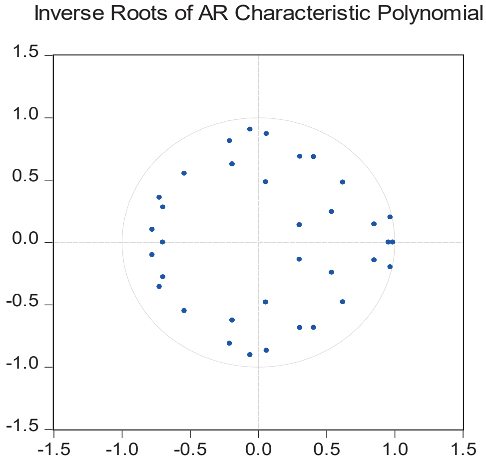
VAR Residual Serial Correlation LM Tests						
Sample: 2009Q1 2018Q3						
Included observations: 116						
Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	27.94517	25	0.3104	1.127564	(25, 257.8)	0.3113
2	38.22563	25	0.0440	1.572705	(25, 257.8)	0.0443
3	28.03068	25	0.3064	1.131197	(25, 257.8)	0.3074
4	26.43870	25	0.3845	1.063749	(25, 257.8)	0.3855
5	12.57372	25	0.9813	0.492889	(25, 257.8)	0.9814
6	24.94836	25	0.4653	1.000969	(25, 257.8)	0.4662
7	46.73706	25	0.0053	1.954325	(25, 257.8)	0.0053
8	22.53832	25	0.6045	0.900178	(25, 257.8)	0.6054

Appendix 4

LA_ATL Polynomial



LA_TA Polynomial



Appendix 5

LA_ATL Heteroskedasticity Tests

VAR Residual Heteroskedasticity Tests (Levels and Squares)		
Sample: 2009Q1 2018Q3		
Included observations: 128		
Joint test:		
Chi-sq	**df**	**Prob.**
703.4260	660	0.1174

LA_TA Heteroskedasticity Tests

VAR Residual Heteroskedasticity Tests (Levels and Squares)		
Sample: 2009Q1 2018Q3		
Included observations: 116		
Joint test:		
Chi-sq	df	Prob.
1165.857	1110	0.1189