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AN EMPIRICAL ANALYSIS OF THE RELATIONSHIP BETWEEN CAPITAL, MARKET RISKS, AND LIQUIDITY SHOCKS IN THE BANKING INDUSTRY

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Abstract: This study explores the relation between capital, market risks and banks' liquidity conditions. In estimating the SVAR regression model, Granger causality, impulse-response functions and forecast error variance decomposition were employed and used for estimation of the results. The data sample comprised of commercial banks over the 2009 to 2018 period. The empirical results showed that liquidity shocks are caused by a combination of structural shocks. The Granger causality, impulse-response functions and forecast error variance decomposition documented that sensitivity to market risk is the key factor affecting liquidity conditions in the banking sector in the long run. In addition, the empirical results showed that capital adequacy has minimal impact on liquidity conditions in the short run. The reforming rate to sensitivity to market risk policies, capital adequacy policies and liquidity policy measures can be valuable policy tools to minimize liquidity shortages and avoid insolvent banks.

JEL classification: C40, C52, E51, E58, G32;
Keywords: capital; market risks; liquidity shocks; banking industry; financial stability

1. Introduction

The global financial crisis of 2007-2008 was characterized by a lack of liquidity in banks and other financial institutions, which led to the bailout and closure of several financial institutions around the world (Nicolò, 2016). In banking, liquidity is the capability of banks to meet obligations and unexpected demand withdrawals from depositors (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

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(2015) pointed out that liquidity is essential for any institution working with money. Financial regulation and liquidity risk management are critical to financial stability of any economy. The fundamental role of banks in the maturity transformation of short-term deposits into long-term loans makes banks inherently vulnerable to liquidity risks both of an institution-specific nature and those which affect markets in general (BCBS, 2008). Banks are intermediaries between those aiming to save their money and those aiming to borrow from other banks. The rationale for intermediation between savers and borrowers is necessitated by different needs in terms of liquidity, maturity and yield. In playing this intermediary role, the banks are exposed to maturity transformation risks such as bank loans arising from the maturity mismatch of assets and liabilities 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 depositors (Angora and Roulet, 2011). As a result, banks are inherently exposed to maturity transformation risks which derive from a maturity mismatch of assets and liabilities from a balance sheet. Thus, banks are fully located in maturity transformation and risk management (Hartlage 2013), while regulators ensure the safety and soundness of the banking system and maintain confidence and economic prosperity.

Capital adequacy within financial institutions is a crucial element and that determine banking operations and stability in terms of the available capital in the banks. Considering other previous works conducted by Hossain, Khan and Sadique (2018:10), Casu, Pietro and Trujillo-Ponce (2017:19), Distinguin, Roulet and Tarazi (2013:20); Horvath, Seidler, and Weill (2014:17) and Kapan and Minoiu (2017:15); Hossain *et al.* (2018:10) they have documented relationship between capital and liquidity conditions. For example, Horvath *et al.* (2014:17) found that higher capital ratio such as Tier 1 leads to deterioration of liquidity conditions of banks.

The 2007-09 global financial crisis exposed 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), Vermorken and Vermorken (2011), Giustiniani and Thornton (2011) cite the above-mentioned factors as the root causes of the crisis. The works of Casu et al. (2017:20), and Banti and Phylaktis (2019:86) also documented the relationship between market systemic risks and banks' liquidity conditions. Prior works by Le (2017:4) also established the relationship between interest rates, exchange rates and prices against the liquidity conditions of banks.

The remainder of this article is organized as follows. Section 2 provides a review of the literature on the relationships between capital, market risks and banks' liquidity conditions. Section 3 describes the methodology and structural VAR model for liquidity shocks in Namibia. Section 4 presents results and discusses robustness checks. Section 5 provides conclusions.

2. Literature review

The International Monetary Fund (2018:7) conducted Namibia's financial system stability assessment and arrived at sentiments that commercial banks faced liquidity shortages over time and they obtained funds from wholesale funding to provide loans to needy borrowers. Based on the available literature, there are limited studies that have attempted to identify the liquidity shocks in Namibia.

However, the knowledge gap has been persisting in this area of study which thus necessitated the present study to uncover the liquidity shocks in the Namibian context. It is against this backdrop that the present study sought to contribute to the liquidity management body of knowledge by identifying and establishing the liquidity shocks not only in Namibia but also for rest of the world. This study is vital for banking institutions, regulatory bodies and the economy as a whole since it focuses on liquidity risks which affect banking performances that could lead to bank failure. Besides, contributing to the body of knowledge, this research paper offers insights to bank managers in preventing liquidity risks.

Numerous studies have used the CAMELS approach in analyzing the performance of banking institutions over time. The Uniform Financial Institution Rating system which is referred to by the acronym CAMELS represents six components in evaluating the banks' conditions and these are capital adequacy, asset quality, management efficiency, earnings quality, liquidity, and sensitivity to market risks. The focus of this paper was to study the relationship between capital adequacy, sensitivity to market risks and banks' liquidity conditions.

Capital is one of the vital factors that determine banking operations and stability in terms of the available capital in the banks. Capital adequacy refers to the availability of capital from a bank to cover unexpected losses and to avoid reductions in asset value which could cause a banking institution's failure, and the banks' ability to satisfy depositors if they require their investments (Rena, 2006; Venkatesh and Suresh, 2014). Baek, Balasubramanian and Lee (2015) scrutinized US commercial banks from 2000 to 2013 covering the subprime crisis using quarterly data between failed and non-failed banks. The study used Tier 1 risk-based capital ratio and that revealed that Tier 1 capital ratio is a useful indicator and it is significant for detecting the bank's financial distress. Tier 1 refers to core capital which comprises common stock and surplus, undivided profits (retained earnings), qualifying non-cumulative perpetual preferred stock, minority interest in the equity accounts of consolidated subsidiaries, and selected identifiable intangible assets less goodwill and other intangible assets (Rose and Hudgins 2008).

Venkatesh and Suresh (2014) undertook a study on Bahrain banks for the period spanning from 2006 to 2012 comprising four banks. The study revealed that the Tier1 capital ratio was low which is associated with a bank's financial distress. This result was also demonstrated in the study of Kandrac (2014), who found that it would be better to enter the crisis with a higher Tier 1 capital ratio to absorb unanticipated losses with enough margins to enable the bank to continue as a going concern. Thus, the results suggest the significance of Tier 1 capital in detecting the likelihood of a bank's financial distress. Consequently, higher capital ratios (Tier 1) and lower liquidity creation lead to illiquidity amongst banks. This was supported by the works of Hossain *et al.* (2018:9), Casu, Pietro and Trujillo-Ponce (2017), Distinguin *et al.* (2013), Horvath, Seidler and Weill (2014), and Kapan and Minoiu (2017) who studied the influence of Tier 1 on the liquidity conditions of banks. In this view, the findings established the influence of capital adequacy on the liquidity conditions of a bank which lead to liquidity shocks and financial distress in the long run.

Sensitivity to market risk refers to the ability of a bank to identify, monitor, manage and control market risks that may impact the income (Tripathi, Meghani and Mahajan, 2014; Karri, Meghani and Mishra, 2015). It is used to measure the market risks that are associated with the movement of prices such as interest rates, foreign exchange rates, commodity prices and equity prices on how they impact the income of a bank (Le, 2017). Venkatesh and Suresh (2014) stress that sensitivity to market risk looks at how the banks react to risks that adversely affect earnings and are derived from the movement of prices in terms of interest rate, commodity prices, equity prices, and currency rates.

Le (2017) undertook a study on Vietnamese banks over the 2008 to 2013 period, using the rate-sensitive assets to measure their sensitivity to market risks. The results revealed that rate-sensitive assets are significant in detecting the likelihood of bank financial shocks by differentiating between best and worst-performing banks. In addition, the works of Casu *et al*. (2017), and Rena, 2006 and Banti and Phylaktis (2019) also documented the effects of interest rates on the liquidity conditions of banks. Casu *et al.* (2017) found that an increase in interest rate can affect bank income and liquidity creation. Banti *et al.* (2019) found that any changes to repo rates lead to tightened liquidity conditions in banks and that contributes to the increase in house prices.

3. Methodology

The data was sourced from the Bank of Namibia and the Namibia Statistics Agency (NSA). The data sources were existing banks' balance sheets used to identify the relation between capital, sensitivity to market risks and banks' liquidity conditions in Namibia. Bank's financial data including 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 2007-08 that was caused by the shortage of liquidity among other root causes.

We collected data related to financial variables that were used mostly for measuring capital adequacy, sensitivity to market risks and liquidity conditions. 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 regard to the capital adequacy, the study proxy Tier 1 capital ratio *(*Tier 1 RWCR*),* which measures the total equity to total assets (Hossain *et al.* 2018)? Tier 1 capital ratio is a key indicator of capital adequacy within banks which is used by regulatory bodies in many parts of the world and recommended by the Basel Committee on Banking Supervision. Accordingly, banks with higher capital adequacy and profitability are likely to survive (Cole and Wu, 2014, Papanikolaou, 2017). Prior works by Casu *et al.* (2017); Horvath *et al.* (2014); Kapan *et al.* (2017) find a strong relationship between Tier 1 RWCR and liquidity conditions that could lead to liquidity shocks.

As regard to the sensitivity to market risk, the study proxies the rate-sensitive assets and rate-sensitive liabilities to total assets. The rate-sensitivity asset refers to assets or liability which is "repriced at or near the current market interest rates within a maturity bucket" (Saunders *et al*., 2017:205). Accordingly, change in currency value and cumulative gaps adversely affect bank income (Saunders *et al*., 2017:205 and Le, 2017:7). Prior studies find a positive correlation between bank income and liquidity conditions (Ghurtskaia and Lemonjava, 2016:1611; Pradhan and Shrestha, 2016:7). The results are assumed to be affected by interest rates, foreign exchange rates and prices and that could be one of the sources of liquidity shocks in banks.

In addition to the above 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. 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 a bank's probability of default (Angora *et al*. 2011). In addition, numerous researchers argued that an 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 the macroeconomic conditions of a country which 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's financial distress. In data analysis, all variables have been converted into natural logs except for GPD and SIB_CDR due to their lower values against the other ratios.

Econometric model

The study adopted the structural vector autoregressive (SVAR) to identify the relation between capital adequacy, sensitivity to market risks and banks' liquidity conditions. 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:

$$L_{it} + a_T T_t = B_L + B_{LT1} T_{it-1} + B_{LT2} T_{it-2} + B_{LL1} L_{it-1} + B_{LL2} L_{it-2} + C_L GDP_{it} + e_L$$
$$a_L L_{it} + T_{it} = B_T + B_{TT1} T_{it-1} + B_{TT2} T_{it-2} + B_{TL1} L_{it-1} + B_{TL2} L_{it-2} + C_T GDP_{it} + e_{T\ldots3.1}$$

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 (T- test varience)
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 test provides causation links between variable 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 one variable on forecasting another variable (Wei, 2013). The Granger causality test has been used to establish causality between bank capital adequacy (Tier 1 Risk-Weighted Capital Ratio (RWCR), asset quality or Non-Performing Loans (NPL) and earnings quality which means Return on Assets (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 variable over time. Yu, Ju'e and Youmin (2008) point out that 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 bank capital adequacy (Tier 1 RWCR), asset quality (NPL) and earnings quality (ROA).

In relation to impulse response function, forecast error variance decomposition provides complementary analysis by identifying which variable contributes mostly in causing the shocks (Lanzarotti cited by Amisano, 1997). The variance decomposition displays the disparity of an endogenous variable in causing the shocks. For example, which of these bank capital adequacy (Tier 1 RWCR), asset quality (NPL) and earnings quality (ROA) is contributing mostly shocks to the liquidity conditions in Namibia.

4. Results and Discussion

In this paper, we identify the relationship between capital adequacy, sensitivity to market risks and banks' liquidity conditions for the period 2009 to 2018. We test the relationships between capital adequacy and sensitivity to market risks against the liquidity conditions of banks. Thus, we estimate a Structural VAR model by relating capital adequacy and sensitivity to market risks against liquidity ratios, namely, total loans to total customer deposit ratio (LO_DEPO), Natural Logarithm of Total Bank Assets (LNTA), Rate Sensitivity to Assets and Liabilities (RSA_RSL) and total loans to total assets ratio (LO_TA). 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

Variables	Mean	Median	Max	Min	Std Dev	Observations
TIER1 RWCR	12	12	16	8	2	185
LO_TA	74	74	87	17	9	188
LO_DEPO	90	89	158	66	12	188
RSA_RSL	98	97	184	74	17	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

The Tier 1 capital has a mean value of 12 with a standard deviation of 2 and a minimum and maximum value of 8 and 16 respectively. The results suggest that banks are profitable and adequately capitalised by scoring higher percentages over 8% required. The LO_TA ratio indicates an average value of 74 which is close to the 75 per cent statutory minimum requirement. The standard deviation stood at 9 while the minimum and maximum is 17 and 87 respectively. The average LO_DEPO reported for sampled banks is 90, while the standard deviation stood at 12 values. On the other hand, minimum and maximum values are 66 and 158 respectively. The RSA_RSL shows an average value of 98 with a standard deviation of 17. On the other hand, the minimum and maximum values are 74 and 184 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 is at 0.48 values. However, the reported minimum and maximum are 15.57 and 17.5 respectively. Lastly, the Spread of the one-month interbank rate and the Central Bank policy Rate (SIB_CDR) variable has an average value of 0 during the sample period. Therefore it is not statistically significant. 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 LO_DEPO and other CAMELS variables, Tier1 RWCR is Granger causing the liquidity variable at a 6% level of significance. This implies that the causality between Tier1 RWCR and LO_DEPO is weak. Further to this, NPL accounts for about 21% of Granger causality towards liquidity variables. This means that there is no causality between NPL and LO_DEPO. The ROA is Granger causing the liquidity variable at a 73% level of significance. This means that there is no causality between income and liquidity. Finally, RSA_RSL account for about 11% level of significance of Granger causality. This means that there is no causality between RSA_RSL and LO_DEPO. This indicates that it is only Tier 1 RWCR that has minimal Granger causality with LO_DEPO (see Appendix 1).

Considering impulse responses, Panel (a) in Figure 1, displays that LO_DEPOs positively respond to the availability of liquidity impulses. Thus, availability liquidity shocks affect the liquidity conditions in Namibia. The Panel (b) displays that LO_DEPOs positively respond to capital requirements impulses at an early stage and then afterwards respond negatively for the remainder of the study period. The results suggest that Tier 1 RWCR significantly lower liquidity in banks in the long run. Finally, Panel (c) displays that LO_DEPOs respond positively to rate sensitivity assets and liabilities in the first 3 years and then remain closed to zero or borderline. The performance demonstrated that the relationship is weak. Overall, all ratios have effects on the liquidity conditions in Namibia.

Fig. 1: Response of LO_DEPO to other CAMELS indicators

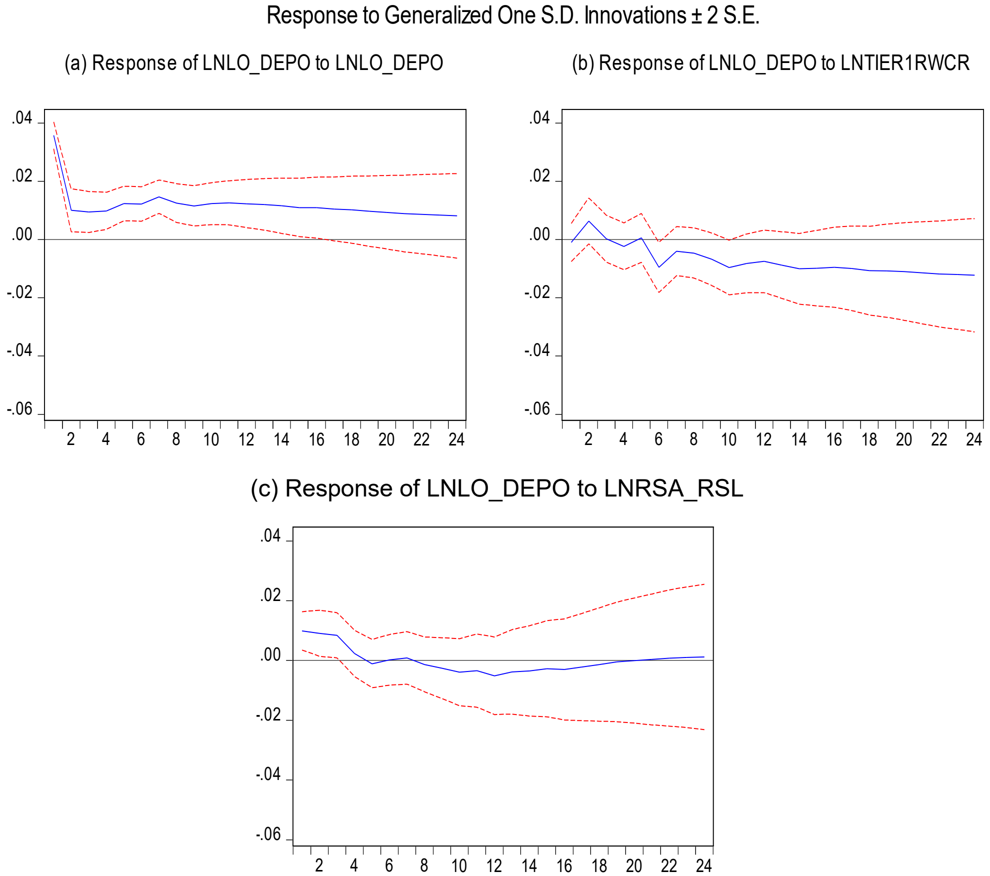
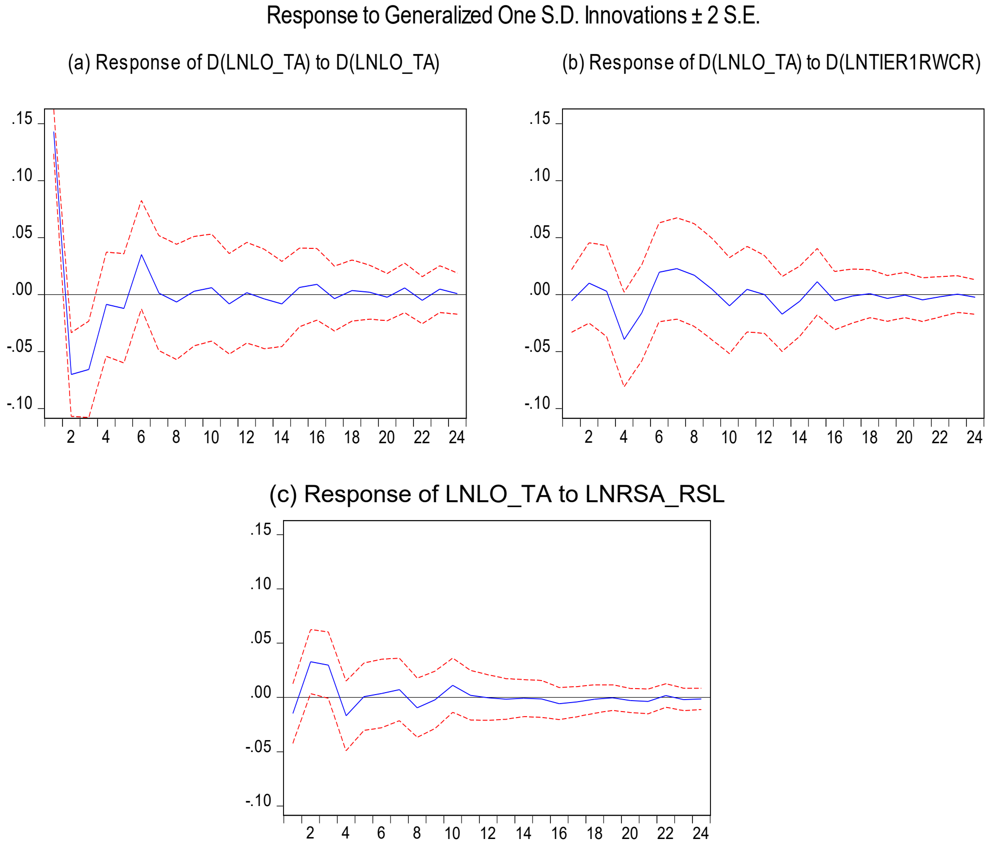


Table 2 displays the importance of Tier1 RWCR, NPL, ROA and RSA_RSL on the forecast error variance of liquidity conditions. Accordingly, Tier 1 RWCR shocks are the most important factor in the forecast error variance of liquidity conditions.

Tier 1 RWCR shocks increase from 0% to 11% over the period. In contrast, RSA_RSL shocks have the least important impact on the forecast error variance of liquidity conditions. Thus, Tier 1 RWCR shocks have the most important impact on the forecast error variance of liquidity conditions. Again, the SVAR Model is efficient and the results can reliable.

Considering the Granger causality between LO_DEPO and other CAMELS variables, Tier1 RWCR is Granger causing the liquidity variable at a 6% level of significance. This implies that the causality between Tier1 RWCR and LO_DEPO is weak. Furthermore, RSA_RSL account for about 11% level of significance of Granger causality. This means that there is no causality between RSA_RSL and LO_DEPO. This indicates that it is only Tier 1 RWCR that has minimal Granger causality with LO_DEPO (see Appendix 1).

Fig. 2: Response of LO_TA to other CAMELS indicators



Considering impulse responses, the Panel (a) in Figure 2, displays that LO_DEPOs positively respond to the availability of liquidity impulses. Thus, availability liquidity shocks affect the liquidity conditions in Namibia. The Panel (b) displays that LO_DEPOs positively respond to capital requirements impulses at an early stage and then afterwards respond negatively for the remainder of the study period. The results suggest that Tier 1 RWCR significantly lowers liquidity in banks in the long run. Finally, Panel (e) displays that LO_DEPOs respond positively to rate sensitivity assets and liabilities in the first 3 years and then remain closed to zero or borderline. The performance demonstrated that the relationship is weak. Overall, all ratios have effects on liquidity conditions in Namibia.

Considering the forecast error variance of liquidity conditions, Tier 1 RWCR shocks are the most important factor in the forecast error variance of liquidity conditions. Tier 1 RWCR shocks increase from 0% to 11% over the study period. In contrast, RSA_RSL shocks have the least important impact on the forecast error variance of liquidity conditions. Thus, Tier 1 RWCR shocks have the most important impact on the forecast error variance of liquidity conditions. Again, the SVAR Model is efficient and the results can reliable.

In this section, the study reveals the robustness checks concerning the efficiency of the SVAR model and liquidity shocks. The summarised statistics are derived from LO_DEPO and LO_TA ratios. Considering the residual normality test of LO_DEPO results, the results suggest that the residuals from the SVAR model are normally distributed or asymptotically normally distributed. In addition, the results also indicated that LO_TA are also normally distributed.

Table 3: LO_DEPO normality test

Normality test results

Component	*Jarque-Bera*	*df*	*Prob.*
1	4.124284	2	0.1272
2	2.151541	2	0.341
3	0.776663	2	0.6782
4	0.322413	2	0.8511
5	6384.244	2	0

Source: Authors' Own calculation from E-views 8

Focusing on autocorrelation, both LO_DEPO and LO_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).

Table 4: LO_TA normality test

Normality test results

Component	*Jarque-Bera*	*df*	*Prob.*
1	721.3787	2	0
2	2.820746	2	0.2441
3	1.696334	2	0.4282
4	0.844069	2	0.6557
5	3805.11	2	0

Source: Authors' own calculation from E-views 8

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. Conclusion

The results revealed that sensitivity to market risk (RSA_RSL) is the most important sources of liquidity shocks. The RSA_RSL demonstrated a strong relationship with LO_TA, which caused liquidity shocks. The empirical literature findings revealed that an increase in the spread between the one-month interbank rate and the policy rate of the regulatory bodies leads to illiquid in the banking system (Distinguin, Roulet and Tarazi, 2013:21; Casu, Pietro and Trujillo-Ponce, 2017:20; and Banti and Phylaktis, 2019:86). The market risks are associated with the fluctuation of interest rate, foreign exchange rates and prices. These results raised concerns for bank managers and regulatory institutions to monitor the movement of interest rates and ensure that banks are coping with set interest rates. The results show that capital adequacy (Tier 1 RWCR) is the least source of liquidity shocks. The Tier 1 RWCR demonstrated a relationship with LO_DEPO, which could cause liquidity shocks. The empirical literature findings also revealed that higher capital ratios lower liquidity creation and lead to illiquidity amongst banks (Hossain et al. 2018:9; Casu et al. 2017:19; Distinguin et al. 2013:20; Horvath et al. 2014:17; and Kapan et al. 2017:15). These results raised some important concerns for bank managers and regulatory institutions to monitor capital adequacy and ensure that banks are within the required capital on their books.

The empirical results reveal robust implications for financial policy and other related financial regulations. The effects of sensitivity to market risk (RSA_RSL) on liquidity shocks will be a wakeup call for macroeconomic policy design. Again, considerable efforts should be placed on current financial regulations derived from Basel III. The findings shed a light on the importance to investigate why commercial banks are exposed to market risks, thus led to liquidity shocks in the long run. The findings provide strong policy implications for sensitivity to market risk such as fluctuation of interest rate, currency and prices and so on. The findings are in line with empirical literature, for example, that fluctuation of interest rate, currency and prices lead to illiquid in the banking system (Distinguin *et al.* 2013:21; Casu *et al.* 2017:20; and Banti *et al.* 2019:86). The findings of this study call for a strong policy implications both for the banks and regulatory institutions (Central Bank), which may protect banks against unfavourable conditions and market risks. Lastly, capital adequacy (Tier 1 RWCR) also plays a role in influencing shocks in the short run. The findings provide strong evidence of the relationship with liquidity conditions of banks in the short run. The findings are consistent with empirical literature that higher capital ratios lower liquidity creation can lead to illiquidity amongst banks (Hossain et al. 2018:9; Casu et al. 2017:19; Distinguin et al. 2013:20; Horvath et al. 2014:17; and Kapan et al. 2017:15). This paper propose the liquidity measures as part of the Basel III that may strengthen the liquidity conditions of the banks.

Appendix: 1 Variance decomposition of LO_DEPO

Period	S.E.	LNLO_DEPO	LNTIER1RWCR	LNRSA_RSL
1	0.035789	100.0000	0.000000	0.000000
2	0.038340	93.93917	3.011774	2.589726
3	0.040131	91.24699	2.764608	4.912446
4	0.041656	90.22019	2.825410	4.578429
5	0.044129	88.16727	2.560885	4.924219
6	0.046992	84.47720	6.106959	4.595984
7	0.050591	81.27836	5.773490	4.129495
8	0.053281	78.77999	5.863125	4.221530
9	0.056263	74.83727	6.572736	4.392866
10	0.059720	70.66541	8.240098	4.843653
11	0.063576	66.26800	8.813684	4.920396
12	0.067814	61.52817	8.861746	5.262102
13	0.071955	57.44767	9.256505	5.158175
14	0.076177	53.55874	9.892820	4.921565
15	0.080318	50.04169	10.31680	4.590314
16	0.084841	46.50335	10.43395	4.258862
17	0.089173	43.47391	10.60811	3.915893
18	0.093647	40.60691	10.86186	3.563490
19	0.098077	38.00032	11.04102	3.249024
20	0.102621	35.53066	11.17941	2.974523
21	0.107034	33.35097	11.36447	2.752158
22	0.111377	31.40756	11.58581	2.575827
23	0.115658	29.65189	11.77492	2.433618
24	0.119864	28.06435	11.97188	2.317295

Source: Authors' Own calculation from E-views 8

Variance decomposition of LO_TA

Period	S.E.	DLNLO_TA	DLNTIER1RWCR	DLNRSA_RSL
1	0.143182	100.0000	0.000000	0.000000
2	0.162780	95.97559	0.205202	2.866783
3	0.184394	87.49815	0.160258	3.953947
4	0.190350	82.30886	4.526760	4.823345
5	0.192320	81.02928	5.177398	4.741041
6	0.200513	77.59451	5.859732	4.375687
7	0.207242	72.64097	6.711851	4.172288
8	0.208550	71.83217	7.275347	4.371319
9	0.209044	71.51390	7.295832	4.358921
10	0.209746	71.11835	7.455157	4.599626
11	0.210382	70.84360	7.453080	4.577620
12	0.210504	70.76774	7.444487	4.577184
13	0.211684	70.01381	8.025847	4.527869
14	0.212706	69.49351	8.033932	4.495933

15	0.213981	68.75418	8.231847	4.468128
16	0.214490	68.60456	8.249411	4.477407
17	0.214795	68.43677	8.230712	4.481087
18	0.214949	68.36591	8.220621	4.476661
19	0.215101	68.27809	8.232513	4.474381
20	0.215557	68.00144	8.198139	4.461143
21	0.215883	67.86991	8.213594	4.452364
22	0.215979	67.86382	8.216335	4.452798
23	0.216054	67.86566	8.211271	4.457299
24	0.216174	67.79156	8.212974	4.452717

Source: Authors' Own calculation from E-views 8

Appendix 2: Depended variable: LO_DEPO

VAR Granger Causality/Block Exogenety Wald Tests			
Sample: 2009Q1 2018Q3			
Included observations: 120			
Dependent variable: LNLO_DEPO			
Excluded	Chi-sq	df	Prob.
LNTIER1RWCR	11.72844	6	0.0683
LNNPL	8.298996	6	0.2170
LNROA	3.572932	6	0.7342
LNRSA_RSL	10.34406	6	0.1109
All	45.88996	24	0.0046

Depended variable: LO_TA

VAR Granger Causality/Block Exogeneity Wald Tests			
Sample: 2009Q1 2018Q3			
Included observations: 108			
Dependent variable: D(LNLO_TA)			
Excluded	Chi-sq	df	Prob.
D(LNTIER1RWCR)	6.242541	8	0.6201
D(LNNPL)	14.73268	8	0.0646
D(LNROA)	9.934967	8	0.2696
D(LNRSA_RSL)	17.55064	8	0.0249
All	49.86702	32	0.0230

Appendix 3: LO_DEPO autocorrelation

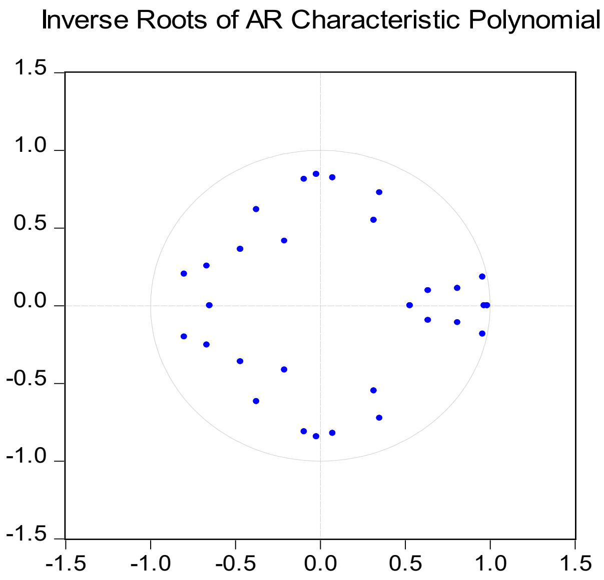
VAR Residual Serial Correlation LM Tests						
Sample: 2009Q1 2018Q3						
Included observations: 120						
Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	20.00602	25	0.7465	0.795849	(25, 291.3)	0.7470
2	21.42263	25	0.6688	0.854222	(25, 291.3)	0.6694

VAR Residual Serial Correlation LM Tests						
Sample: 2009Q1 2018Q3						
Included observations: 120						
3	30.29914	25	0.2133	1.226268	(25, 291.3)	0.2139
4	32.97919	25	0.1316	1.340758	(25, 291.3)	0.1321
5	27.40050	25	0.3362	1.103574	(25, 291.3)	0.3369
6	21.92509	25	0.6401	0.874992	(25, 291.3)	0.6407
7	26.70662	25	0.3707	1.074377	(25, 291.3)	0.3715

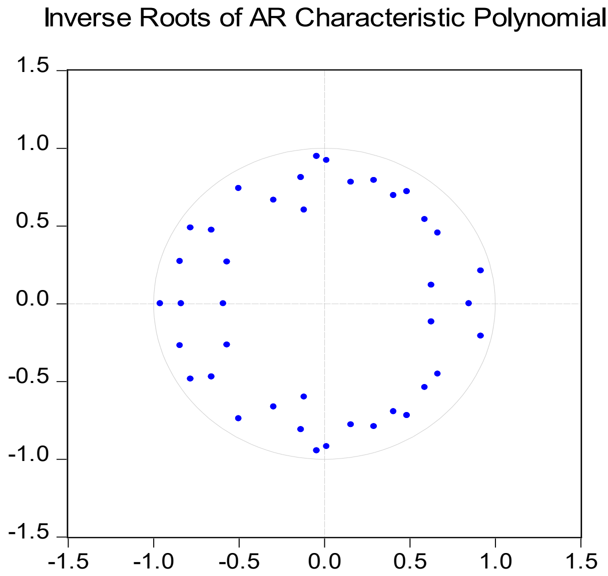
LO_TA autocorrelation

VAR Residual Serial Correlation LM Tests						
Sample: 2009Q1 2018Q3						
Included observations: 108						
Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	21.17548	25	0.6828	0.842671	(25, 209.5)	0.6839
2	27.54485	25	0.3292	1.112340	(25, 209.5)	0.3306
3	16.40961	25	0.9021	0.645914	(25, 209.5)	0.9025
4	40.06743	25	0.0287	1.665729	(25, 209.5)	0.0291
5	37.33317	25	0.0537	1.542209	(25, 209.5)	0.0542
6	19.08837	25	0.7929	0.755983	(25, 209.5)	0.7937
7	19.92142	25	0.7509	0.790485	(25, 209.5)	0.7519
8	21.49972	25	0.6644	0.856212	(25, 209.5)	0.6656
9	26.07054	25	0.4038	1.049226	(25, 209.5)	0.4053

Appendix 4: LO_DEPO Polynomial



LO_TA Polynomial



Appendix 5: LO_DEPO Heteroscedasticity Tests

VAR Residual Heteroscedasticity Tests (Levels and Squares)					
Sample: 2009Q1 2018Q3					
Included observations: 120					
Joint test:					
Chi-sq	df	Prob.			
1003.721	960	0.1591			

LO_TA Heteroscedasticity Tests

VAR Residual Heteroscedasticity Tests (Levels and Squares)					
Sample: 2009Q1 2018Q3					
Included observations: 108					
Joint test:					
Chi-sq	df	Prob.			
1263.877	1260	0.4640			

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