International Journal of Business and Management Review

Vol.1, No.2, pp.26-34, December 2013

Published by European Centre for Research Training and Development UK (www.ea-journals.org)

BANK CREDIT RISK AND INTEREST RATE VOLATILITY- GRANGER CAUSALITY VS. VAR-GARCH APPROACH

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ABSTRACT: *The study develops VAR-GARCH models with Granger causality framework to examine the direction of causality flows, information transmission and trade-off between credit risk and interest rate volatility, using time series data collected from the CBN statistical bulletin and the annual accounting reports of deposit money banks for a period of 1981 to 2011. Our findings show that there is zero causality between credit risk and interest rate volatility; also, a transmission mechanism or a "pass through" is not found between the two variables. However, the two variables maintain non-monotonic relationship for the specified period.*

KEYWORDS: Interest Volatility; Credit risk; Information transmission; Causality; VAR-GARCH.

Jel Classification Code: C3; C8; E4; G2

INTRODUCTION

The lending activities of banks are undoubtedly accomplished with risk otherwise known as credit risk. Thus, credit risk is the probability that an existing borrower may fail either willing or unwilling to honour his or her obligations as they fall due. This inability to honour debt obligations is often occasioned by the variability of some macroeconomic factors. In view of this, the relationships between credit risk and macroeconomic variables have been examined by many authors in the past. The examination of these relationships is basically referred to macro-stress testing of the banks.

Recently macroeconomic models explicitly analysis the trade-off between bank credit risk and interest rate variables in the context of dynamic stochastic general equilibrium specification for example, Angeloni and Faia (2009), Zhang 2009, Meh and Movan 2010, Dib 2010 employ these models in their studies and documented that the impact of expansionary shocks on bank lending is unequivocally positive in nature; specifically, Angeloni and Fala (2009) conclude that reduction in interest rate due to positive supply or monetary policy shock, declines the funding cost of banks and consequently increases the probability of repayments. In a similar study by (Altunbas, Gambacorta & Marques, 2009), evidence is issued in favour of the hypothesis that low interest rate increases bank risk. Tanase(2013) affirms that default rate reacts quickly with

modification in macroeconomic variables the same evidence is found in the work of (Diaz & Olivero, 2011). Conversely Demirguc-Kunt and Detragiache, (1998) state that adverse economic condition in which growth is low or negative, coupled with high interest and inflation, are favorable to banking crises.
All of these studies major on how low or high interest rate resulting from monetary policy/economic conditions influence bank crises or credit risk, but they fail to look at the direction of information flows and as well as the volatility clustering characterizing the intricate trade-off between credit risk and interest rate. This is therefore a critical issues awaiting empirical investigation. The respond to this long standing issue has motivated us to explore the information transmission network and direction of flows between credit risk and interest rate volatility in the frameworks of Granger causality and VAR-GARCH models. Therefore, the objectives of this study are to examine the credit risk-interest rate volatility relationship, the non-linear functions of the variables and the direction of information transmissions/flows between credit risk and interest volatility. The rests of the paper are structured as: literature review, methodology and data, discussion of results, conclusion and recommendations.

LITERATURE REVIEW

Interest rate seems to be a strong determinant of credit risk because it influences the debt burden of borrowers. This means that the trade-off between interest rate and credit risk is expected to be positive. In fact, a rise in debt burden caused by an upward increase in interest rates could lead to a higher rate of classified loan (Aver, 2008; Louzis, et al. 2011; Nkusu, 2011). Richard (1999) discovers a significant but negative relationship between real interest rate and bank failure. Contrary, Fofack (2005) in Sub-Sarahan Africa finds positive relationship between real interest rate and credit risk. This implies that a rising interest rate could trigger the cost of investment and thereby necessitate higher possibility of default or failure to honour debt obligations consequently leading to non-performing loans. In different study, Jiménez and Saurina (2006) employ interbank interest rate to measure the impact of interest rate on toxic loans. They find a significant and positive relationship between toxic loans and interest rate. Quagliariello (2007) discovers the same relationship between the interest rate measured by ten year Italian Treasury bond and the loan loss provision. Castro (2012) conducts study in Greece, Ireland, Portugal, Spain and Italy (GIPSI) from 1997 to 2011 and discovers monotonic relationship between long term interest rate and credit risk. This overwhelmingly supports the convention that high interest rate increases the obligation of borrowers and thus increases the banks credit risk or failour. In Australia, Ali and Daly (2010) find no any significant relationship between short-term interest rate and credit risk. Aggregated indebtedness as well as the deterioration of macroeconomic factors is one of the main reasons for an increase of aggregated credit risk in the banks sector (Fainstein & Novikov, 2011). They categorically affirm that if it is impossible for borrowers to honor their obligations as they fall due it would result in negative chain reaction in a financial system. Thus, part of the outstanding loans created by the banking sector could turn out to become toxic debts. Diaz and Olivero (2011) have vigorously explained that during economic downturn banks switch their asset portfolios towards more liquid assets because credit risk increases for risky and illiquid assets more than for readily liquid/less-risky assets. This reaction could make credit to be more expensive; hence the firms' production and investment activities could be disrupted. Fei, Fuertes and Kalotychou (2012) conclude that both real GDP and unemployment maintain correlated with the risk of default likewise Claessens, Ariccia, Igan, and Laeven (2010) ascertain that few macroeconomic variables are found to be statistically significant and consistent with credit risk during financial crisis. The model of (Angeloni & Faia, 2009) and (Angeloni et al. 2010) predicts that in an instance of a positive productivity shock, rates of inflation and interest are bound to fall while output increases. It is further asserted in the model that the deposit rate moves in the same proportion with the policy rate. Thus, a reduction in the interest rate associates with a decrease in the cost of banks' funding. Also, a decrease in the deposit rate raises the probability that returns of projects are high enough to cover the all claims of depositors. The reduction in interest rates reduces banks' return on assets. This reduction together with the more fragile balance sheet composition increases bank risk. Invariably, banks optimally increase the ratio of external funding in an attempt to maximize return to bank capital. Therefore interest rate volatility corresponds to changes in the volatility of market interest rates that undoubtedly constitutes a central source of systematic risk to banks. Apart from a rise in market interest rates volatility, whose positive effect is an increase in bank returns for newly created or variable interest bearing credit, banks bear a danger of increased credit risk. According to the asymmetric information theories, a high interest rate tends to worsen the problem of "adverse selection" (that is, the selection of borrowers with high probability of adverse project outcomes or "bad risks in the context of credit relationships). Off course, high interest rates volatility deters potential borrowers with almost risk free projects, so that the risk composition of the stream of loan applicants tilts toward bad risks. Thus, a rise in interest rates changes the *ex post* incentives for borrowers inducing them to take on riskier projects (Stiglitz &Weiss 1981).It is logical that in a world of information asymmetries a rise in interest rates volatility if all factors are held constant increases credit risk on balance sheets of banks.

METHOD

We adapt in part the credit risk model that was originated developed by (Wilson, 1997a, b). The specification of Wilson apparently relates default risk to some set of randomly selected macroeconomic variables and it is rooted on the relatively simplicity of the logistic equation often employed in ordinary Least Square regression analysis. Wilson's specification is characterized with non linear logistic functions which are more empirically suitable for analyzing a relationship in a non linear model than the linear ones. Wilson's model was first developed for Mckinsy Company as credit portfolio specification which placed credit risk proxied by default rate as an explained variable on macroeconomic variables. Thus, our specification expresses a relationship between credit risk and interest rate volatility. The specification follows a logical process as:

$$cc_{b,t} = \frac{1}{1 + e^{-xv,t}} \qquad (1)$$

The equation can be rewritten as follows

$$cc_{b,t}\,(1 + e^{-yb,t}) = 1 \qquad (2)$$

$$cc_{b,t} + cce^{-yb,t} = 1 \qquad (3)$$

$$cce^{-yb,t} = 1 - cc_{b,t} \qquad (4)$$

$$\text{In}\,[cc_{bt}] = \frac{1- cc_{b,t}}{[y_{b,t}]} \qquad (5)$$

$$Y_{b,t} = \mathrm{In}\frac{[cc_{b,t}]}{[1-cc_{b,t}]} \tag{6}$$

Where: $y_{b,t}$ is the banking sector-specific index at time (t), ln is the natural log, $cc_{b,t}$ is the classified credit ratio (i.e. default at time (t))
Therefore, we employ Boss' (2002) approach to formulate the banking sector-specific index ($y_{b,t}$) which is contrary to the approach adopted by Virolainen (2004).
Note: lower value of $y_{b,t}$ with lower $cc_{b,t}$ implies healthy state of the economy. Hence, index ($y_{b,t}$) represents overall state of the economy and it can be expressed as the linear function of any exogenously selected economic factors, thus:

$$Y_t = \alpha_0 + \sum^{n}_{i=n} \lambda_{t-1} Vir_{t-1} + \mu_t \tag{7}$$

Where: y represents credit risk
Vir is the volatility of interest rate
α_0 is the constant term
λ is the parameter
μ is error term

Following Zellner and Palm 1974, we propose a VAR model in the context of GARCH framework as follows:

$$y_t = C_O + \sum^{n}_{i=1} c_{t-I}\, y_{t-1} + \sum^{n}_{i=1} D_{t-i} Vir_{t-I} + e_t \tag{8}$$

$$Vir_t = \lambda_0 + \sum^{n}_{i=1} \lambda_{t-i} Vir_{t-1} + \sum^{n}_{i=1} \prod_{t-i} y_{t-1} + e_t \tag{9}$$

Borrowing from the studies of (Hamao, Masulis & Ng (1990) and (Chan, Chan & Karolyi, 1991), we transfer the VAR equation above into multi-variant GARCH models as follows:

$$\delta_{y,t} = a_0 + a_1\delta_{y,t-1} + a_2 e^2_{y,t-1} + a_3 e^2_{vir,t-1} \tag{10}$$

$$\delta_{virt} = b_0 + b_1\delta_{vir,t-1} + b_2 e^2_{vir,t-1} + b_3 e^2_{y,t-1} \tag{11}$$

$$\delta_{y,vir,t} = a_0 b_0 + a_1 b_1 \delta_{y,vir,t-1} + a_2 b_2 e^2_{y,vir,t-1} + a_3 b_3 e^2_{y,vir,t-1} \tag{12}$$

$$\delta_{y,virt} = a_0 b_0 + a_1 b_1 \delta_{y,vir,t-1} + a_2 b_2 (e^2_{y,vir,t-1} + abe^2_{y,virt-1}) \tag{13}$$

The estimated coefficients of a_3 and b_3 actually show whether information flows or volatility spills from credit risk to interest rate and vice-versa.

The Granger Causality Model

This model in respect of credit risk and interest volatility can be stated as:

$$y_t = \sum^{n}_{i=1} \lambda_i vir_{t-i} + \sum^{n}_{i=1} \alpha_i y_{t-i} + \mu_{it} \tag{14}$$

$$vir_t = \sum^{n}_{i=1} P_i vir_{t-i} + \sum^{n}_{i=1} \beta_i y_{t-i} + \mu_{2t} \tag{15}$$

Where: y and vir are credit risk and volatility of interest rate respectively.
It is assumed that the error terms μ_1 and μ_2 are uncorrelated.

The Box Jenkin Q statistic

$$Q = T\,(T+2) \sum^{m}_{i=1} (A\hat{}^2/T\text{-}i)^2\, x^2_m \tag{16}$$

Where: Q is Box Jenkin Q statistic
T is the total sample
M is the maximum lag-length
$A^{\wedge}$ is the autoregressive coefficient

The BJ (Q)-statistic is used in testing the linear dependency of a series while the BJ (Q^2)-statistic is used in testing the non-linear dependency of a series.

Data Description and sources
The data that are applied in this study are purely secondary data in nature. Those data relating to non classified credit are collected from the annual statement of account for each of the banks; while, interest rate, data are sourced from the various volumes of CBN statistical bulletin to cover a reasonable period of years ranging from 1981 to 2011.

DISCUSSION OF FINDINGS

Our first empirical endeavor is to examine the series of credit risk and interest rate based on their mean value, standard deviation. The stationarity, linearity, non-linearity and the ARCH effect of these series are also investigated using the Augmented Dickey Fuller (1981) Box-Jenkin (1976) and Engle (1982) Approaches. The results from these tests are reported in table 4.1

Table 4.1 Showing Mean Value, Standard Deviation, ADF statistic, Q-Statistic, Q^2-Statistic and ARCH-Statistic

Variable ⟶		Credit Risk		Interest Rate
Mean	-1.12		0.05	
SD		0.77		0.22
ADF(0)		-4.71^a		-5.72^a
Q(1)	4.14^b			
$Q^2(1)$	2.26			
Q(4)			10.10^b	
$Q^2(4)$			3.84	
ARCH(1)		0.77		-0.50

Note: a and b represents 1% and 5% levels of significance, Q(1), Q(2) and Q(4), Q^2 (4) are the Box-Jensins Q statistics for autocorrelation of the series of credit risk for interest rate respectively, ARCH(1) is the Engel (1982) statistic for ARCH(1).
Source: Extracted from E-view Windom (7)

The results above show a mean values (-1.2 and 0.05) for credit risk and interest rate respectively. This means credit risk has a decreasing tendency while interest rate manifest increasing tendency through the study period 1981 to 2011. The value of the standard deviation of credit risk is approximately pegged at 77% while that of interest rate is 22% implying that credit risk is more volatile than interest rate. The report of the ADF statistics reveals that both series are stationary at level. The Q(1) statistic is significant at 5% while $Q^2(1)$ is not. This means credit risk exhibits a linear tendency at lag (1). Also, the statistic of Q(4) is significant while $Q^2(4)$ is not providing evidence in support of linearity tendency of the series of interest rate. The Lagrange Multiplier (LM) statistic at lag (1) shows that the null hypothesis that there is no ARCH effect is not rejected. However, the linearity tendencies of these series are further investigated using the Brook et al 1996 approach.

The BDS Test Results
The Brook, Dechert and Scheinkman (BDS) (1987) statistical values are often employed to evaluate a series if it exhibits non-linearity tendency. Therefore, the BDS for AR (p) ordinary

residual series and standardized residual series from the GARCH (p) model are estimated up to 5 dimensions for each specified series. The results are reported in table 4.2

Table 4.2 Showing the BDS Statistics for the Credit Risk and Interest Rate Series

Panel (1) BDS Statistics for AR(p) Residual Series for Credit Risk and Interest Rate.				
Credit Risk	2	3	4	5
AR(2)	1.82	0.70	-0.47	-0.23
AR(3)	-1.24	0.24	-1.07	-0.31
AR(4)	1.12	-0.11	-0.65	-0.08
AR(5)	-0.25	-0.65	-0.22	-0.24
Interest Rate				
AR(2)	-0.97	(-0.05)[b]	0.33	0.83
AR(3)	-0.50	0.67	1.69	1.26
AR(4)	1.31	0.42	1.11	1.04
AR(5)	-1.71	1.77	2.07	1.54
Panel (2) BDS Statistics for GARCH (PI) Standardized Residual Series for Credit Risk and Interest Rate				
Interest Rate				
GARCH (2)	-1.41	-1.17	-0.90	-1.92
GARCH (2)	-1.24	-0.96	-0.71	-1.82
GARCH (4)	-1.64	-1.42	-1.04	-1.88
GARCH (5)	-1.08	-1.10	-1.05	-2.45
Credit Risk				
GARCH (2)	(4.22)[a]	(3.67)[a]	(3.62)[a]	(3.17)[a]
GARCH (3)	(3.94)[a]	(3.78)[a]	(3.75)[a]	(3.41)[a]
GARCH (4)	(4.03)[a]	(3.85)[a]	(3.71)[a]	(3.37)[a]
GARCH (5)	(4.13)[a]	(3.69)[a]	(3.46)[a]	(3.03)[a]

Note: a and b means significant at 1% and 5% respectively.
Source: Extracted from E-view Window (7)

The is observed that the BDS statistics for AR(p) in which p takes values from 1 to 5 are not statistically significant for the series of both credit risk and interest rate except in the AR(2), dimension (3) where the series of interest rate appears to be significant exactly at 5%. Thus, we can conclude that the BDS test does not strikingly reject the null hypothesis of no nonlinearity in the AR(p) errors for the credit risk and interest rate series. The same results are evident in the BDS test of GARCH(p) standardized residual series for interest rate. But, however, the BDS test for GARCH(p) standardized residual series for credit risk reject the null hypothesis of no none linearity for credit risk. In summary, the series of credit risk displays none linear structure while interest rate is linear in nature. Therefore, we try to model the volatility of interest rate as an independent variable on credit risk and vice-verse using the VAR-GARCH approach. The estimate results from the relationships are presented in table 4.3.

Table 4.3: Showing the Results of the VAR-GARCH Models

Item	Coefficient	z-stat	p.v
a_0	-0.09	-0.06	0.96
a_1	1.17	$(3.67)^a$	0.00
a_2	-1.97	-0.07	0.95
b^0	0.003	0.30	0.76
b_1	-0.63	-0.21	0.83
b_2	-0.00	-0.23	0.82

note: a implies significant @ 1%.

Source: Extracted from E-view Window (7)

The results of the VAR-GARCH model in table 4.3 show that all the coefficients in both the credit risk and interest rate models are not significant except in the case of the GARCH (a_1) coefficient in credit risk model. This means that there is effect of GARCH nut there is no information transmission between the credit risk and interest rate due to insignificance of a_2 and b_2 for credit risk and interest rate model respectively. It is also discover that the sign of the a_2 and b_2 is negative in both models implying that an increase in interest rate volatility will lead to a decrease in credit risk and vice-verse. Therefore, shocks to credit risk would have opposite effect on prices of loan able funds in Nigerian banking and investment environments but information in respect of interest rate does not significantly affect credit risk. Now, the question is can we predict the variations in credit risk by the shocks or volatility of interest rate? To answer this question, we estimated the Granger causality model and the results are presented in table 4.4

Table 4.4 Granger Causality Test Results

Null hypothesis	obs	F-stat	p.v
VIR does not Granger Cause y	30	2.09	0.16
Y does not Granger cause VIR		0.01	0.91

Source: Extracted from E-view Windom (7)

The results in table 4.4 reveal that the null hypothesis of no Granger causality is rejected in both case indicating that there is no or zero causality between the credit risk and interest rate. Therefore, the results of the VAR-GARCH models are confirmed that there is absence of flows between the two variables and hence, prediction of one of the variables from the changelings in the other is not possible.

CONCLUSION

The study examines the relationships between credit risk and interest rate volatility in the frameworks of VAR-GARCH and Granger-causality models. The findings in both models are similar as the former reveal that no information flows or transmission between credit risk and interest rate, also, the later shows that there is zero causality between the two variables. However, the relationship between credit risk and interest rate volatility is found to be negative but insignificant thereby providing barely insignificant evidence in support of the study of (Demirguc-Kunt & Detragiache, 1998) and negating the position of (Angeloni and Faia, 2009, Zhang, 2009, Meh & Moran, 2010).

RECOMMENDATIONS

In view of our findings, credit risk is more volatile than interest rate; therefore banks should reduce their sources of credit risk and increase interest rate so as to maintain a profitable margin. The sources of credit risk can be minimized by placing reasonable restriction on the inflows of loan able funds. Also, banks should restructure the existing non-performing credit in a flexible manner will look attractive to their defaulters or if possible non-performing credit should be factored at a reasonable price to interested buyers. This will relieve banks from excessive toxic facilities.

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