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Effect of Financial Market Frictions and Flight to Quality on Credit Supply in Kenya

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Abstract:
Adverse shocks to the economy may be amplified by financial market conditions. Before implementation of financial market frictions in Kenya, the Banking sector was highly profitable, with industry return on equity's average of 20%. The ratio of credit supply to gross domestic product was 35%. However, after its adoption, Sector loan book decelerated from a growth rate of 16.8% to 4.3%. Studies relating to financial market frictions and credit supply have produced mixed results. It was on this basis that the study sought to establish the effect of financial market frictions and flight to quality on credit supply in Kenya. Correlational research design was adopted. Secondary data from the Kenyan Market for the period January 2009 to December 2019 was analyzed. ADF and Philips-perron unit-root test was used to test the stationarity of the data. VECM was estimated to establish the long run relationships amongst the variables; Wald statistics was also estimated to establish short run causalities amongst the variables. The error correction term indicated a negative sign and was significant at 5% level (C (1) = -0.015897, .0218 < P= 0.05), an indication that there is a long run causality running from the explanatory variables to credit supply. Wald statistics also revealed that the estimated coefficients in the VECM were insignificantly different from zero (.5823; .0539; .5498; .4150> p= 0.05), an indication that there is no short run causality running from the explanatory variables to credit supply. The study therefore recommends that for Micro finance institutions to maximize their profits they should adopt new technologies like Mobile Banking for credit facilities which does not require administrative and operation costs, to cope with the market shocks and frictions.

Keywords: *Financial market frictions, flight to quality, credit supply, Kenya*

1. Introduction

Frictions are understood as various disturbances in trading processes. Many authors place nonsynchronous trading, bid/ask spread, other transaction costs in a broad class of market frictions (Olbrys & Majewska, 2014). In the context of the capital asset pricing model (CAPM), this study defines a financial market friction as anything that interferes with trade. Financial market frictions cause a market participant to deviate from holding the market portfolio. By implication, these frictions can cause a market participant to be exposed to more or less risk than he/she might prefer (Mahony & Qian, 2009; Kiyotaki & Wright, 1989; Trejos & Wright, 1995). It is worth noting that the presence of frictions in trading processes confirms market illiquidity, and therefore plays a significant role in asset pricing (Olbrys & Majewska, 2014). The first fundamental theorem of welfare economics demonstrates that competitive equilibrium leads to efficient resource allocation and Pareto efficiency (Arrow & Hahn 1970). Under the neoclassical competitive equilibrium paradigm, firms are considered as a production function and earn zero economic rent in the long-run equilibrium (Arrow & Hahn 1970; Cyert, Kumar & Williamson 1993). Market frictions are manifested in a variety of ways such as market power indivisibilities leading to economies of scale, economies of scope, sunk costs, asset specificity, imperfect information, incomplete market asymmetric information externalities and positive transaction costs (Mahony & Qian, 2009). The random matching/search formalization of the friction in trade has a very classical implication: in the rare case where two agents have a double coincidence of wants and meet to trade, they will trade their goods or services directly for one another (Kiyotaki & Wright, 1989; Trejos & Wright, 1995). An analysis of some empirical implications of frictions in trading processes has been performed, especially in the case of emerging stock markets. In times of economic distress, interlinked macro-economic and capital market episodic crises and severe disruptions to credit markets, we often observe investors rebalance their portfolios towards less risky and more liquid securities, especially in fixed-income markets. Kashyap, Stein, and Wilcox, (1993) basing their argument on investment–savingand liquidity preference–money supply curves model, commonly referred to as IS-LM Model or Hicks – Hansen Model, found that following tightening of monetary policy, there were systematic increases in the relative quantity of commercial paper compared to bank lending. This argument introduces the concept of flight-to-quality. Individuals in the verge of starting up a business enterprise needs starting capital, which could mean that when their savings are not enough to foot the bills needed for startup, most entrepreneurs seek out a loan. Onyango and Odondo, (2018) termed the act of lending money in small amounts to individuals with the aim of starting a small business as micro lending. According to Childer, (2015), the history of micro lending began in Bangladesh in 1974.

In an economically depressed area of Bangladesh, Yunus (1974) issued the first microloans to basket weavers. According to Yunus and Jolis, (1999), in order to purchase materials for weaving, the weavers needed to be advanced some startup money in the form of a loan as they were economically deprived. They therefore, relied on loans from local lenders who charged exorbitant interest rates that left weavers with meagre profit upon loan repayment. As elaborated by Childers, (2015),to save weavers from this predatory lending, and to break this cycle of poverty, Yunus realised that the basket weavers needed a loan with favorable terms that would maximize their profits, a program that later evolved into Grameen Bank. Because of the notion of informational barriers, higher risks and high costs of intermediation, micro enterprises often cannot obtain long-term finance in the form of debt and equity Avevor, (2016).According to Djankova, McLiesha, and Shleifer, (2007), when lenders know more about borrowers, their credit history and are able to get collaterals from the borrowers, they are more willing to extend credit. Due to Government regulations on market conditions, the forces of supply and demand may not interact freely to find the equilibrium quantity and price. When there is an artificial ceiling, and the equilibrium price is above the ceiling, the allocation of resources is distorted, the consequence is that people who may need loans, but due to insufficient collaterals and at times uncreditworthy and do not qualify at the ceiling, are denied access, (Mohane, Coetzee &Grant, (2002); Khandare &Alshebami, (2015); Onyango and Odondo, (2018).

Economic theory suggests that market imperfections result from the inability of lenders to identify client's potential for repayment and risky borrowers, hence information asymmetry and may lead to adverse selection and moral hazard. According to Onyango and Odondo, (2018); Maimbo and Gallegos, (2014), microfinance institutions generally charge higher interest rates than Banks due to their higher costs of funds associated with higher overhead costs than that of commercial Banks.

Interest rate ceilings can be justified on the basis that financial institutions are making excessive profits by charging exorbitant interest rates to clients, ceilings therefore, guarantee access to credit due to favourable interest rates and facilitate prosecution of exploitative and deceptive lenders (Miller,2013; Maimbo & Gallegos ,2014); Onyango &Odondo, 2018). This is the usury argument, and is essentially one of the market failures: government intervention is required to protect vulnerable clients from predatory lending practices. According to Miller, 2013; Onyango and Odondo, (2018; Maimbo and Gallegos, (2014), this argument is based on the assumption that demand for credit at higher rates is price inelastic, postulates that financial institutions are able to exploit information asymmetry to the detriment of their clients. The preceding discussion suggests that previous studies have continued to yield contradicting results with respect to the relationship between micro lending and interest rate ceiling.

Successful adoption of International Financial reporting standards (IFRS) entails assessing technical accounting, tax implications, internal processes, and statutory reporting, technology infrastructure, software harmonization and organizational issues, (DeFond, Hu, Hung, & Li, 2011; Tan, Wang, & Welker, 2011). International openness is a source of proliferation of existing relationships between the different stakeholders of the company where each relationship can be characterized by an information asymmetry. Solving problems of information asymmetry requires the establishment of means of control. Financial reporting can represent a source of reducing information asymmetry, leading to an increase in the volume of trading in the capital market (Ernst & Young, 2006). A number of studies (Bernanke and Lown (1991), Gambacorta and Shin (2016), Kishan and Opiela (2000, 2006), Cohen and Scatigna (2016) have established that bank capitalization has a significant impact on lending behaviour, suggesting that, to the extent that the provisions were taken out of capital, this would have dampened subsequent lending. On the other hand, in a study by Chen, Chin, Wang, & Yao, 2013, indicated that IFRS adoption led to higher interest rates, greater likelihood of demand for collateral and shorter maturities. From the aforementioned literature, IFRS adoption and loan contracts have yielded inconsistent results with regard to consequences for the creditor - debtor relationship.

Credit markets asymmetric information problems indicated that lenders neither knew the past behavior and the characteristics, nor the intentions of credit applicants before the implementation of credit reference bureau (CRB) reports. This created a moral hazard problem that forced lenders to make credit decisions based on the average characteristics of borrowers rather than on individual characteristics (Bustelo, 2011). CRB reduces borrowing cost and loan delinquencies to a moderate extent; it enhances effective risk identification/monitoring and microcredit extension, (Gaitho, 2013). Credit information sharing undoubtedly plays a pivotal role in reducing the information asymmetry that exists between banks and borrowers, (Bustelo, 2011). Information sharing is associated with improved availability and lower cost of credit, particularly in transition countries with weak creditor protection. Information sharing and firm-level accounting transparencies are substitutes in enhancing credit availability: the correlation between information sharing and credit access is stronger for opaque firms than for transparent ones. From the foregoing literature, it is overt that empirical studies have been carried out on the nexus between financial market frictions, flight to quality and credit supply. Nevertheless, the exact relationship is not well defined as there are varying results. While some studies argue that financial market frictions protect consumers from exploitation by guaranteeing access to credit at reasonable interest rates, others are of the opinion that imposing market frictions is an inefficient tool as it limits access to credit, reduces transparency and promotes lending to only individuals who is credit worthy.

Furthermore, related studies largely focused on developed countries whose GDP were higher than those of developing countries. Therefore, results from such economies should be treated with a lot of caution in relation to developing economies like Kenya. Consequently, a country specific study is inevitable for clear policy formulation. It is on this basis that the study sought to establish the relationship between financial market frictions and credit supply. The guiding hypotheses were;

- H_{01} Central Bank rate does not affect credit supply in Kenya.
- H_{02}Provisions in anticipation of loan losses do not affect credit supply in Kenya.
- H_{03} Non-performing loans does not affect credit supply in Kenya.
- H_{04}Flight to quality and credit supply in Kenya does not have a long run relationship.

2. Research Methodology

2.1. Correlation Analysis

This study adopted correlational research design. Correlational research design is suitable for studies that seek to establish relationships. The study employed secondary data from the Kenyan Market for the period January 2009 to December 2019. The dependent variable was credit supply while the independent variables were Interest rate ceiling (Otherwise obtained by analyzing Central Bank Rate), International Financial Reporting Standard (IFRS) 9 – more particularly provisions in anticipation of loan losses, Credit Reference Bureaus information sharing – Nonperforming loans and flight to quality – especially purchase of Government securities, like in this case Treasury bills.

2.2. Model Specification

A general Vector Autoregressive Model (VAR) of order 'P' below was used to generate VECM;

$$Y_t = \nu + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \tag{1.0}$$

Where: $\nu =$ Is a fixed $(K \times 1)$ vector of intercept terms, A_i are fixed ($K \times K$) coefficient matrices for $i = 1$, P is a positive integer, ε_t is assumed to be multivariate normal, is a white noise with zero and positive definite covariance matrix $\varepsilon_t \sim \text{iidN}\left(0, \sigma^2 \varepsilon\right)$.

VECM was applied to find long-run relationships. We developed the following model, to assess the short-run and long-run coefficients of the variables, which is equation (1.0) differenced to form a VECM model (VAR is differenced to form a VECM) and is generated recursively as;

$$\Delta CS_t = \alpha + \sum_{i=1}^{k-1} \alpha_i \Delta CS_{t-i} + \sum_{j=1}^{k-1} \alpha_j \Delta CBR_{t-j} + \sum_{m=1}^{k-1} \alpha_m \Delta PALL_{t-m} +$$

$$\sum_{p=1}^{k-1} \alpha_p \Delta NPL_{t-p} + \sum_{n=1}^{K-1} \alpha_n \Delta TBLL_{t-n} + \lambda_i ECT_{t-1} + \mu_{it} \tag{1.1}$$

Where: $k-1$ = Shows the lag length, which is reduced by 1.

$\alpha_i, \alpha_j, \alpha_m, \alpha_p$ and α_n = are short run dynamic coefficients of the model's adjustment long run equilibrium. λ_i = This is the Speed of adjustment parameter with a negative sign.

It measures the speed at which the dependent variable(s) returns to equilibrium after changes in independent variables.

μ_{it} = Residuals (Stochastic error term).

CS = Credit Supply
CBR = Central Bank Rate
PALL = Provisions in Anticipation of Loan Losses
NPL = Non-Performing Loans
TBLL= Treasury Bills

ECT = (Error Correction Term), it is the lagged value of the residuals obtained from the cointegrating regression of the dependent variable on the regressors. It contains long-run information derived from the long-run cointegrating relationships. This study expresses the lagged OLS residual obtained from the long-run cointegrating equations as;

$$Y_t = \sigma + \eta_j X_t + \xi_m R_t + \mu_t \tag{1.2}$$

From equation (1.5) we can re-write Error Correction Term (ECT) as;

$$ECT_{t-1} = \left[Y_{t-1} - X_{t-1}\eta_1 - R_{t-1}\xi_1\right] \tag{1.3}$$

2.3. Data Analysis

Data was subjected to unit root test for stationarity. The analysis was done using Augmented Dickey Fuller (ADF) and Philips perron (PP) unit root tests to check the stationarity on the basis of a null hypothesis that the time series were non stationary (i.e., $\delta = 0$) and alternative hypothesis that the time series were stationary (i.e., $\delta \neq 0$).

The ADF unit root test will take the form of;

$$\Delta Y_t = a_0 + \alpha Y_{t-1} + b_2 \Delta Y_{t-1} + b_3 \Delta Y_{t-2} + \ldots + \varepsilon_t \tag{1.4}$$

Where; Δ is the difference operator, a_0 is a constant, and α is the autoregressive lag coefficient. The ADF then tests the hypothesis; the null hypothesis for the test is given below;

$H_0: \alpha = 0$, there exists a unit root problem. Decision rule**:** If t-statistic > ADF critical value, accept the null hypothesis. Unit root exists in this case. If t-statistic < ADF critical value, reject the null hypothesis. Gujarat, (2004), shows that the Dickey–Fuller test statistics have been criticized for their low power, especially in distinguishing between unit roots and near unit roots and in small sample data.

On the other hand, the Phillips–Perron (PP, 1988) test is more robust to serial correlation, time dependent heteroscedasticity and regime changes (Gujarat, 2004), The Phillips-Perron (PP) unit root tests differ from the ADF test mainly in how it deals with serial correlation and heteroscedasticity in the errors. The PP test ignores any serial correlation in the test regression.

2.4. Cointegration Test

The study adopted Johansen (1988) and Johansen and Joselius (1990) Cointegration test, the two proposed two different likelihood ratio tests: the trace test and maximum eigenvalue test, as shown in equations (1.9) and (1.10) respectively.

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln\left(1-\hat{\lambda}_i\right) \qquad (1.5)$$

$$J_{\max} = -T \ln\left(1-\hat{\lambda}_{r+1}\right) \qquad (1.6)$$

Where: T is the sample size and $\hat{\lambda}_i$ is the i^{th} largest canonical correlation. The trace test tests the null hypothesis of 'r' cointegrating vectors against the alternative hypothesis of **'n'** cointegrating vectors. The maximum eigenvalue test, on the other hand, tests the null hypothesis of 'r' cointegrating vectors against the alternative hypothesis of r +1 cointegrating vectors.

3. Results and Discussions

3.1. Descriptive Statistics

Table 1 presents the descriptive statistics for the data collected. Mean average Credit Supply was *M* = 1789853 (*SD* = 738328.6), this means that the average loans disbursed during the period of review was Kshs.1, 789,853 Million. Central Bank Rate, Non-performing loans, Provisions in anticipation of loan losses and Treasury Bills had a mean of *M* = 12.57765 (*SD* = 3.707730) ; *M* = 171556.1 (*SD* = 87523.47); *M* = 137850.5 (*SD* = 32506.62); and *M* = 249731.3 (*SD* = 164627.2) respectively, an indication that during the period of review, the Banking sector had an average of 12.575% CBR, Loans amounting to Kshs.171,556.1 Million were non performing, total provisions was Kshs.137,850.5 Million and had invested in kshs. 249,731.3 Million in treasury bills.

	CS	**CBR**	**NPL**	**PALL**	**TBLL**
Mean	1789853.	12.57765	171556.1	137850.5	249731.3
Median	1787217.	11.50000	160800.0	134900.0	188468.9
Maximum	2945270.	18.75000	347700.0	216700.0	610220.7
Minimum	655194.0	8.500000	56500.00	55600.00	39161.20
Std. Dev.	738328.6	3.707730	87523.47	32506.62	164627.2
Skewness	-0.085832	0.438742	0.553438	0.090422	0.779435
Kurtosis	1.544946	1.526030	2.244132	4.655888	2.401986
Jarque-Bera	11.80658	16.18411	9.880808	15.26068	15.33234
Probability	0.002730	0.000306	0.007152	0.000485	0.000468
Sum	2.36E+08	1660.250	22645400	18196267	32964535
Sum Sq. Dev.	7.14E+13	1800.892	1.00E+12	1.38E+11	3.55E+12
Observations	132	132	132	132	132

Table 1: Descriptive Statistics - Financial Market Frictions, Flight to Quality and Credit Supply
Key: CS= Credit Supply, CBR= Central Bank Rate, NPL= Non-Performing Loans,
PALL= Provisions in Anticipation of Loan Losses, TBLL= Treasury Bills.
Source: Author's Computations (2020)

3.2. Diagnostic Tests

3.2.1. Normality Test

Normality test was then conducted using Jarque-Bera statistics and the results are presented in Figure 1.0. In Figure 1.0, the P- value for the Jarque-Bera statistics is more than 5% (i.e., 27.50 % > p=0.05). An indication that the data used were normally distributed.

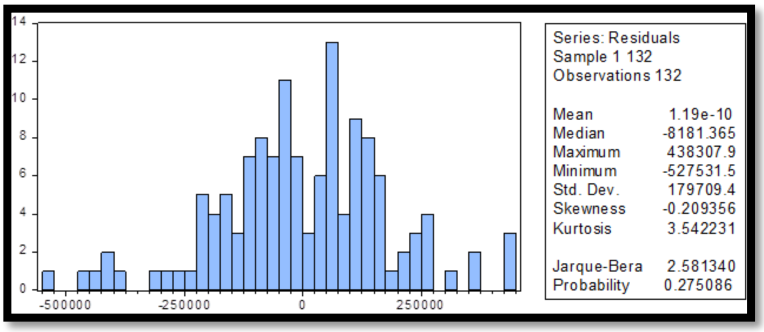

Figure 1: Normality Test for Market Frictions, Flight to Quality and Credit Supply Data
Source: Author's Computations (2020)

3.2.2. Test for Heteroskedasticity

The study further tested for the Breusch-Pagan-Godfrey Heteroskedasticity effect, with the null hypothesis that the error term was not heteroskedastic. Since the estimated P-value(s) corresponding to the observed R-squared was 0.2605> 0.05, the null hypothesis that the error term was not heteroskedastic was confirmed as seen in Table 2.

F-statistic	**1.32076**	**Prob. F(4,127)**	**0.2658**
Obs*R-squared	5.271737	Prob. Chi-Square(4)	0.2605
Scaled explained SS	6.20295	Prob. Chi-Square(4)	0.1845

Table 2: Breusch-Pagan-Godfrey Heteroskedasticity Test for Credit Supply and the Explanatory Variables
Source: Author's computations (2020)

3.3: Correlation Analysis.

Table 3 provides a matrix of the correlation coefficients for the variables; Central Bank rate, Provisions in anticipation of loan losses, Non-performing loans, Treasury bills and Credit Supply. Central Bank Rate was negatively associated with credit supply (r = -.883498) an indication that 88.34% decrease in credit supply was associated with CBR, this is interdem with Khandare and Alshebami, (2015); Onyango and Odondo, (2018) who found a negative association between credit supply and interest rate ceiling . Nonperforming loans (NPLs) was negatively associated with credit supply (r = -.240472) an indication that 24.04% decrease in Credit Supply was associated with NPLs, Provisions in anticipation of loan losses (PALL) and Treasury Bills (TBLL) were positively associated with credit supply with a correlation coefficient of r = .408610 and r = .843574 respectively. This shows that 40.86 % and 84.35 % increase in credit supply was associated with provisions and treasury bills respectively.

Correlation					
Probability	**CS**	**CBR**	**NPL**	**PALL**	**TBLL**
CS	1				
CBR	-0.8835	1			
	0				
NPL	-0.24047	0.210076	1		
	0.0055	0.0156			
PALL	0.40861	-0.32143	0.105641	1	
	0	0.0002	0.228		
TBLL	0.843574	-0.69115	0.17625	0.589743	1
	0	0	0.0432	0	

Table 3: Correlation Matrix of Credit Supply, Flight to Quality and Financial Market Frictions
Key: CS= Credit Supply, CBR= Central Bank Rate, NPL= Non-Performing Loans, PALL= Provisions in Anticipation of Loan Losses, TBLL= Treasury Bills.
Source: Author's Computations (2020)

3.4. Unit Root Test

Time series data in most cases generally follows a trend such that anything that grows overtime will fit any aggregated time series data. According to Baumohl and Lyocsa (2009), these results in the problem of spurious regression not suitable for policy implication, where there is a high, but no relationship among the variables. Stationarity of the time series data is crucial in ensuring that a proper and accurate forecasting of events is realised. Therefore, the time series data was first subjected to stationarity test by using Augmented Dickey-Fuller test (ADF) and Philips perron test (PP) in Eviews 10. For stationarity of data to be achieved, the classical properties of a system should not vary over time. This implies that the overall behavior of the data set should remain constant (Gujarat, 2004). As a rule of thumb, since the null hypothesis assumes the presence of unit root, the p-value obtained should be less than the significance level (e.g., 0.05) and the absolute value of the test statistics is less than the critical value for the rejection of the null hypothesis, thereby inferring that the series is stationary and the vice versa is true. Referring to the above rule of thumb, the data sets for CS, CBR, NPL, PALL and TBLL in table 4 have unit root. The ADF p-values obtained for each data set was greater than 5% (p=0.05 < .9087, .1201, .3655, .9327, .9428), this compares well with the p-values for PP in table 5 (p=0.05 < .9485, .2535, .3659, .0809, .9472) which are also clearly greater than 5%. Similarly, the absolute values of the test statistics for each of the variables for both the ADF and PP are less than the corresponding absolute values of the test statistics at 5% level of significance. The study thus concludes that the series are non-stationary at levels.

Augmented Dickey-Fuller Test Statistics						
Variable	At levels	p-value	1%	5%	10%	Observation
CS	-0.376265	0.9087	-3.481217	- 2.883753*	-2.578694	Unit Root exists
CBR	-2.490339	0.1201	-3.480818	-2.883579*	-2.578601	Unit Root exists
NPL	-1.828236	0.3655	-3.480818	-2.883579*	-2.578601	Unit Root exists
PALL	-0.212380	0.9327	-3.483312	-2.884665*	-2.579180	Unit Root exists
TBLL	-0.130156	0.9428	-3.480818	-2.883579*	-2.578601	Unit Root exists

Table 4: Unit Root Test of the Variables in Level
Key: CS= Credit Supply, CBR= Central Bank Rate,
NPL= Non-Performing Loans, PALL= Provisions In Anticipation of
Loan Losses, TBLL= Treasury Bills.
Source: Author's Computations (2020)

Variable	**At levels**	**p-value**	**1%**	**5%**	**10%**	**Observation**
CS	-0.078603	0.9485	-3.480818	-2.883579*	-2.578601	Unit Root exists
CBR	-2.079143	0.2535	-3.480818	-2.883579*	-2.578601	Unit Root exists
NPL	-1.827297	0.3659	-3.480818	-2.883579*	-2.578601	Unit Root exists
PALL	-2.676218	0.0809	-3.480818	-2.883579*	-2.578601	Unit Root exists
TBLL	-0.091013	0.9472	-3.480818	-2.883579*	-2.578601	Unit Root exists

Table 5: Unit Root Test of the Variables In Level
Philips – Perron Unit Root Test Statistics
Key: CS= Credit Supply, CBR= Central Bank Rate,
NPL= Non-Performing Loans, PALL= Provisions in Anticipation of
Loan Losses, TBLL= Treasury Bills
Source: Author's Computations (2020)

Table 6 and 7 shows the unit root test results for the series at first difference. From Tables 6 and 7 we can deduce that unit root does not exist in each of the series at first difference since the p-values for both the ADF and PP are less than 5% level of significance (p=0.05 < 0.0000). The deduction is further supported by the absolute value of the test statistics for each of the variables which are more than the corresponding absolute value of the test statistics at 5% level of significance. The study thus concludes that the series are stationary at first difference.

Variable	**At Levels**	**p-value**	**1%**	**5%**	**10%**	**Observation**
D(CS)	-6.191710	0.0000	-3.481217	-2.883753*	-2.578694	No Unit Root
D(CBR)	-13.93340	0.0000	-3.481217	-2.883753*	-2.578694	No Unit Root
D(NPL)	-11.46304	0.0000	-3.481217	-2.883753*	-2.578694	No Unit Root
D(PALL)	-8.858641	0.0000	-3.483312	-2.884665*	-2.579180	No Unit Root
D(TBLL)	-11.18445	0.0000	-3.481217	-2.883753*	-2.578694	No Unit Root

Table 6: Unit Root Test of the Variables after 1st Difference
Augmented Dickey-Fuller Test Statistics
Source: Author's Computations (2020)
Key: CS= Credit Supply, CBR= Central Bank Rate, NPL= Non-Performing Loans,
PALL= Provisions in Anticipation of Loan Losses, TBLL= Treasury Bills

Variable	At Levels	p-Value	1%	5%	10%	Observation
D(CS)	-6.1028	0	-3.48122	-2.883753*	-2.57869	No Unit Root
D(CBR)	-21.082	0	-3.48122	-2.883753*	-2.57869	No Unit Root
D(NPL)	-11.5183	0	-3.48122	-2.883753*	-2.57869	No Unit Root
D(PALL)	-11.6279	0	-3.48122	-2.883753*	-2.57869	No Unit Root
D(TBLL)	-11.1835	0	-3.48122	-2.883753*	-2.57869	No Unit Root

Table 7: Unit Root Test of the Variables after 1st Difference
Philips – Perron Unit Root Test Statistics
Key: CS= Credit Supply, CBR= Central Bank Rate
NPL= Non-Performing Loans, PALL= Provisions in Anticipation of
Loan Losses, TBLL= Treasury Bills
Source: Author's computations (2020)

3.5. Vector Auto Regression (VAR) Lag Order Selection Criteria

Table 8 shows VAR lag order selection criteria for Credit Supply and the explanatory variables**.** From the Table 8, Final prediction error (FPE), LR and Akaike information criterion (AIC) test statistic suggests lag 7 as the optimal lag. Schwarz information criterion (SC) and the Hannan-Quinn information criterion (HQ) suggests lag 1. According to Liew (2004), most economic sample data can seldom be considered large in size, and therefore, AIC is recommended for the estimation of their autoregressive lag length. Since the observations in this study were relatively large, the Akaike information criterion (AIC) which suggested lag 7 at 93.77780*was chosen for the autoregressive lag length for credit supply.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-6646.938	NA	2.71e+40	107.2893	107.4030	107.3355
1	-5809.479	1593.873	5.52e+34	94.18515	94.86748*	94.46233*
2	-5779.189	55.20717	5.08e+34	94.09982	95.35075	94.60797
3	-5766.066	22.85841	6.18e+34	94.29139	96.11093	95.03053
4	-5736.551	49.03317	5.80e+34	94.21857	96.60671	95.18869
5	-5704.722	50.31006	5.27e+34	94.10842	97.06517	95.30952
6	-5665.417	58.95767	4.28e+34	93.87770	97.40305	95.30978
7	-5634.224	44.27446*	4.00e+34*	93.77780*	97.87176	95.44086
8	-5616.339	23.94243	4.68e+34	93.89257	98.55513	95.78661

Table 8: VAR Lag Order Selection Criteria for Credit Supply and the Explanatory Variables
** Indicates Lag Order Selected by the Criterion*
LR: Sequential Modified LR Test Statistic (Each Test at 5% Level)
FPE: Final Prediction Error
AIC: Akaike Information Criterion
SC: Schwarz Information Criterion
HQ: Hannan-Quinn Information Criterion
Source: Author's Computations (2020)

3.6. Cointegration Test

Data was then subjected to Cointegration test for stationarity, Johansen (1988) and Johansen and Joselius (1990) two different likelihood ratio tests were adopted. This is because the variables were stationary at first difference as shown in table 6 and 7, that is, they are *I* (1) series (meaning integrated of order one). Cointegration test was therefore, necessary to establish a long run relationship. Based on the Trace statistics and Maximum Eigenvalue Statistics as captured in Table 9 and Table 10 respectively, there is one (1) cointegrating equation or one error term >> At most 1, p=0.1740=17.4% and p= 0.2474 = 24.74% Trace statistics and Maximum Eigenvalue Statistics respectively at 5% level of significance, meaning all the variables are cointegrating. The null hypothesis that there is no Cointegrating equation is thus rejected. The results therefore, suggest that in the long run, the variables move together or have a long run association.

Hypothesized		**Trace**	**0.05**	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.251669	77.42472	69.81889	0.0109
At most 1	0.159154	41.47590	47.85613	0.1740
At most 2	0.110730	19.98086	29.79707	0.4241
At most 3	0.040164	5.428931	15.49471	0.7617
At most 4	0.002785	0.345865	3.841466	0.5565

Table 9: Unrestricted Cointegration Rank Test (Trace) for Credit Supply and the explanatory variables
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level*
***MacKinnon-Haug-Michelis (1999) p-values*
Source: Author's computations (2020)

Hypothesized		**Max-Eigen**	**0.05**	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.251669	35.94882	33.87687	0.0279
At most 1	0.159154	21.49504	27.58434	0.2474
At most 2	0.110730	14.55193	21.13162	0.3215
At most 3	0.040164	5.083066	14.26460	0.7313
At most 4	0.002785	0.345865	3.841466	0.5565

Table 10: Unrestricted Cointegration Rank Test (Maximum Eigenvalue) for Credit Supply and the Explanatory Variables
Max-Eigenvalue Test Indicates 1 Cointegrating Eqn(S) at the 0.05 Level
** Denotes Rejection of the Hypothesis at the 0.05 Level*
***Mackinnon-Haug-Michelis (1999) P-Values*
Source: Author's Computations (2020)

Table 11 shows normalized cointegrating coefficients. From the table it can be deduced that Central Bank Rate and Non-performing loans, on average, had a negative effect on credit supply in the long run, Ceteris Paribus while Provision in anticipation for loan losses and treasury bills, on average, had a positive effect on credit supply, ceteris paribus. The coefficients are statistically significant at 5% level. The signs of the coefficients of Johansen normalized cointegration are reversed in the long run, the coefficients have to be interpreted as ceteris paribus effects since they are just OLS estimates (Green, (2003); Gujarat and Porter, (2009); Wooldridge, (2009)). The null hypothesis that there is no Cointegrating equation is thus rejected. This means that there is a cointegrating relationship in the model. The cointegrating relation is a variable defined as a linear combination of variables of which at least two have the same order of integration. This stationary combination even without any normalization can enter a dynamic equation in a VAR or single equation dynamic model. Prior to the notion of cointegration such variables entered dynamic models as error correction terms usually with unit coefficients. In the earliest estimated model, the error correction term was the logarithmic real wage. In the case where there is a single cointegrating relation it is possible to identify the vector by a single restriction and often this is the imposition of a single unit coefficient. By setting the vector to zero it is possible to reformulate the cointegrating vector as a long-run equation and in this case the coefficients in the vector are the reverse of the equation normalized in this way. An alternative is to normalize on -1 and then the resulting coefficients in the cointegrating vector are the same as those in the long-run equation, this explains the reverse interpretations of the signs above.

1 Cointegrating Equation(s):		**Log likelihood**	**-5637.077**		
CS	CBR	NPL	PALL	TBLL	
1.000000	188805.3	1.172628	-5.066735	-0.082624	
	(24320.8)	(0.53376)	(2.37272)	(0.67689)	
Adjustment coefficients (standard error in parentheses)					
D(CS)	-0.015897				
	(0.00680)				
D(CBR)	-2.85E-06				
	(6.6E-07)				
D(NPL)	-0.002951				
	(0.01670)				
D(PALL)	0.015660				
	(0.00684)				
D(TBLL)	0.007782				
	(0.01241)				

Table 11: Normalized Cointegrating Coefficients (Standard Error in Parentheses) for Credit Supply
Source: Author's Computations (2020)

3.7. Vector Error Correction Model

3.7.1. Vector Error Correction Estimates for Credit Supply and Its Explanatory Variables

The vector error correction estimates (Appendix 1) were estimated based on the existence of the cointegrating equations. From the Appendix 1, the long run model explains the error correction term that signifies the long run relationship among the variables. As may be inferred from the estimates, the model posits that Central Bank rate and Nonperforming loans are important determinants of credit supply in the long run (t-statistics 2 < 7.76312 and 2 < 2.19694 respectively) and were inversely related to credit supply, the null hypothesis that there is no long run relationship among the variables is rejected. As shown in Appendix 1, one unit change in Central Bank rate and non-performing loans is associated with 188,805.3 units and 1.172628 units respectively, decrease in Credit Supply on average ceteris paribus in the long run. Both the provisions in anticipation of loan losses and Treasury bills were directly related to credit supply. Though, the results shows that provisions in anticipation of loan losses is an important determinant of credit supply (t-statistics 2.13542 >2), the null hypothesis that there is no long run relationship among the variables is rejected, however, treasury bills are not (t-statistics 0.12206 < 2). The table in Appendix 1 posits that one unit change in provisions in anticipation of loan losses and Treasury bills is associated with 5.066735 units and 0.082624 units respectively increase in Credit Supply on average ceteris paribus in the long run.

$$ECT_{t-1} = \begin{bmatrix} 1.00\ CS_{t-1} + 188805.3\ CBR_{t-1} + 1.172628NP\ L_{t-1} - 5.066735PA\ LL_{t-1} \\ -0.082624TB\ LL_{t-1} - 3637613 \end{bmatrix}$$

From the Appendix 1, the previous periods deviation from long run equilibrium is corrected in the current period at an adjustment speed of 1.5 % (CointEq1 = -0.015897). Table 11 shows a make system approach, the results shows that Central Bank rate, provisions in anticipation of loan losses and treasury bills are not important determinants of credit supply in the short run, (t-statistics 2 > 1.314985; 2 > -0.293314 and 2 > -0.536739 respectively), and were statistically insignificant at 5% level in the short run (p=0.05 <0.1920; p=0.05 <0.7700; and p=0.05 <0.5928 respectively), the null hypothesis that there is no short run relationship among the variables is accepted. Nonperforming loans, however, returned as an important determinant of credit supply (t-statistics 2 < 2.030168) and was statistically significant at 5% level (p=0.05 >0.0454), nevertheless, it returned an unexpected positive sign (α = 0.100176), which is not a good sign, an indication that there is no short run relationship between Nonperforming loans and credit supply (Green, (2003); Gujarat and Porter, (2009); Wooldridge, (2009). The null hypothesis that there is no short run relationship between Nonperforming loans and credit supply is accepted.

A Wald test statistic (table's 13a, b, c, and d) is further performed to confirm if indeed there is no short run relationship among the explanatory variables and credit supply.

$$\Delta CS_t = 6504.497 + 0.093348\ \Delta CS_{t-1} + 1468.902\ \Delta CBR_{t-1} - 0.028159\ \Delta PALL_{t-1} +$$

$$0.100176\ \Delta NPL_{t-1} - 0.029576\ \Delta TBLL_{t-1} - 0.015807\ ECT_{t-1}$$

Table 12 shows the vector error correction model (VECM) that was estimated based on the existence of the cointegrating equations. The dependent variable was Credit Supply (CS) while the independent variables were Central Bank Rate (CBR), Non-Performing Loans (NPLs), Provisions in anticipation for Loan Losses (PALL) and Treasury Bills (TBLL).The error correction term indicated the expected negative sign and was significant at 5% level (C (1) = -0.015897, p = .0218< P= 0.05), this indicates that the speed of adjustment towards long run equilibrium is negative and statistically significant; this is an indication that the independent variables have influence on the dependent variable in the long run, implying that there is a long run causality running from Central Bank Rate to credit supply, this observation is supported by Mohane et al, (2002) who argued that interest rate ceilings produces a series of adverse effects on micro lending, since MFIs are not allowed to charge full cost recovery, they either close or go underground and those who survives devise ways to ensure individuals who are not credit worthy and may not be holding adequate collaterals are locked out, this tremendously reduces credit supply. This analogy is further supported by Onyango and Odondo, (2018); Miller, (2013); Acclassato (2006) who argued that interest rate ceilings cause micro lenders to observe quality, tighten their appraisal techniques in a bid to lock out individuals whose credit facilities are likely to move into arrears due to inadequate ability and lack of enough security to cover their loans, and since MFIs are not allowed charge interests that can enable them recover their operating costs, any slippages to watch category is an indication of an eminent loss. This is further supported by Bittner, Bonfim, Heider, Said, Schepens and Soares, (2020), who argued that in Germany, where rates were close to zero before the announcement of unrealistic, negative interest rate policy, Banks with more retail deposits increased risk taking by increasing credit supply, a case that changed to low credit supply.

Non-Performing Loans (NPLs) also had a long run causality running from it to credit supply, and had a negative effect on credit supply, this is interdem with Orebiyi, (2002) who observed that the availability of information on past repayment behaviour allows lenders to condition their offers on the borrowers' reputation. A number of micro enterprises due to their trifling income had a negative listing; as a result, MFIs quashed credit extended to them due fear of default, this greatly reduced credit supply to micro individuals. This however, contradicts Brown et al, (2009), who observed that information sharing and firm level accounting transparencies are substitutes in enhancing credit availability, and are actually are associated with improved availability of credit. The long run positive causality running from Provisions in anticipation for Loan Losses (PALL) to credit supply, this observation corroborates Sikhwari and Manda, (2016), who cited ease of access to finance as an indirect benefit when IFRS 9 provisioning policy is implemented, Ali and Salim, (2009) also supported this analogy by arguing that MSMEs financial statements will gain validity when IFRS 9 is implemented and therefore, through their financial statements, access to credit will be guaranteed. Their arguments however, contradicts Bouvatier and Lepetit (2008) who documented that discretionary loan loss provisions – particularly related to income smoothing behavior, have no significant impact on bank loan growth. This dissenting opinion is in agreement with Cortavarria, Dziobek, Kanaya, and Song, (2000), who explained that from an accounting perspective, there are two types of provisions for bank credit risk: specific and general provisions. While specific provisions address identified impaired loans through an increase in loan loss reserves, general provisions are associated with a broad assessment of possible future losses on the entire bank portfolio. As banks need to estimate general provisions, such provisions may be influenced by subjective judgments related to managers' discretionary behavior and might not have a significant impact on credit supply in the long run. There was also a long run causality running from Treasury Bills (TBLL) to Credit Supply (CS), this observation corroborates Bernanke, and Blinder, (1988) who argued that recessions that follow a tightening of monetary policy are perhaps most likely to involve a flight to quality because monetary tightening may reduce flows of credit, this argument is further supported by Guler and Ozlale, (2005); Caballero and Krishnamurthy, (2008); and Durand et al, (2010) who all pointed out to the existence of flight to quality. They argued that, when investors fly to quality they move out of assets with higher expected risk, such as equities and increase demand for less risky assets such as bonds. Kashyap, Stein, and Wilcox (1993) argued that following tightening of monetary policy, there were systematic increases in the relative quantity of commercial paper compared to bank lending.

Dependent Variable: D(CS)
Method: Least Squares (Gauss-Newton / Marquardt steps)
Sample (adjusted): 9 132
Included observations: 124 after adjustments
D(CS) = C(1)*(CS(-1) + 188805.320373*CBR(-1) + 1.1726278533*NPL(-1) - 5.06673524069*PALL(-1) - 0.0826235032957*TBLL(-1) - 3637613.12708) + C(2)*D(CS(-1)) + C(3)*D(CS(-2)) + C(4)*D(CS(-3)) + C(5)*D(CS(-4)) + C(6)*D(CS(-5)) + C(7)*D(CS(-6)) + C(8)*D(CS(-7)) + C(9)*D(CBR(-1)) + C(10)*D(CBR(-2)) + C(11)*D(CBR(-3)) + C(12)*D(CBR(-4)) + C(13)*D(CBR(-5)) + C(14)*D(CBR(-6)) + C(15)*D(CBR(-7)) + C(16)*D(NPL(-1)) + C(17)*D(NPL(-2)) + C(18)*D(NPL(-3)) + C(19)*D(NPL(-4)) + C(20)*D(NPL(-5)) + C(21)*D(NPL(-6)) + C(22)*D(NPL(-7)) + C(23)*D(PALL(-1)) + C(24)*D(PALL(-2)) + C(25)*D(PALL(-3)) + C(26)*D(PALL(-4)) + C(27)*D(PALL(-5)) + C(28)*D(PALL(-6)) + C(29)*D(PALL(-7)) + C(30)*D(TBLL(-1)) + C(31)*D(TBLL(-2)) + C(32)*D(TBLL(-3)) + C(33)*D(TBLL(-4)) + C(34)*D(TBLL(-5)) + C(35)*D(TBLL(-6)) + C(36)*D(TBLL(-7)) + C(37)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.015897	0.006804	-2.336282	0.0218
C(2)	0.424819	0.108861	3.902397	0.0002
C(3)	0.089467	0.115834	0.772375	0.4420
C(4)	0.025099	0.115715	0.216908	0.8288
C(5)	-0.088233	0.112584	-0.783705	0.4353
C(6)	0.097645	0.113686	0.858903	0.3928
C(7)	0.093348	0.121686	0.767128	0.4451
C(8)	0.050148	0.109034	0.459929	0.6467
C(9)	1994.193	1326.930	1.502862	0.1365
C(10)	2500.228	1402.615	1.782547	0.0781
C(11)	1605.824	1319.775	1.216740	0.2270
C(12)	2367.028	1265.407	1.870567	0.0648
C(13)	2197.575	1124.843	1.953673	0.0540
C(14)	1468.902	1117.048	1.314985	0.1920
C(15)	769.8257	1052.534	0.731402	0.4665
C(16)	-0.020236	0.043642	-0.463675	0.6440
C(17)	-0.009762	0.043809	-0.222823	0.8242
C(18)	0.023694	0.044517	0.532247	0.5959
C(19)	-0.070679	0.046525	-1.519151	0.1324
C(20)	0.094689	0.045628	2.075262	0.0409
C(21)	0.100176	0.049344	2.030168	0.0454
C(22)	0.053245	0.052580	1.012643	0.3140
C(23)	0.019766	0.103102	0.191713	0.8484
C(24)	0.021923	0.099631	0.220042	0.8264
C(25)	0.082690	0.085234	0.970152	0.3347
C(26)	0.116160	0.086920	1.336401	0.1849
C(27)	-0.014744	0.087177	-0.169129	0.8661
C(28)	-0.028159	0.096005	-0.293314	0.7700
C(29)	-0.144252	0.102549	-1.406670	0.1631
C(30)	-0.049233	0.055772	-0.882760	0.3798
C(31)	-0.008545	0.054779	-0.155999	0.8764
C(32)	-0.024219	0.053359	-0.453884	0.6510
C(33)	-0.005503	0.053666	-0.102550	0.9186
C(34)	0.126395	0.052466	2.409072	0.0181
C(35)	-0.029576	0.055103	-0.536739	0.5928
C(36)	0.025792	0.055094	0.468142	0.6409
C(37)	6504.497	2875.514	2.262029	0.0262
R-squared	0.494146	Mean dependent var		18111.65
Adjusted R-squared	0.284827	S.D. dependent var		14451.94
S.E. of regression	12221.70	Akaike info criterion		21.90221
Sum squared resid	1.30E+10	Schwarz criterion		22.74375
Log likelihood	-1320.937	Hannan-Quinn criter.		22.24407
F-statistic	2.360733	Durbin-Watson stat		1.997653
Prob(F-statistic)	0.000607			

Table 12: Vector Error Correction Model (VECM) and the System Equation for Credit Supply
Source: Author's Computations (2020)

3.8. Short run Causalities

3.8.1. Short Run Casualties for Credit Supply and Its Explanatory Variables

The study further employed Wald statistics to test whether or not the estimated coefficients in the VECM were significantly different from zero, the Chi-square probability corresponding to the null hypothesis on core inflation as presented in Table 13-d were more than 5% (.5823; .0539; .5498;.4150> p= 0.05). Thus, the null hypothesis of C (9) =C (10) =C (11) =C (12) =C (13) = C (14) =C(15)=0; C(16)=C(17)=C(18)= C(19)=C(20)=C(21)=C(22)=0; C(23)=C(24)=C(25)=C(26)=C(27)=C(28)=C(29)=0; C(30)=C(31)= C(32)= C(33)=C(34)=C(35)= C(36)=0 is accepted, implying that there is no short run causality running from Central Bank Rate to Credit supply as shown in Table 13. Table 14 shows a similar observation on Nonperforming loans which had no short run causality running from it to credit supply. In addition, Table 15 shows that there is no short run causality running from Provision in anticipation of loan losses to credit supply. And lastly, Table 16, indicates that there is no short run causality running from Treasury Bills to credit supply. These findings corroborate Changjun, Probir and Niluthpaul, (2019) who found out that the short-run results of industry-specific variables show that bank loan growth has an insignificant positive relationship with non-performing loans.

Wald Test: Equation: Untitled			
Test Statistic	Value	df	Probability
F-statistic	0.805753	(7, 87)	0.5848
Chi-square	5.640269	7	0.5823
Null Hypothesis: C(9)=C(10)=C(11)=C(12)=C(13)=C(14)=C(15)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(9)		1994.193	1326.930
C(10)		2500.228	1402.615
C(11)		1605.824	1319.775
C(12)		2367.028	1265.407
C(13)		2197.575	1124.843
C(14)		1468.902	1117.048
C(15)		769.8257	1052.534
Restrictions are linear in coefficients.			

Table 13: Wald Test for Central Bank Rate Coefficients on Credit Supply
Source: Author's computations (2020)

Wald Test: Equation: Untitled			
Test Statistic	Value	df	Probability
F-statistic	1.978725	(7, 87)	0.0670
Chi-square	13.85108	7	0.0539
Null Hypothesis: C(16)=C(17)=C(18)=C(19)=C(20)=C(21)= C(22)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(16)		-0.020236	0.043642
C(17)		-0.009762	0.043809
C(18)		0.023694	0.044517
C(19)		-0.070679	0.046525
C(20)		0.094689	0.045628
C(21)		0.100176	0.049344
C(22)		0.053245	0.052580
Restrictions are linear in coefficients.			

Table 14: Wald Test For Non-Performing Loans Coefficients On Credit Supply
Source: Author's Computations (2020)

Wald Test: Equation: Untitled			
Test Statistic	Value	df	Probability
F-statistic	0.844912	(7, 87)	0.5533
Chi-square	5.914387	7	0.5498
Null Hypothesis: C(23)=C(24)=C(25)=C(26)=C(27)=C(28)= C(29)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(23)		0.019766	0.103102
C(24)		0.021923	0.099631
C(25)		0.082690	0.085234
C(26)		0.116160	0.086920
C(27)		-0.014744	0.087177
C(28)		-0.028159	0.096005
C(29)		-0.144252	0.102549
Restrictions are linear in coefficients.			

Table 15: Wald Test for Provision in Anticipation of Loan Losses Coefficients on Credit Supply
Source: Author's Computations (2020)

Wald Test: Equation: Untitled			
Test Statistic	Value	df	Probability
F-statistic	1.019191	(7, 87)	0.4236
Chi-square	7.134340	7	0.4150
Null Hypothesis: C(30)=C(31)=C(32)=C(33)=C(34)=C(35)= C(36)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(30)		-0.049233	0.055772
C(31)		-0.008545	0.054779
C(32)		-0.024219	0.053359
C(33)		-0.005503	0.053666
C(34)		0.126395	0.052466
C(35)		-0.029576	0.055103
C(36)		0.025792	0.055094
Restrictions are linear in coefficients.			

Table 16: Wald Test for Treasury Bills Coefficients on Credit Supply
Source: Author's Computations (2020)

3.9. Post Analysis Diagnostic Tests

Table17 shows Breusch-Godfrey Serial Correlation LM Test for credit supply that was conducted on the data post the analysis to assess any possibility of serial correlation. The test yielded an observed R^2 of 3.877813 P = .7937 >0.05, suggesting lack of serial correlation.

F-statistic	**0.181272**	**Prob. F(2,85)**	**0.8345**
Obs*R-squared	0.526641	Prob. Chi-Square(2)	0.7685

Table 17: Breusch-Godfrey Serial Correlation LM Post Analysis Test for Credit Supply
Source: Author's Computations (2020)

The study further tested for the Autoregressive Conditional Heteroskedasticity (ARCH) effect on credit supply, with the null hypothesis that there was no ARCH effect. Since the estimated P-value corresponding to the observed R squared was .8356> 0.05, the null hypothesis that there was no ARCH effect was confirmed as seen in Table 18.

F-statistic	**0.394833**	**Prob. F(1,121)**	**0.5310**
Obs*R-squared	0.400054	Prob. Chi-Square(1)	0.5271

Table 18: Heteroskedasticity Post Analysis Test: ARCH for Credit Supply
Source: Author's Computations (2020)

4. Summary and Conclusion

The study investigated the long-run and short- run relationships among financial market frictions, flight to quality and credit supply using Johansen's methodology of multivariate cointegration analysis and Vector Error Correction Model. Based on the study findings, correlation results shows that Central Bank rate was negatively associated with credit supply and was significant at 5% level (r = -.883498; .0000> p=.05); vector error correction estimates indicated that Central Bank rate is an important determinant of credit supply in the long run (t-statistics 2 < 7.76312). Vector error correction term coefficient shows that one unit change in Central Bank rate was associated with 188,805.3 units decrease in Credit Supply on average ceteris paribus in the long run. The null hypothesis that there is no long run relationship between Central Bank rate and credit supply is therefore, rejected and the alternative accepted. Wald statistics results shows that there is no short run casualty running from Central Bank rate to credit supply and was not significantly different from zero at 5% level (C(9) =C(10)= C(11)=C(12)=C(13)= C(14)= C(15)= 0; (.5823> p= 0.05). The null hypothesis that there is no short run relationship between Central Bank rate and credit supply is therefore, accepted and the alternative rejected. This is interdem with Mohane et al, (2002) who argued that interest rate ceilings produces a series of adverse effects on micro lending, since MFIs are not allowed to charge full cost recovery , therefore, those who do not qualify at the prevailing interest ceiling but require credit may be denied access .The study therefore, concludes that central Bank rate greatly interferes with the forces of supply and demand interacting freely to find the equilibrium quantity of supply, the allocation of resources is therefore distorted and the result is that credit supplied is reduced for individuals not qualifying at the prevailing ceiling rate.

The second objective was to establish the effect of provisions in anticipation of loan losses on credit supply in Kenya. From the research findings, correlation results revealed that provisions in anticipation of loan losses was positively associated with credit supply and was significant at 5% level (r = .408610; .0000> p=.05); vector error correction estimates denoted that provisions in anticipation of loan losses are an important determinant of credit supply in the long run (t-statistics 2 < -2.13542). Vector error correction term coefficient suggested that one unit change in provisions in anticipation of loan losses was associated with 5.066735 units increase in Credit Supply on average ceteris paribus in the long run. The null hypothesis that there is no long run relationship between provisions in anticipation of loan losses and credit supply is therefore, rejected and the alternative accepted. Wald statistics results shows that there is no short run casualty running from provisions in anticipation of loan losses to credit supply and was not significantly different from zero at 5% level C(23) =C(24)=C(25)=C(26)= C(27)=C(28)= C(29)=0; (.5498> p= 0.05). The null hypothesis that there is no short run relationship between provisions in anticipation of loan losses and credit supply is therefore, accepted and the alternative rejected. These findings negate this study's second null hypothesis that provisions in anticipation of loan losses do not affect credit supply in Kenya, instead, the Study accepts the alternative hypothesis that provisions in anticipation of loan losses affects credit supply in Kenya.

Daske et al, (2008); Li, (2010); DeFond et al, (2011) observed that provisions can promote market liquidity as MFIs would be striving to create a pull funds to be set aside for provisioning, reduced equity costs, increased accuracy in credit analysis, thereby boosting MFIs morale to advance more credit due to improved confidence which was lacking due expected loan losses. Financial reporting is a source of reducing information asymmetry leading to increase in trading in the capital market, consequently increasing credit uptake. Peek et al, (2009) noted that the need to set aside for provisioning does not in any way bind MFIs decisions to lend freely during upswings. This study therefore concludes that provisions in anticipation of loan losses can actually inform a decision by MFIs to give more loans due to enough deposits held as a result of the liquidity requirement.

The third objective was to assess the effect of non-performing loans on credit supply in Kenya. As depicted in the research findings, correlation results evidenced that non-performing loans was negatively associated with credit supply and was significant at 5% level (r = -.240472; .0055> p=.05); vector error correction estimates elucidated that non-performing loans is an important determinant of credit supply in the long run (t-statistics 2 < 2.19694). Vector error correction term coefficient inferred that one unit change in non-performing loans was associated with 1.172628 units decrease in Credit Supply on average ceteris paribus in the long run. The null hypothesis that there is no long run relationship between non-performing loans and credit supply is therefore, rejected and the alternative accepted. Wald statistics results shows that there is no short run casualty running from non-performing loans to credit supply and was not significantly different from zero at 5% level C(16)=C(17)=C(18)=C(19)=C(20)=C(21)= C(22)=0; (.0539> p= 0.05). The null hypothesis that there is no short run relationship between non-performing loans and credit supply is therefore, accepted and the alternative rejected. Moreover, a further analysis on ordinary least squire regression model was done to establish long run relationships. From the regression results, non-performing loans had a negative effect on credit supply and was significant at 5% level (α =-2.282068, p = .0000 < .05), this regression result also confirms a long run relationship. These findings negate this study's third null hypothesis that non-performing loans does not affect credit supply in Kenya, instead, the Study accepts the alternative hypothesis that non-performing loans affects credit supply in Kenya. According to Craig et al, (2006); Cheng, (2010), borrowers credit history and credit worthiness coupled with his or her repayment history has an inverse relationship with the MFIs credit risk level. This means that borrowers with questionable past loan repayment experiences and those negatively listed in CRBs may be deemed to have high risk levels and consequently denied access to credit. This study therefore, concludes that non-performing loans provide an important prerequisite in credit scoring and determination of whether to offer credit to individuals with default history or not depending on what might have occasioned the default in a case-by-case basis, in most cases, the decision is that their loan limits are either reduced or they are denied access to credit, as a result, the sector registers a decrease in credit supply.

The fourth objective was to determine the long run relationship between flight to quality and credit supply in Kenya. From the research findings, correlation results revealed that flight to quality was positively associated with credit supply and was significant at 5% level (r = .843574; .0000> p=.05); vector error correction estimates elucidated that flight to quality is not an important determinant of credit supply in the long run (t-statistics 2 > -0.12206). Vector error correction term coefficient inferred that one unit change in flight to quality was associated with 0.082624 units increase in Credit Supply on average ceteris paribus in the long run. The null hypothesis that there is no long run relationship between non-performing loans and credit supply is therefore, rejected and the alternative accepted. Wald statistics results shows that there is no short run casualty running from flight to quality to credit supply and was not significantly different from zero at 5% level C(30) =C(31)=C(32)=C(33)=C(34)=C(35)= C(36)=0; (.4150> p= 0.05). The null hypothesis that there is no short run relationship between flight to quality and credit supply is therefore, accepted and the alternative rejected. These findings negate this study's forth null hypothesis that flight to quality and credit supply in Kenya does not have a long run relationship; instead, the Study accepts the alternative hypothesis that flight to quality affects credit supply in Kenya, though the effect cannot be concluded to be an important determinant. Gubareva and Borges, (2013) explains that financial panics, turmoil like those experienced due financial market frictions effects on emerging markets, like that experienced in Kenya can lead to flight to quality. This study therefore concludes that in order to remain profitable, MFIs have to diversify lending with investments in safe securities, even if such decisions do not wholly determine credit supply as depicted from the results, flight to quality is therefore an important area that MFIs must venture into fully in order to realize their full potential.

4.1. Recommendation

In view of the findings and conclusions of the study, the explanatory variables for financial market frictions and flight to quality significantly affects credit supply in the long run, Central Bank rate (CBR) had a negative significant effect on credit supply, which could mean financial institutions became stringent with their loan offering , this negates the Government and CBK efforts on financial inclusion as those who evidently could not qualify for credit at the ceiling rate could not access or had their credit worthiness or ability reduced substantially, this however, was a mitigation to the risk of loans advanced degenerating into watch or classified doubtful and eventually loss due to adverse effects and shocks caused by financial frictions, in a sector that was already pondering on how to stay afloat due to high NPLs . Nevertheless, other financial market frictions, for instance, IFRS 9, CRB information sharing and the fact that they can invest in safer securities was a big reprieve to MFIs, and is evidenced from the study to have increased credit supply., nonetheless, based on the findings, this study recommends that pegging interest rates on Central Bank rate is good as it protects unsuspecting individuals from being exploited by the MFIs, however, the Government should incorporate MFIs opinions and views in a way that will allow them charge interests which are neither high or low but enough cover their costs to remain business, this way, they will continue lending to micro individuals. In order to have enough cash cover for provisioning, MFIs are also advised to invest in non-funded income to maximize their profit. It is also prudent for MFIs to invest in online and mobile lending in order to reduce administrative and operating costs.

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Appendix

Vector Error Correction Estimates Sample (adjusted): 8 132 Included observations: 125 after adjustments Standard errors in ( ) & t-statistics in [ ]					
Cointegrating Eq:	CointEq1				
CS(-1)	1.000000				
CBR(-1)	188805.3				
	(24320.8)				
	[7.76312]				
NPL(-1)	1.172628				
	(0.53376)				
	[2.19694]				
PALL(-1)	-5.066735				
	(2.37272)				
	[-2.13542]				
TBLL(-1)	-0.082624				
	(0.67689)				
	[-0.12206]				
C	-3637613.				
Error Correction:	D(CS)	D(CBR)	D(NPL)	D(PALL)	D(TBLL)
CointEq1	-0.015897	-2.85E-06	-0.002951	0.015660	0.007782
	(0.00680)	(6.6E-07)	(0.01670)	(0.00684)	(0.01241)
	[-2.33628]	[-4.33823]	[-0.17668]	[2.29075]	[0.62706]
D(CS(-1))	0.424819	6.63E-07	0.047550	0.066541	-0.206897
	(0.10886)	(1.1E-05)	(0.26718)	(0.10937)	(0.19856)
	[3.90240]	[0.06305]	[0.17797]	[0.60839]	[-1.04197]
D(CS(-2))	0.089467	5.78E-06	-0.087518	-0.021751	0.200366
	(0.11583)	(1.1E-05)	(0.28430)	(0.11638)	(0.21128)
	[0.77237]	[0.51659]	[-0.30784]	[-0.18690]	[0.94834]
D(CS(-3))	0.025099	5.75E-06	-0.124965	0.031087	-0.158440
	(0.11571)	(1.1E-05)	(0.28400)	(0.11626)	(0.21106)
	[0.21691]	[0.51492]	[-0.44001]	[0.26740]	[-0.75067]
D(CS(-4))	-0.088233	-1.12E-05	0.388812	-0.070601	-0.202036
	(0.11258)	(1.1E-05)	(0.27632)	(0.11311)	(0.20535)
	[-0.78371]	[-1.03447]	[1.40711]	[-0.62417]	[-0.98384]
D(CS(-5))	0.097645	-5.75E-06	-0.144130	-0.048370	0.132529
	(0.11369)	(1.1E-05)	(0.27902)	(0.11422)	(0.20736)
	[0.85890]	[-0.52362]	[-0.51655]	[-0.42348]	[0.63912]
D(CS(-6))	0.093348	-5.40E-06	0.009927	-0.140172	0.037080
	(0.12169)	(1.2E-05)	(0.29866)	(0.12226)	(0.22195)
	[0.76713]	[-0.46002]	[0.03324]	[-1.14654]	[0.16706]
D(CS(-7))	0.050148	-1.24E-06	-0.064719	0.155318	0.252897
	(0.10903)	(1.1E-05)	(0.26761)	(0.10955)	(0.19888)
	[0.45993]	[-0.11736]	[-0.24185]	[1.41784]	[1.27162]
D(CBR(-1))	1994.193	0.259042	1711.361	-6349.531	4941.534
	(1326.93)	(0.12809)	(3256.73)	(1333.16)	(2420.32)
	[1.50286]	[2.02236]	[0.52548]	[-4.76276]	[2.04169]
D(CBR(-2))	2500.228	0.237340	-388.5758	-2316.756	-2501.997
	(1402.62)	(0.13540)	(3442.49)	(1409.20)	(2558.37)
	[1.78255]	[1.75294]	[-0.11288]	[-1.64402]	[-0.97796]
D(CBR(-3))	1605.824	0.287505	3921.540	-2776.995	-3207.454
	(1319.78)	(0.12740)	(3239.17)	(1325.97)	(2407.27)
	[1.21674]	[2.25674]	[1.21066]	[-2.09431]	[-1.33240]
D(CBR(-4))	2367.028	0.135307	-4957.781	-2588.643	-1391.202
	(1265.41)	(0.12215)	(3105.73)	(1271.35)	(2308.10)
	[1.87057]	[1.10771]	[-1.59633]	[-2.03614]	[-0.60275]
D(CBR(-5))	2197.575	0.176865	-684.0661	-2677.900	2452.847
	(1124.84)	(0.10858)	(2760.74)	(1130.13)	(2051.71)
	[1.95367]	[1.62887]	[-0.24778]	[-2.36956]	[1.19551]

D(CBR(-6))	1468.902	0.261889	-1326.478	-2180.196	-3253.016
	(1117.05)	(0.10783)	(2741.61)	(1122.29)	(2037.50)
	[1.31498]	[2.42874]	[-0.48383]	[-1.94262]	[-1.59657]
D(CBR(-7))	769.8257	0.151797	-1173.555	59.33007	-901.6393
	(1052.53)	(0.10160)	(2583.27)	(1057.48)	(1919.82)
	[0.73140]	[1.49404]	[-0.45429]	[0.05611]	[-0.46965]
D(NPL(-1))	-0.020236	5.04E-06	0.005906	-0.022315	0.097493
	(0.04364)	(4.2E-06)	(0.10711)	(0.04385)	(0.07960)
	[-0.46368]	[1.19522]	[0.05514]	[-0.50892]	[1.22474]
D(NPL(-2))	-0.009762	3.49E-06	-0.074951	-0.044932	-0.147847
	(0.04381)	(4.2E-06)	(0.10752)	(0.04401)	(0.07991)
	[-0.22282]	[0.82582]	[-0.69707]	[-1.02083]	[-1.85023]
D(NPL(-3))	0.023694	-3.23E-06	0.038500	0.007522	0.381407
	(0.04452)	(4.3E-06)	(0.10926)	(0.04473)	(0.08120)
	[0.53225]	[-0.75241]	[0.35237]	[0.16819]	[4.69722]
D(NPL(-4))	-0.070679	-2.98E-07	-0.134752	-0.020785	0.004176
	(0.04653)	(4.5E-06)	(0.11419)	(0.04674)	(0.08486)
	[-1.51915]	[-0.06625]	[-1.18009]	[-0.44465]	[0.04921]
D(NPL(-5))	0.094689	1.51E-05	0.039910	0.032350	0.041543
	(0.04563)	(4.4E-06)	(0.11199)	(0.04584)	(0.08322)
	[2.07526]	[3.43865]	[0.35639]	[0.70568]	[0.49917]
D(NPL(-6))	0.100176	-1.13E-05	-0.128437	0.044025	-0.042229
	(0.04934)	(4.8E-06)	(0.12111)	(0.04958)	(0.09000)
	[2.03017]	[-2.36288]	[-1.06053]	[0.88804]	[-0.46920]
D(NPL(-7))	0.053245	-5.97E-06	0.018068	-0.050999	0.217176
	(0.05258)	(5.1E-06)	(0.12905)	(0.05283)	(0.09591)
	[1.01264]	[-1.17595]	[0.14001]	[-0.96541]	[2.26446]
D(PALL(-1))	0.019766	-1.79E-05	-0.059560	-0.170447	-0.007105
	(0.10310)	(1.0E-05)	(0.25305)	(0.10359)	(0.18806)
	[0.19171]	[-1.79539]	[-0.23537]	[-1.64547]	[-0.03778]
D(PALL(-2))	0.021923	-6.38E-06	0.300208	0.027575	0.590689
	(0.09963)	(9.6E-06)	(0.24453)	(0.10010)	(0.18173)
	[0.22004]	[-0.66310]	[1.22770]	[0.27548]	[3.25041]
D(PALL(-3))	0.082690	2.77E-05	-0.250355	0.004574	-0.100817
	(0.08523)	(8.2E-06)	(0.20919)	(0.08563)	(0.15547)
	[0.97015]	[3.36733]	[-1.19677]	[0.05341]	[-0.64848]
D(PALL(-4))	0.116160	-1.31E-05	-0.309736	0.174354	-0.276167
	(0.08692)	(8.4E-06)	(0.21333)	(0.08733)	(0.15854)
	[1.33640]	[-1.55974]	[-1.45190]	[1.99653]	[-1.74191]
D(PALL(-5))	-0.014744	-5.24E-06	-0.279497	-0.434966	0.096181
	(0.08718)	(8.4E-06)	(0.21396)	(0.08759)	(0.15901)
	[-0.16913]	[-0.62304]	[-1.30630]	[-4.96616]	[0.60487]
D(PALL(-6))	-0.028159	-1.83E-05	-0.178096	-0.305519	-0.187524
	(0.09600)	(9.3E-06)	(0.23563)	(0.09646)	(0.17511)
	[-0.29331]	[-1.97141]	[-0.75583]	[-3.16746]	[-1.07087]
D(PALL(-7))	-0.144252	-1.41E-06	0.359423	0.005667	0.464809
	(0.10255)	(9.9E-06)	(0.25169)	(0.10303)	(0.18705)
	[-1.40667]	[-0.14271]	[1.42804]	[0.05500]	[2.48495]
D(TBLL(-1))	-0.049233	5.02E-06	0.108451	-0.028717	0.095546
	(0.05577)	(5.4E-06)	(0.13688)	(0.05603)	(0.10173)
	[-0.88276]	[0.93239]	[0.79230]	[-0.51250]	[0.93924]
D(TBLL(-2))	-0.008545	6.21E-07	-0.029491	-0.039161	-0.146986
	(0.05478)	(5.3E-06)	(0.13444)	(0.05504)	(0.09992)
	[-0.15600]	[0.11747]	[-0.21935]	[-0.71156]	[-1.47110]
D(TBLL(-3))	-0.024219	-3.19E-06	0.287842	0.025197	0.074966
	(0.05336)	(5.2E-06)	(0.13096)	(0.05361)	(0.09733)
	[-0.45388]	[-0.61918]	[2.19792]	[0.47002]	[0.77025]
D(TBLL(-4))	-0.005503	1.00E-05	-0.084089	-0.117201	-0.062511
	(0.05367)	(5.2E-06)	(0.13172)	(0.05392)	(0.09789)
	[-0.10255]	[1.93122]	[-0.63841]	[-2.17366]	[-0.63860]
D(TBLL(-5))	0.126395	-8.81E-06	0.008294	-0.092986	-0.132959

	(0.05247)	(5.1E-06)	(0.12877)	(0.05271)	(0.09570)
	[2.40907]	[-1.73894]	[0.06441]	[-1.76402]	[-1.38935]
D(TBLL(-6))	-0.029576	6.02E-06	0.143437	0.116979	-0.044312
	(0.05510)	(5.3E-06)	(0.13524)	(0.05536)	(0.10051)
	[-0.53674]	[1.13152]	[1.06060]	[2.11299]	[-0.44087]
D(TBLL(-7))	0.025792	-3.89E-06	0.038389	0.039023	-0.010902
	(0.05509)	(5.3E-06)	(0.13522)	(0.05535)	(0.10049)
	[0.46814]	[-0.73115]	[0.28391]	[0.70499]	[-0.10849]
C	6504.497	0.234307	-2863.886	958.9871	3700.299
	(2875.51)	(0.27757)	(7057.48)	(2889.02)	(5244.94)
	[2.26203]	[0.84412]	[-0.40579]	[0.33194]	[0.70550]
R-squared	0.494146	0.574219	0.209148	0.605722	0.476765
Adj. R-squared	0.284827	0.398033	-0.118102	0.442572	0.260253
Sum sq. resids	1.30E+10	121.0910	7.83E+10	1.31E+10	4.32E+10
S.E. equation	12221.70	1.179767	29996.15	12279.09	22292.39
F-statistic	2.360733	3.259173	0.639108	3.712674	2.202032
Log likelihood	-1320.937	-174.4765	-1432.271	-1321.518	-1395.465
Akaike AIC	21.90221	3.410912	23.69793	21.91158	23.10428
Schwarz SC	22.74375	4.252448	24.53946	22.75312	23.94581
Mean dependent	18111.65	-0.076613	-392.7419	805.6452	3934.282
S.D. dependent	14451.94	1.520583	28367.75	16446.44	25918.81

Table 19: Normalized Vector Error Correction Estimates for Credit Supply
Source: Author's Computations (2020)
Key: Cs= Credit Supply, Cbr= Central Bank Rate, Npl= Non Performing Loans,
Pall= Provisions in Anticipation of Loan Losses, Tbll= Treasury Bills