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An impulse response function analysis of the impact of modern payment technologies on money demand in Nigeria[1]

Tersoo IORNGURUM[2]
Veritas University Abuja, Nigeria
tersoodavid.ti@gmail.com
Godwin NWAOBI[3]
Veritas University Abuja, Nigeria
nwaobig@veritas.edu.ng

Abstract. *In order to assess the efficacy of modern payment technologies in facilitating access to liquidity services in Nigeria, this study employs impulse response function (IRF) analysis and variance decomposition (VD) analysis to study the relationship between modern payment technology patronage and money demanded primarily for liquidity services (currency) in the Nigerian economy during the period 2009Q1 to 2019Q1. Firstly, via impulse response function (IRF) analysis, the study finds that the money demanded primarily for liquidity services responds positively to shocks in modern payment technology transactions during the period under investigation. Secondly, via variance decomposition (VD) analysis, the study finds that a substantial proportion of the variation in money demanded primarily for liquidity services is attributable to modern payment technology transactions as well as other conventional money demand determinants in the short-term horizon (4 quarters) and the long-term horizon (20 quarters). In conclusion, based on the fact that money demanded primarily for liquidity services responds positively and non-negligibly to modern payment technology transactions, we recommend that modern payment technology patronage should be promoted by Nigeria's monetary authority in order to extend liquidity services to more Nigerians.*

Keywords: money demand, liquidity, modern payment technologies, impulse response function analysis, variance decomposition analysis.

JEL Classification: E42, E41.

1. Introduction

Conventionally, the mandate of Nigeria's central banking system entails promoting economic stability and welfare through popular monetary policy instruments like interest rates and exchange rates. This mandate often translates into lower inflation, higher growth, lower unemployment, and financial stability in the Nigerian economy (Tule, et al., 2018).

In recent times however, the widespread deployment and adoption of modern payment technologies such as automated teller machines (ATM), point of sales terminals (PoS), web-based payment platforms, and mobile-based payment platforms have gained recognition as some of the core objectives of Nigeria's central banking system (Kama and Adigun, 2013). To start with, this is partially because the Nigerian economy consists of a large rural sector which lacks access to basic financial services, and therefore needs these technologies in order aid the extension of digitized financial services from the urban developed financial sector to the rural undeveloped sector (Olayinka and Ibukun, 2020). Secondly but equally importantly, in view of the fact that cash remains the predominant medium for economic transactions in both the urban and rural sectors, this is also due to the fact that the provision of cash and liquidity services through these cost-effective modern payment technologies is actually a stepping stone to long-term growth and development in the Nigerian economy as a whole (Bloomberg, 2018; Brelof and Parbhoo, 2016).

Therefore, in this paper we seek to examine the efficacy of modern payment technologies in providing financial services by enhancing access to liquidity in the Nigerian economy, especially as measured by the quantity of currency aggregates held with the public. We attempt to do this with quarterly time series data covering the period 2009Q1 to 2019Q1 and with the aid of impulse response functions (IRF) and forecast error variance decomposition (FEVD) functions obtained from vector error correction models (VECM).

Subsequently, we choose to organize this paper in five main sections. The first section contains the introduction. The second section contains the literature review. The third section contains the methodological content. The fourth content contains the empirical results. And the fifth section contains the relevant conclusions.

2. Empirical Literature Review

Literature on the application of impulse response functions in money demand analysis has grown dramatically over the years. In this section, we attempt to offer a concise review of some empirical studies conducted within the last two decades, namely: Brand and Cassola (2000: pp. 18-23); Rinaldi (2001: pp. 19-21); Schoellner (2002: pp. 75-78); Greiber and Setza (2007: pp. 15-18); Korhonen and Mehrotra (2007: pp. 16-24); Caporale and Soliman (2010: pp. 9-12); Nirmala and Widodo (2011: pp. 42-43); Oyelami and Yinusa (2013: pp. 256-258); and Kombo (2017: pp. 39-40).

Brand and Cassola (2000: pp. 18-23) explored money demand (M3) in the Euro area during the period 1980Q1 to 1993Q3. With the aid of impulse response functions, the study discovered that shocks to GDP growth led to increment in money demand (M3) growth while shocks to short term interest rate led to decrement in money demand (M3) growth in the Euro area.

Rinaldi (2001: pp. 19-21) explored card payment and money demand relations in Belgium during the period 1960 to 1999. With the aid of impulse response functions, the study discovered that a shock from GDP had a positive permanent effect on money demand, while shocks due to increment in the number of cards and the number of merchants accepting them had a negative momentary effect on money demand.

Schoellner (2002: pp. 75-78) explored money demand in the US during the period 1957 to 1998. With the aid of impulse response functions, the study discovered that money demand (M1) and real GDP responded negatively to impulses from the federal funds rate, while price level (CPI) responded negatively to impulses from the federal funds rate.

Greiber and Setza (2007: pp. 15-18) explored money demand and housing relations in the Euro area and the US during the periods 1981Q1 to 2006Q4 and 1986Q1 to 2006Q4 respectively. With the aid of impulse response functions, the study discovered that money demand in the Euro area responded positively and significantly to house price shocks, but responded negatively and significantly to long-term interest rate shocks. On the other hand, money demand in the US responded positively and insignificantly to house price shocks, but responded negatively and significantly to long-term interest rate shocks.

Korhonen and Mehrotra (2007: pp. 16-24) explored money demand in post-crisis Russia during the period 1991M1 to 2006M12. With the aid of impulse response functions, the study discovered that income shocks led to growth in money demand, while shocks in currency depreciation and inflation led to decrement in money demand in post-crisis Russia.

Caporale and Soliman (2010: pp. 9-12) explored stock prices and money demand relations in the UK, US, and Germany during the period 1992Q1 to 2008Q3. With the aid of impulse response functions, the study discovered that money demand responded positively to shocks from stock prices, but responded negatively to shocks from short and long-term interest rates in the three countries.

Nirmala and Widodo (2011: pp. 42-43) explored card payment technologies and money demand relations in Indonesia during the period 2005M1 to 2010M12. With the aid of impulse response functions, the study discovered that M2 money demand responded positively to impulses from card payment technology patronage, while M1 money demand, GDP, and price level responded negatively to impulses from card payment technology patronage.

Oyelami and Yinusa (2013: pp. 256-258) explored alternative payment systems and currency demand relations in Nigeria during the period 2008M1 to 2010M12. With the aid of impulse response functions, the study discovered that currency demand responded positively to impulses from credit cards (ATM) and Point of Sales (PoS), but responded negatively to impulses from internet payment and mobile money.

Kombo (2017: pp. 39-40) explored real money demand in Kenya during the period 2000Q1 to 2016Q4. With the aid of impulse response functions the study discovered that real money demand responded positively to impulses from income, exchange rate, and inflation rate, but responded negatively to an impulse from interest rate.

3. Data, Model, and Methodology

3.1. Data

Quarterly time series data were sourced electronically from the financial database of the Central Bank of Nigeria from 2009Q1 to 2019Q1. These include data on money demand (currency aggregates held with the non-bank public), modern payment technology transactions, gross domestic product, savings interest rate, and inflation rate. Modern payment technology transactions include monetary transactions performed with automated teller machines (ATM), point of sales terminals (PoS), mobile devices, and web-based payment platforms.

3.2. Model

Building on Oyelami and Yinusa (2013: pp. 256) and Egbetunde, et al. (2015: pp. 87), our empirical model for money demand is specified as a function of modern payment technology transactions as well as scalar variables and opportunity cost variables. Here, quarterly gross domestic product is adopted as our scalar variable, while quarterly savings interest rate and quarterly inflation rate are adopted as our opportunity cost variables. The empirical money demand model therefore takes the following functional form:

$$m_d = f(mpt, y, sr_1, \pi)$$

Here, m_d denotes quarterly liquid money (currency) aggregates demanded by the non-bank public, *mpt* denotes quarterly modern payment technology transactions, *y* denotes quarterly gross domestic product, s*r* denotes quarterly savings interest rate, and π denotes quarterly inflation rate.

3.3. Methodology

We generate impulse response functions from a cointegrating system with the following steps. First of all, we examine the properties of the time series variables with a suitable unit root test. Here, the break-point unit root test proposed by Perron (1989: pp. 1361-1401) is adopted to weigh the unit root hypotheses ($\alpha = 0$) against their alternatives ($\alpha < 0$) based on the following equations:

$$m_t = \kappa + \Omega LBD_t(B_t) + zOTBD_t(B_t) + \Phi m_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta m_{t-1} + v_t$$

$$m_t = \kappa + \beta t + \Omega LBD_t(B_t) + zOTBD_t(B_t) + \Phi m_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta m_{t-1} + v_t$$

$$m_t = \kappa + \beta t + \Lambda TBD_t(B_t) + \Phi m_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta m_{t-1} + v_t$$

$$m_t = \kappa + \beta t + \Omega LBD_t(B_t) + \Lambda TBD_t(B_t) + zOTBD_t(B_t) + \Phi m_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta m_{t-1} + v_t$$

where $LBD_t(B_t)$, $TBD_t(B_t)$, and $OTBD_t(B_t)$ are break dummies given by:

$$LBD_t(B_t) = \begin{cases} 0, & if\ t \leq B_t \\ 1, & if\ t > B_t \end{cases}$$

$$TBD_t(B_t) = \begin{cases} 0, & if\ t \leq B_t \\ 1(t - B_t + 1), & if\ t > B_t \end{cases}$$

$$OTBD_t(B_t) = \begin{cases} 0, & if\ t \neq B_t \\ 1, & if\ t = B_t \end{cases}$$

- the first equation includes the level-break dummy (LBD_t) which captures level-breaks in the unit root test;
- the second equation includes a trend and the level-break dummy which captures level-breaks with the presence of a trend specification in the unit root test;
- the third equation includes a trend and the trend-break dummy (TBD_t) which captures trend-breaks in the unit root test;
- the fourth equation includes the trend-break and the level-break dummies which capture trend-breaks and level-breaks in the unit root test.

Secondly, we employ some information criteria to determine the optimal lag length of our vector auto regression model. The Akaike (*AC*) and Schwarz (*SC*) information criteria are adopted for this purpose and they involve the following computations:

$$AC = M * ln\left|\Sigma\right| + 2P$$

$$SC = M * ln\left|\Sigma\right| + P * log(M)$$

Here, *AC* represents the Akaike statistic, *SC* represents the Schwarz statistic, *M* represents the frequency of observations, $ln\left|\Sigma\right|$ represents the covariance matrix's logarithm, and *P* represents the number of parameters captured in the VAR (Lütkepohl, 2005).

Thirdly, we employ non-residual based methods to test for cointegration in our vector auto regression model. The Trace test and the Maximum Eigen Value test are adopted for this purpose based on the framework developed by Johansen (1995: pp. 3-131). The Max Eigenvalue test weighs a null hypothesis which stipulates *n* number of cointegrating relations against its alternative (*n*+1 cointegrating relations) with the following statistic:

$$MaxEig = -T\, ln(1 - \lambda_{n+1}) = -T \sum_{i=n+1}^{m} ln(1 - \lambda_i) + T \sum_{i=n+2}^{m} ln(1 - \lambda_i)$$

for $n = 0,1, \ldots, m\text{-}1$.

On the other hand, the Trace test weighs a null hypothesis which stipulates *n* number of cointegrating relations against its alternative (*m* cointegrating relations), with the following statistic:

$$Trace = -T \sum_{i=n+1}^{m} ln(1 - \lambda_i)$$

for $n = 0, 1, \ldots, m\text{-}1$.

Fourthly, we estimate our vector error correction (VEC) model based on evidence of cointegration. This is captured in the following system of equations:

$$\Delta m_t^d = \lambda_0 + \sum_{i=0}^{p} \lambda_{1i}\Delta y_{t-i} - \sum_{i=0}^{p} \lambda_{2i}\Delta sr_{1t-i} - \sum_{i=0}^{p} \lambda_{3i}\Delta\pi_{t-i} + \sum_{i=0}^{p} \lambda_{4i}\Delta mpt_{t-i} + \sum_{i=1}^{p} \lambda_{5i}\Delta m_{t-1}^d + \theta_{1i}ECT_{t-1} + u_{1t}$$

$$\Delta y_t = \partial_0 + \sum_{i=0}^{p} \partial_{1i}\Delta m_{t-i}^d - \sum_{i=0}^{p} \partial_{2i}\Delta sr_{1t-i} - \sum_{i=0}^{p} \partial_{3i}\Delta\pi_{t-i} + \sum_{i=0}^{p} \partial_{4i}\Delta mpt_{t-i} + \sum_{i=1}^{p} \partial_{5i}\Delta y_{t-i} + \theta_{2i}ECT_{t-1} + u_{2t}$$

$$\Delta sr_{1t} = \ell_0 + \sum_{i=0}^{p} \ell_{1i}\Delta y_{t-i} - \sum_{i=0}^{p} \ell_{2i}\Delta m_{t-i}^d - \sum_{i=0}^{p} \ell_{3i}\Delta\pi_{t-i} + \sum_{i=0}^{p} \ell_{4i}\Delta mpt_{t-i} + \sum_{i=1}^{p} \ell_{5i}\Delta sr_{1t-i} + \theta_{3i}ECT_{t-1} + u_{3t}$$

$$\Delta\pi_t = \psi_0 + \sum_{i=0}^{p} \psi_{1i}\Delta y_{t-i} - \sum_{i=0}^{p} \psi_{2i}\Delta sr_{1t-i} - \sum_{i=0}^{p} \psi_{3i}\Delta m_{t-i}^d + \sum_{i=0}^{p} \psi_{4i}\Delta mpt_{t-i} + \sum_{i=1}^{p} \psi_{5i}\Delta\pi_{t-i} + \theta_{4i}ECT_{t-1} + u_{4t}$$

$$\Delta mpt_t = \varphi_0 + \sum_{i=0}^{p} \varphi_{1i}\Delta y_{t-i} - \sum_{i=0}^{p} \varphi_{2i}\Delta sr_{1t-i} - \sum_{i=0}^{p} \varphi_{3i}\Delta\pi_{t-i} + \sum_{i=0}^{p} \varphi_{4i}\Delta m_{t-i}^d + \sum_{i=1}^{p} \varphi_{5i}\Delta mpt_{t-1} + \theta_{5i}ECT_{t-1} + u_{5t}$$

Finally, from our vector error correction model (VECM), we perform impulse response function analysis and variance decomposition analysis. Based on intuition from Lütkepohl (2005: pp. 419-446) and Nwaobi (2012: pp. 14-20), the impulse response functions are obtainable from the following moving average system:

$$\begin{bmatrix} \Delta m_t^d \\ \Delta y_t \\ \Delta sr_t \\ \Delta\pi_t \\ \Delta mpt_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} I_{11}(i) & I_{12}(i) & I_{13}(i) & I_{14}(i) & I_{15}(i) \\ I_{21}(i) & I_{22}(i) & I_{23}(i) & I_{24}(i) & I_{25}(i) \\ I_{31}(i) & I_{32}(i) & I_{33}(i) & I_{34}(i) & I_{35}(i) \\ I_{41}(i) & I_{42}(i) & I_{43}(i) & I_{44}(i) & I_{45}(i) \\ I_{51}(i) & I_{52}(i) & I_{53}(i) & I_{54}(i) & I_{55}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-i} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-i} \\ \varepsilon_{4,t-i} \\ \varepsilon_{5,t-i} \end{bmatrix}$$

Here, $I_{jk}(i)$ denotes the response of the j^{th} variable to a shock in the k^{th} variable from the t-i^{th} period, μ_j denotes the intercepts, and ε_j denotes the Cholesky factored errors obtained from the vector error correction model.

On the other hand, the forecast error variance decomposition profiles are obtainable from:

$$w_{jk,h} = \frac{\sum_{i=0}^{h-1}(e_j' I_i e_k)^2}{\sum_{i=0}^{h-1}\sum_{k=1}^{K}(e_j' I_i e_k)^2}$$

where

$$I_i = \begin{bmatrix} I_{11}(i) & I_{12}(i) & I_{13}(i) & I_{14}(i) & I_{15}(i) \\ I_{21}(i) & I_{22}(i) & I_{23}(i) & I_{24}(i) & I_{25}(i) \\ I_{31}(i) & I_{32}(i) & I_{33}(i) & I_{34}(i) & I_{35}(i) \\ I_{41}(i) & I_{42}(i) & I_{43}(i) & I_{44}(i) & I_{45}(i) \\ I_{51}(i) & I_{52}(i) & I_{53}(i) & I_{54}(i) & I_{55}(i) \end{bmatrix}$$

Here, $w_{jk,h}$ denotes the forecast error variance of the jth variable attributed to exogenous shocks from the kth variable, K denotes the total number of variables, e_j denotes the jth column of the K by K covariance matrix of errors, e_k denotes the kth column of the K by K covariance matrix of errors, h denotes the h-step, and I_i denotes the K by K matrix of moving average coefficients.

4. Empirical Results

The break point unit root test results are presented in the following tables.

Table 1. *Levels Unit Root Test Results*

Variables	Lags Included	Trend Specification	Break Date	ADF Test Statistic	5% Critical Value	Decision
m_t^d	4	Intercept/Trend	2013Q1	-4.9726	-5.1757	Non-Stationary
mpt_t	0	Intercept/Trend	2012Q4	-3.1151	-5.1757	Non-Stationary
y_t	0	Intercept/Trend	2017Q2	-3.4816	-5.1757	Non-Stationary
sr_{1t}	0	Intercept/Trend	2013Q2	-4.9782	-5.1757	Non-Stationary
π_t	3	Intercept/Trend	2016Q1	-3.8090	-5.1757	Non-Stationary

Note(s): Schwarz Information Criterion (SIC) adopted for choosing lag length.

Table 2. *First Differences Unit Root Test Results*

Variables	Lags Included	Trend Specification	Break Date	ADF Test Statistic	5% Critical Value	Decision
Δm_t^{d2}	2	Intercept/Trend	2016Q3	-5.6202	-5.1757	Stationary
Δmpt_t	0	Intercept/Trend	2017Q2	5.4177	-5.1757	Stationary
Δy_t	1	Intercept/Trend	2017Q2	-7.1531	-5.1757	Stationary
Δsr_{1t}	2	Intercept/Trend	2016Q1	-9.7627	-5.1757	Stationary
$\Delta \pi_t$	2	Intercept/Trend	2015Q4	-9.7057	-5.1757	Stationary

Note(s): Schwarz Information Criterion (SIC) adopted for choosing lag length.

Based on Tables 1 and 2 all the variables are first difference stationary.

Therefore we proceed to select the optimal lag length for our VAR in order to test for cointegration.

The Akaike and Schwarz criteria results are presented in Table 3.

Table 3. *Lag Length Selection Criteria*

Lag	AC	SC
0	-14.3815	-14.1638
1	-18.7686	-17.4624*
2	-18.9631*	-16.5685
3	-18.3164	-14.8333
4	-18.7302	-14.1586

Note: * indicates lag order selected by criterion.

The Akaike criterion indicates 2 lags while the Schwarz criterion indicates 1 lag. We select 2 lags in accordance with the Akaike criterion because it leads to a well behaved VAR. Next, we test for cointegration with the Trace and the Maximum Eigenvalue test.

Table 4. *Trace and Maximum Eigenvalue Cointegration Tests by Model*

Data Trend	None	None	Linear	Linear	Quadratic
Deterministic Specification	No Constant No Trend	Constant No Trend	Constant No Trend	Constant Trend	Constant Trend
Number of Cointegrating Relations by Trace Test	1	1	1	2	2
Number of Cointegrating Relations by Maximum Eigen Value Test	1	1	1	2	2

In Table 4, under the assumption that our model is linear with no trend, the Trace and the Maximum Eigen Value tests indicate only 1 cointegrating relation between money demand and the other endogenous variables. This leads us to the following tabularized vector error correction model.

Table 5. *Tabularized Vector Error Correction Model*

Equation	$\Delta logm^d_t$	$\Delta logmpt_t$	$\Delta logy_t$	$\Delta logsr_{1t}$	$\Delta log\pi_t$
$\Delta logm^d_{t-3}$	0.1039 (0.1722) [0.6036]	-1.9493 (0.7072) [-2.7562]**	-1.1075 (0.5000) [-2.2149]**	-0.0023 (0.0459) [-0.0511]	2.2384 (1.2341) [1.8136]*
$\Delta logmpt_{t-3}$	0.0807 (0.0500) [1.6136]	0.4710 (0.2053) [2.2940]**	-0.0196 (0.1451) [-0.1353]	0.0094 (0.0133) [0.7124]	-0.7481 (0.3583) [-2.0877]**
$\Delta logy_{t-3}$	0.1951 (0.0642) [3.0358]**	0.3417 (0.2639) [1.2947]	-0.1240 (0.1866) [-0.6647]	0.0311 (0.0171) [1.8193]*	-1.2444 (0.4606) [-2.7015]**
$\Delta logsr_{1t-3}$	-0.8183 (0.9727) [-0.8413]	-4.6621 (3.9935) [-1.1674]	0.7385 (2.8235) [0.2615]	-0.2168 (0.2591) [-0.8365]	-2.5477 (6.9690) [-0.3655]
$\Delta log\pi_{t-3}$	-0.0389 (0.0321) [-1.2104]	-0.1579 (0.1321) [-1.1953]	-0.0153 (0.0934) [-0.1646]	0.0067 (0.0085) [0.7829]	-0.4514 (0.2306) [-1.9572]*
C	0.0022 (0.0045) [0.4955]	0.0264 (0.0185) [1.4282]	0.0315 (0.0130) [2.4111]**	-0.0007 (0.0012) [-0.6615]	0.0490 (0.0323) [1.5183]
ECT_{t-1}	-0.4538 (0.1834) [-2.4737]**	2.0985 (0.7532) [2.7860]**	0.2633 (0.5325) [0.4944]	-0.0539 (0.0488) [-1.1035]	0.4918 (1.3144) [0.3742]
R-squared *Adj. R-SQ* *F-statistic* *J-B Prob*	0.4559 0.3539 4.4703** 0.1349	0.2755 0.1397 2.0287 0.0000**	0.1764 0.0220 1.1430 0.0000**	0.3021 0.1712 2.3087 0.4407	0.4599 0.3587 4.5431** 0.3591
Akaike Criterion: -18.4330; *F-critical Value*: 2.53**; *White*: 0.6914; *LM (4)*: 0.1014					

Notes: Standard errors in parenthesis ( ); t-statistics in brackets [ ]; *J-B* denotes Jarque-Bera normality test's p-values; White denotes Whites' heteroskedasticity test's p-values; LM denotes LM serial correlation test's p-values; ** and * indicate significance at 5% and 10% levels respectively.

This tabularized form can be re-written its linear form:

$$\Delta logm_t^d = 0.0022 + 0.1039\Delta logm_{t-3}^d + 0.0807\Delta logmpt_{t-3} + 0.1951\Delta logy_{t-3} - 0.8183\Delta logsr_{1t-3} - 0.0389\Delta log\pi_{t-3} - 0.4538ECT_{t-1} + u_{1t}$$

$$\Delta logmpt_t = 0.0264 - 1.9493\Delta logm_{t-3}^d + 0.4710\Delta logmpt_{t-3} + 0.3417\Delta logy_{t-3} - 4.6621\Delta logsr_{1t-3} - 0.1579\Delta log\pi_{t-3} + 2.0985ECT_{t-1} + u_{2t}$$

$$\Delta logy_t = 0.0315 - 1.1075\Delta logm_{t-3}^d - 0.0196\Delta logmpt_{t-3} - 0.1240\Delta logy_{t-3} + 0.7385\Delta logsr_{1t-3} - 0.0153\Delta log\pi_{t-3} + 0.2633ECT_{t-1} + u_{3t}$$

$$\Delta logsr_{1t} = -0.0007 - 0.0023\Delta logm_{t-3}^d + 0.0094\Delta logmpt_{t-3} + 0.0311\Delta logy_{t-3} - 0.2168\Delta logsr_{1t-3} + 0.0067\Delta log\pi_{t-3} + 0.0539ECT_{t-1} + u_{4t}$$

$$\Delta log\pi_t = 0.0490 + 2.2384\Delta logm_{t-3}^d - 0.7481\Delta logmpt_{t-3} - 1.2444\Delta logy_{t-3} - 2.5477\Delta logsr_{1t-3} - 0.4514\Delta log\pi_{t-3} + 0.4918ECT_{t-1} + u_{5t}$$

Here, there are several coefficients to be interpreted. However we are only interested in the error correction coefficient (*ECT_{t-1}*) of the first money demand equation which shows the rate of adjustment to long-run equilibrium. This error correction coefficient (0.4538) appears to be negative and statistically innegligible at the 5% level of significance. This implies equilibrium and also suggests that 45.38 percent of all deviations from long-run equilibrium will be corrected in each period.

Further, based on the moving average representation of the estimated vector error correction model, we can now generate the relevant impulse response functions and obtain the relevant forecast error variance decomposition profile.

4.1. Impulse Response Functions and Variance Decompositions

The impulse response function (IRF) graphs are given in figures 1 to 5. They depict the responses of money demand to shocks arising from itself and the other endogenous variables over a time horizon of 20 periods (quarters).

Figure 1. *IRF Graph of Payment Technology Transactions and Money Demand*

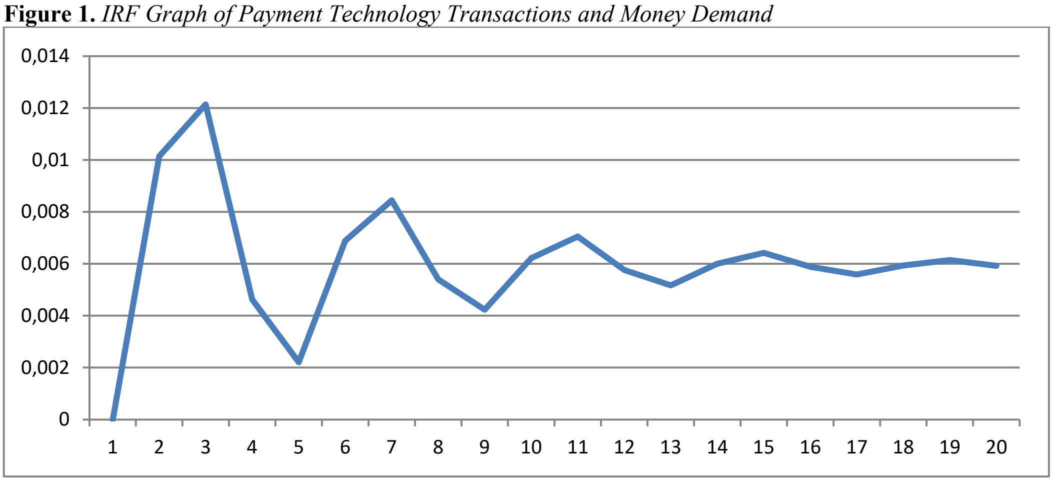


Figure 2. *IRF Graph of Money Demand*

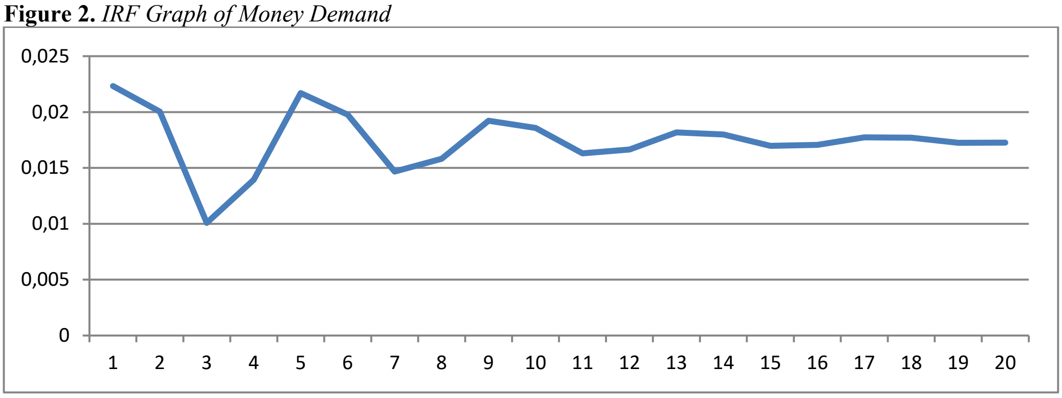


Figure 3. *IRF Graph of Gross Domestic Product and Money Demand*

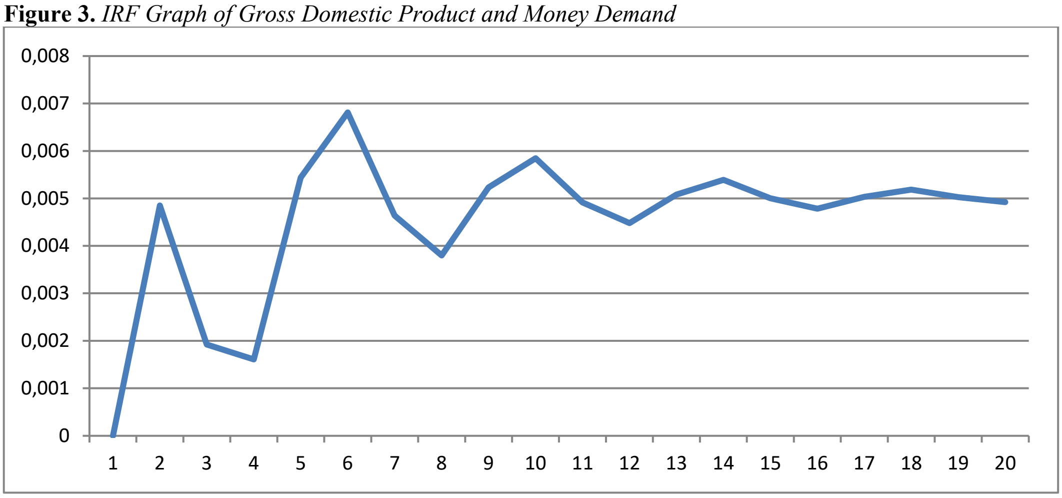


Figure 4. *IRF Graph of Savings Interest Rate and Money Demand*

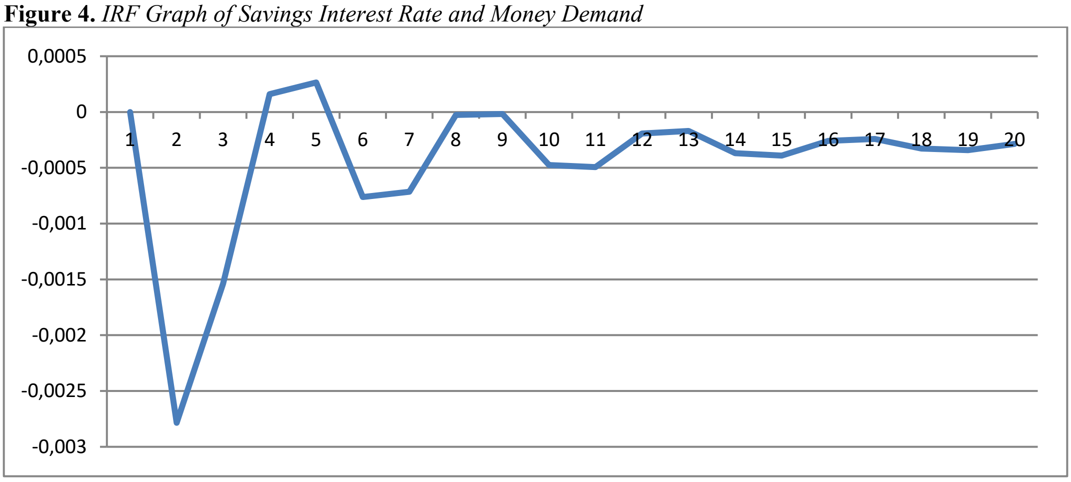
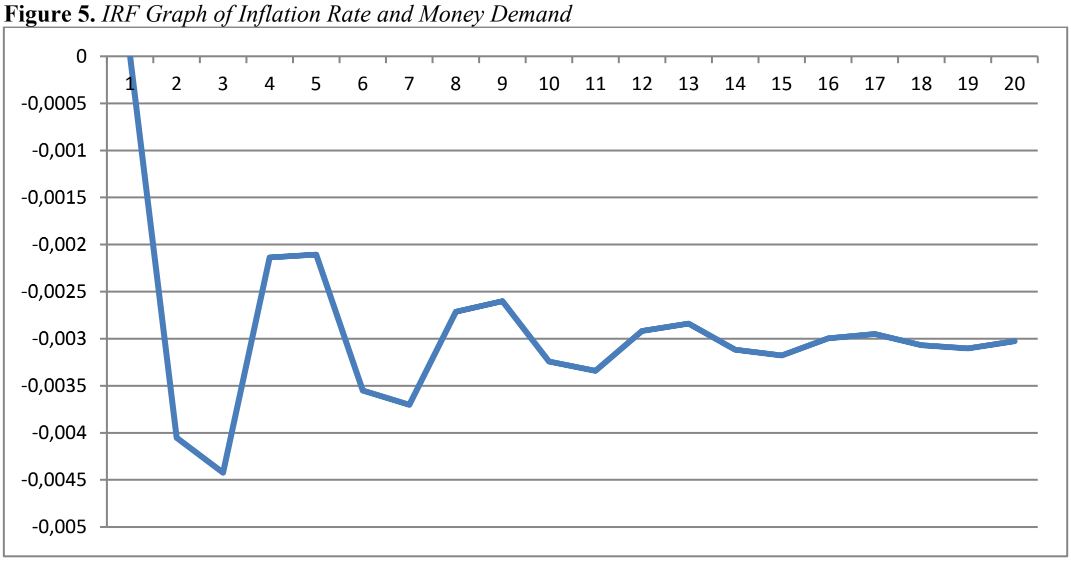


Figure 5. *IRF Graph of Inflation Rate and Money Demand*



The IRF graph in figure 1 shows the positive response of money demand to a unit shock from modern payment technology transactions. It reveals that a unit shock from modern payment technology transactions leads to a rapid rise in money demand within the initial 3 quarters. Thereafter, money demand oscillates to a new positive steady-state within the subsequent 17 quarters.

The IRF graph in figure 2 shows the response of money demand to a unit shock from itself. It reveals that money demand oscillates to a new permanent steady-state after a shock from itself.

The IRF graph in figure 3 shows the positive response of money demand to a unit shock from gross domestic product. It reveals that a unit shock from gross domestic product leads to a rise in money demand within the initial 2 quarters. Thereafter, money demand oscillates to a higher positive steady-state within the subsequent 18 quarters.

The IRF graph in figure 4 shows the negative response of money demand to a unit shock from savings interest rate. It reveals that a unit shock from savings interest rate leads to a decline in money demand within the initial 2 quarters. Thereafter, money demand oscillates to a new negative steady-state within the subsequent 18 quarters.

The IRF graph in figure 5 shows the negative response of money demand to a unit shock from inflation rate. It reveals that a unit shock from inflation rate leads to a decline in money demand within the initial 3 quarters. Thereafter, money demand oscillates to a new negative steady-state within the subsequent 17 quarters.

On the hand, the forecast error variance decomposition (FEVD) graphs are given in figures 6 to 10. They depict the decomposed share of money demand’s total forecast error variance (FEV) with regards to itself and the other endogenous variables.

Figure 6. *Share of Payment Technology Transactions Shocks in FEV of Money Demand*

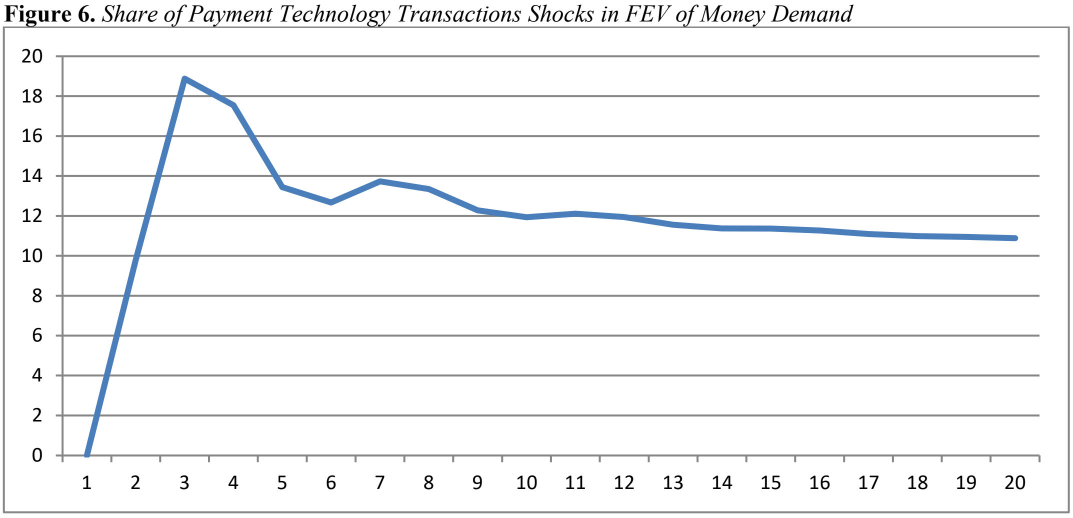


Figure 7. *Share of Money Demand Shocks in FEV of Money Demand*

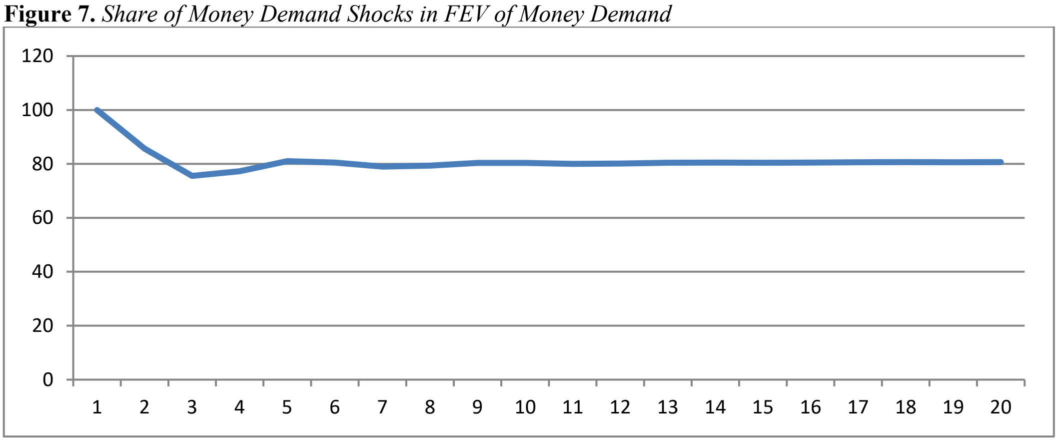


Figure 8. *Share of Gross Domestic Product Shocks in FEV of Money Demand*

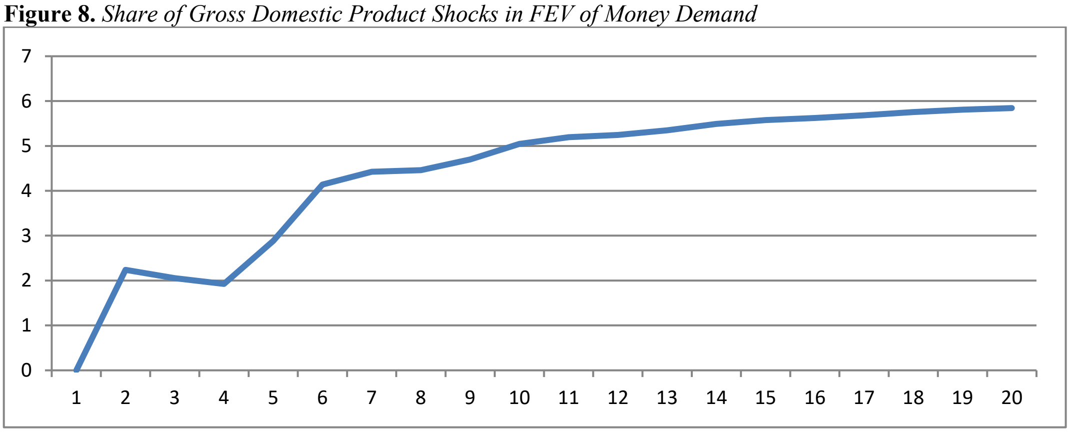


Figure 9. *Share of Savings Interest Rate Shocks in FEV of Money Demand*

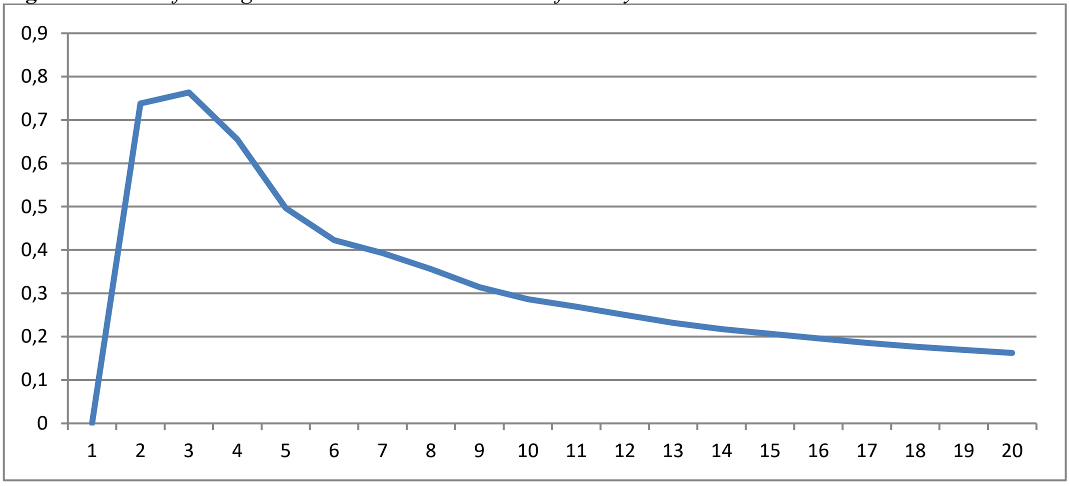
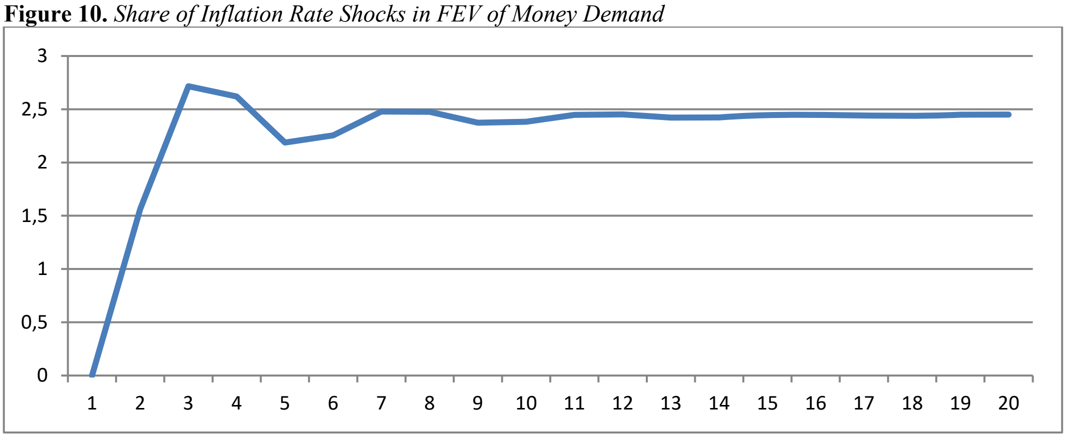


Figure 10. *Share of Inflation Rate Shocks in FEV of Money Demand*



In figure 6, shocks from money demand contribute 100 percent, 77.25 percent, and 80.66 percent to its total forecast error variance in the first, fourth, and twentieth quarters respectively.

In figure 7, shocks from modern payment technology transactions contribute 7.72 percent and 2.51 percent to the total forecast error variance of money demand in the fourth and twentieth quarters respectively.

In figure 8, shocks from gross domestic product contribute 12.13 percent and 14.31 percent to the total forecast error variance of money demand in the fourth and twentieth quarters respectively.

In figure 9, shocks from savings interest rate contribute 0.26 percent and 0.07 percent to the total forecast error variance of money demand in the fourth and twentieth quarters respectively.

In figure 10, shocks from inflation rate contribute 2.62 percent and 2.45 percent to the total forecast error variance of money demand in the fourth and twentieth quarters respectively.

Therefore, during the short-term of (4 quarters), money demand contributes 77.25 percent to its total forecast error variance, while gross domestic product, modern payment technology transactions, inflation, and savings interest rate respectively contribute only 12.13 percent, 7.72 percent, 2.62 percent, and 0.26 percent. But during the long-term (20 quarters), money demand contributes 80.65 percent to its total forecast error variance, while gross domestic product, modern payment technology transactions, inflation, and savings interest rate respectively contribute only 14.31 percent, 2.51 percent, 2.45 percent, and 0.07 percent.

5. Conclusion

In a bid to assess the efficacy of modern payment technology in facilitating access to liquidity services in Nigeria, we utilized impulse response function (IRF) analysis and forecast error variance decomposition (VD) analysis to study the relationship between modern payment technology patronage and money demanded for liquidity services in the Nigerian economy during the period 2009Q1 to 2019Q1. Via impulse response function (IRF) analysis, we discovered that money demanded for liquidity responded positively to shocks in modern payment technology transactions during the period under investigation. Secondly, via variance decomposition (VD) analysis, we discovered that a substantial proportion of the variation in money demanded for liquidity is attributable to modern payment technology transactions as well as other conventional money demand determinants in the short-term horizon (4 quarters) and the long-term horizon (20 quarters).

Based on these findings, we concluded that money demanded for liquidity interacts positively and non-negligibly with modern payment technology patronage, and we recommended therefore that modern payment technology patronage should be promoted by Nigeria's monetary authority in order to extend liquidity services to more Nigerians.

Notes

(1) This manuscript was extracted from Tersoo IORNGURUM'S master's dissertation titled "The Impact of Modern Payment Technologies on Money Demand in Nigeria".

(2) Tersoo Iorngurum is a research student in the department of economics, Veritas University, Abuja.

(3) Godwin Nwaobi is a visiting professor with the African Union (AU) and a professor of economics and econometrics in the department of economics, Veritas University, Abuja, Nigeria, West Africa.

References

Bloomberg, 2018. *Cash Remains King for Mobile Weary Nigerians*. [online] Abu Dhabi: The National. Available at: <https://www.thenational.ae/world/africa/cash-remains-king-for-mobile-money-wary-nigerians-1.752102> [Accessed 10 July 2020].

Brand, C. and Cassola, N., 2000. *A Money Demand System for Euro Area M3*. ECB Working Paper Series No. 29. Frankfurt: European Central Bank.

Brelof, P. and Parbhoo, A., 2016. *Cash is Still King in Nigeria*. [online] Massachusetts: Accion. Available at: < https://www.accion.org/cash-still-king-nigeria> [Accessed on 10 July 2020]

Caporale, G.M. and Soliman, A.M., 2010. *Stock Prices and Monetary Policy: An Impulse Response Function Analysis*. Economics and Finance Working Paper Series No. 10-22. West London: Brunel University.

Egbetunde, T., Ayinde, T.O. and Adeyemo, A.A., 2015. Demand for Money and Cashless Policy in Nigeria. *Indian Journal of Management Science*, V(1), pp.83-95

Greiber, C. and Setza, R., 2007. *Money and Housing: Evidence from the Euro Area and the US*. Deutsche Bundesbank Discussion Paper Series No. 12/2007. Frankfurt: Deutsche Bundesbank.

Johansen, S., 1995. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press on Demand.

Kama, U. and Adigun, M., 2013. *Financial Inclusion in Nigeria: Prospects and Challenges*. Central Bank of Nigeria Occasional Paper Series No. 45. Abuja: Central Bank of Nigeria.

Kombo, J.N., 2017. *Empirical Analysis of Money Demand in Kenya: 2000-2016*. MA. University of Nairobi.

Korhonen, L. and Mehrotra, A., 2007. *Money Demand in Post-Crisis Russia: De-Dollarization and Re-Monetization*. BOFIT Discussion Paper Series No. 14.2007. Helsinki: Bank of Finland.

Lütkepohl, H., 2005. *New Introduction to Multiple Time Series Analysis*. Berlin: Springer Science and Business Media.

Nirmala, T. and Widodo, T., 2011. Effect of Increasing the Use of Card Payment in the Indonesian Economy. *Jurnal Bisnis dan Ekonomi*, 18(1), pp. 36-45.

Nwaobi, G.C., 2012. *Modern Econometric Modeling for Developing Countries (Volume III)*. Lagos, Nigeria: Applause Press.

Olayinka, D. and Ibukun, T., 2020. *Financial Inclusion in Rural Nigeria: Challenges Facing Business Viability*. [online] Lagos: Lagos Business School. Available at: <https://www.lbs.edu.ng/lbsinsight/financial-inclusion-in-rural-nigeria-challenges-facing-agent-business-viability/> [Accessed on 10 July 2020]

Oyelami, L.O. and Yinusa, D.O., 2013. Alternative Payment Systems Implication for Currency Demand and Monetary Policy in Developing Economy: A Case Study of Nigeria. *International Journal of Humanities and Social Science*, 3(20), pp. 253-260

Perron, P., 1989. The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica: Journal of Econometric Society*, 1989(1), pp. 1361-1401.

Rinaldi, L., 2001. *Payment Cards and Money Demand in Belgium*. Center for Economic Studies Discussion Paper Series No. 01.16. Leuven: Katholieke Universiteit Leuven.

Schoellner, T.M., 2002. *The Effects of Credit Cards on Money Demand*. PHD. The Ohio State University.

Tule, M.K., Okpanachi, U.M., Ogiji, P. and Usman, N., 2018. A Reassessment of Money Demand in Nigeria. *CBN Journal of Applied Statistics*, 9(1), pp. 47-75.