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DYNAMIC PANEL DATA ANALYSIS USING LINEAR AND NON-LINEAR MOMENT CONDITIONS

Nwakuya, Maureen Tobechukwu[1] and Orumie, Cynthia Ukamaka[2]

[1&2]Department of Mathematics and Statistics, University of Port Harcourt
Email: [1]maureen.nwakuya@uniport.edu.ng and [2]ukamaka.orumie@uiport.edu.ng

ABSTRACT

This study considered data on allocation of loans to all Nigerian states by the federal government from 2017 to 2021. It considered the value of guaranteed loans and number of fully paid loans as the independent variables and number of guaranteed loans as dependent variable. The system generalized method of moments (SGMM) was employed while investigating one-step and two-step method of estimations with linear and nonlinear moment conditions, namely; the one-step linear moment conditions (OSLMC), two-step linear moment conditions (TSLMC), one-step non-linear moment conditions (OSNLMC) and two step non-linear moment conditions (TSNLMC). The result shows that the OSLMC and OSNLMC method produced significant time-dummy coefficients that had predictive power, hence indicating that both could not portray the true representation of the relationship between the variables. Comparing the four methods TSLMC had valid instruments, significant coefficients with predictive power, significant time-dummy coefficients with no predictive power and model estimates with the least standard errors hence the best estimator. It is concluded that TSLMC method is most preferred compared to the OSLMC, TSNLMC and OSNLMC. Based on the best preferred model (TSLMC) the research reveals that the number of guaranteed loans given to any state in Nigeria is dependent on the guaranteed loan given to the state in the previous year with the value of the loan in the previous year and the current value of the loan.

Keyword: System generalized method of moments, one-step linear moment conditions, one-step nonlinear moment conditions, two-step linear moment conditions and two-step nonlinear moment conditions.

1. INTRODUCTION

The recent global economic crisis has adversely affected a lot of countries especially developing countries, Adedoyin et al (2017). Such crisis include the issue of crude oil market where the Organization of Petroleum Exporting Countries (OPEC) was unable to reach an agreement amongst its member countries, hence having a spill over effect on countries that do not even export petroleum products thereby causing global impact. Nigeria as an oil producing country was grossly affected, which invariably affected the economy of every state of the federation, because every state depends majorly on allocation from the federal government and loans allocated to the states. This work studies the impact of value of loans awarded to states and the number of fully paid back loans by the states on the number of guaranteed loans for every state in Nigeria from 2017 to 2021.

The panel data for this research was collected from Annual Statistics bulletin of Nigeria, where the states constitute the cross sections and a time period of 5 years. The analysis considered the dynamic process of the data. Baltagi (2021) stated that most relationships of economic variables are traditionally dynamic in nature, and this allows for a better understanding of the dynamics of the variables. Modeling of dynamic process of a panel data with unobserved individual-specific effects involves the construction lagged dependent variable as one of the explanatory variables. In dynamic panel datamodeling the fixed-effects estimator is found to be inconsistent and biased as stated by Nickell (1981), in literature this bias is called the Nickell's bias. Nikell (1981) reveals that this is as a result of the demeaning process which causes a correlation between the independent variable and error term. Traditionally dynamic panel data modeling is done by first differencing (demeaning)the equation to remove correlated unobserved heterogeneity and applying generalized method moments (GMM) using the lagged levels of the series as instrumental variable (IV). But in the application of this method the traditional generalized method of moments (GMM) have been found to have large finite sample bias and poor precision in simulation studies Allonso-Borreg and Arellano (1996). The works of Arellano and Bover (1995), Blundell and Bond (1998) came up with the fact that there are additional moment conditions that are not exploited by these IV estimators, and they suggested that this additional moment conditions can be imposed in a generalized method of moments (GMM) framework. Hence they proposed the difference and system generalized methods of moments (DSGMM).The acceptance of the difference and system generalized method of moments (DSGMM) estimators for dynamic panels has accelerated in research, mainly because of its ability to handle the fixed effect endogeneity of the independent variable as well as avoiding the Nickell's bias. It also has the advantage of accommodating multiple endogenous variables and unbalanced panels. Some of these includes the works of Holtz-Eakin, et al (1988), Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998).

1.2 The GMM estimators

The GMM for dynamic panel data are estimators constructed to fit linear dynamic models in the presence of unobserved heterogeneity for either wide or short panels. Traditionally the GMM estimation for dynamic panel data can be in two steps. Firstly it uses the weighting matrix to obtain the one-step estimation, thereafter the residuals from the one-step estimation is applied as a weighting matrix to get the two-step estimation.
The dynamic panel model as given by Baltagi (2011) is;

$$y_{it} = \psi y_{i,t-1} + x_{it}^{'}\beta + e_{it}, i = 1, \dots, n \; and \; t = 1, \dots, T \quad (1)$$

$$e_{it} = v_i + \eta_{it} \quad (2)$$

Where $E(v_i) = E(\eta_{it}) = E(v_i, \eta_{it}) = 0$. Given that$i$ represents cross sectional units and t stands for time, x is a vector of the independent variables, sometimes its lagged values are included and y is the dependent variable whose lag is included. $e_{it}$is the disturbance term that is made up of two orthogonal components, namely the unobserved heterogeneity effects (fixed effect)v_i and the idiosyncratic errors η_{it}.
Given model in equation (1), the assumptions as given by Yousef et al (2014) are given as follows;
$v_i \sim iid(0, \sigma_v^2)$,$\eta_{it} \sim (0, \sigma_\eta^2)$, the idiosyncratic errors (η_{it}) is also independent of $v_i$and y_{it} and the initial observation follows a mean stationary process$y_{i1} = \frac{v_i}{1-\psi} + \omega_{i1}$ for i=1,…,N and $\omega_{i1} = \sum_j^\infty \psi^j \, \eta_{i1-j}$ and it is independent of v_i. Yousef et al (2014) also presented that stacking of equation (1) over time as;

$$y_i = \psi y_{i,-1} + e_i \quad (3)$$

Where $y_i = (y_{i3}, \dots, y_{iT})'$, $y_{i-1} = (y_{i2}, \dots, y_{iT-1})'$ and $e_i = (e_{i3}, \dots, e_{iT})'$. They hinted that based on these assumptions three dynamic panel data GMM model estimators were birth, namely first-difference GMM estimator which proposed by Arellano and Bond (1991), level GMM estimator proposed by Arellano and Bover (1995) and the system GMM (SYS) estimator proposed by Blundell and Bond. (1998)

1.3 Literature review

The generalized method of moments (GMM) for dynamic panel data have been applied in many research works. Sebki (2021), employed the generalized method of moments for dynamic panel data in investigating the effect of education by means of secondary and higher institution enrolment on the economic growth of 40 countries for a period of 14 years. The results reveal that secondary enrolment had a negative significant impact while higher institution enrolment has a positive significant impact on the economic growth. Likewise kalan and Gokasar (2020), also used the dynamic panel data method in measuring the effects of highway capital stocks on Gross Domestic Product (GDP) change between 2004 and 2016. The research shows a significant positive impact of highway stock on GDP for local regions in Tukey. The GMM for dynamic panel data has also gone through some improvements in recent times such as the works of; Chudik and Pesaran (2021),who proposed a new estimator for dynamic panels with short time period, this they achieved by supplementing the Anderson and Hsiao (AH) estimator with a quadratic moment conditions in first differences that was bias-corrected. The new estimator was seen to largely boost the performance of the small sample of the AH estimator without violating the underlying assumptions regarding the fixed effects, initial values, and heteroscedasticity of error terms; Kruiniger (2021), that noted that the inconsistency in one-step and two-step GMM is because their weight matrices takes up moment conditions that do not identify the autoregressive parameter and he proposed a new 2-step System estimator that consistent conditioned on the fact the time period is greater than 3;Salamh and Wang (2021), also proposed a second-order least squares method that is built upon the first two conditional moments of the dependent variable given the independent variables. The method proved to be root-N consistent and has an asymptotic variance that approaches a lower bound semi parametric efficiency. The estimator's diagnostic test proved to be very useful in validating the working conditional moments and for model selection purpose.

Fetahi-Vehapi et al (2015) applied the system GMM to investigate the effects of openness to trade on economic growth of South East European (SEE) countries, the results indicate that the positive effects of trade openness on economic growth are conditioned by the initial income per capita and other explanatory variables, otherwise there is not robust evidence between these two variables. Felbermayr (2005) employs the System GMM estimator to investigate the relationship between trade and income and finds evidence of a strong and positive relationship between these variables. Windmeijer (2005) in his paper found out that asymptotic standard errors of the two-step, generalized method of moments (GMM) estimator are severely downward biased in small samples while that of one-step GMM estimators are virtually unbiased, he also hinted that one-step GMM estimators use weight matrices that are independent of estimated parameters, while the two-step GMM estimator weighs the moment conditions by a consistent estimate of their covariance matrix. Vardar and Coskun (2016), probes the dynamic relationship between financial system, through bank/stock market development, and economic growth volatility in overall/specific country group levels for 47 developed/developing/transition countries from 1989-2012 periods. The results for the full sample of countries hints that all variables, except stock market turnover ratio were statistically significant with a negative impact on economic growth volatility, also domestic credit to GDP was seen to be statistically significant with a positive impact.

2. MATERIALS AND METHODS

The study made use of panel data on Nigerian loans given to all the 37 states of the federation, from 2017 to 2021. The data is structured with "value of loans" (VL) and "fully paid loans" (FP) as the independent variables and the dependent variable as "number of guaranteed loans" (GL). This data was obtained from Annual Statistical bulletin of Nigeria. To investigate the relationship between the number of guaranteed loans, value of loans and fully paid loans, the generalized method of moments (GMM) estimators constructed for dynamic panel data models proposed by Blundell and Bond (1998), which is the combination of difference GMM and level GMM was employed. The study investigated four different types of iterations of parameter estimation procedure namely; one-step with linear moment conditions (OSLMC), two-step with linear moment conditions (TSLMC), one-step with non-linear moment conditions (OSNLMC) and two step with non-linear moment conditions (TSNLMC).

2.1 Difference GMM estimator

Given equation (3), there is an extreme correlation between the lagged endogenous variable ($y_{i,-1}$) and the error term (e_i). In other to get rid of the endogeneity effect Blundell and Bond (1998) applied first differencing to obtain;$\Delta y_i = \psi \Delta y_{i,-1} + \Delta e_i$

(4)

Where $\Delta y_i = (y_{i3} - y_{i2}, \dots, y_{iT} - y_{i,T-1})'$, $\Delta y_{i,-1} = (y_{i2} - y_{i1}, \dots, y_{i,T-1} - y_{i,T-2})'$ and $\Delta e_i = (e_{i3} - e_{i2}, \dots, e_{iT} - e_{i,T-1})'$, having that

$$E(\varkappa_i^{Df'}, \Delta e_i) = 0, (Df\ is\ for\ identification\ of\ difference) \quad (5)$$

Where
$$\varkappa_i^{Df} = \begin{pmatrix} y_{i1} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i1} & y_{i2} & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & \cdots & y_{i1} & \dots & y_{i,T-2} \end{pmatrix} \quad (6)$$

Applying equation (5) as the orthogonal condition, the one-step difference GMM estimator is given by;

$$\hat{\psi}^{Df} = \left(\Delta y_{-1}' \varkappa^{Df} \omega^{Df} \varkappa^{Df'} \Delta y_{i,-1}\right)^{-1} \Delta y_{-1}' \varkappa^{Df} \omega^{Df} \varkappa^{Df'} \Delta y_i \quad (7)$$

Where, $\Delta y_{i,-1} = \left(\Delta y_{1,-1}', \dots, \Delta y_{1,-N}'\right)'$, $\Delta y_i = \left(\Delta y_1', \dots, \Delta y_N'\right)'$, $\varkappa^{Df} = \left(\varkappa_1^{Df'}, \dots, \varkappa_N^{Df'}\right)'$ and

$\omega^{Df} = \left(\frac{1}{N}\sum_{i=1}^{N} \varkappa_i^{Df'} D \varkappa_i^{Df}\right)^{-1}$, given that $D = \ell\ell'$and ℓ is a (T-2) X (T-1) 1st difference matrix operator, presented as; $\ell = \begin{pmatrix} -1 & 1 & 0 & \dots & 0 \\ 0 & -1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & -1 & 1 \end{pmatrix}$. The moment conditions are then weighted to obtain the two-step difference GMM estimator, the weight is given by;

$$\omega_{(2)}^{Df} = \left(\frac{1}{N}\sum_{i=1}^{N} \varkappa_i^{Df'} \Delta\hat{e}_i \Delta\hat{e}_i' \varkappa_i^{Df}\right)^{-1} \quad (8)$$

Where $\hat{e}_i$ are the fitted residuals from difference GMM estimator.

2.2 Level GMM estimator

It was observed by Blundell and Bond (1998) that $\varkappa_i^{Df}$ matrix becomes inoperative as ψ increases or gets close to 1, hence causing the instruments to be weak. The work of Arellano and Bover (1995) improved on it by proposing a new method of eliminate the cross sectional effect from instrumental variables. They presented the 2 level GMM estimation model with instrumental variables matrix that is not weak and it is given by;

$$\varkappa_i^{Lv} = \begin{pmatrix} \Delta y_{i2} & 0 & \dots & 0 \\ 0 & \Delta y_{i3} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \Delta y_{i,T-1} \end{pmatrix} \quad (9)$$

Satisfying the orthogonality conditions; $E(\varkappa_i^{Lv'}, e_i) = 0$

$$(Lv\ is\ for\ identification\ of\ level) \quad (10)$$

Given the orthogonality conditions in equation (10), the one-step level GMM estimator is computed thus;

$$\hat{\psi}^{Lv} = \left(y'_{-1}\varkappa^{Lv}\omega^{Lv}\varkappa^{Lv'}y_{i,-1}\right)^{-1} y'_{-1}\varkappa^{Lv}\omega^{Lv}\varkappa^{Lv'}y \quad (11)$$

Where; $y_{i,-1} = \left(y'_{1,-1}, \dots, y'_{1,-N}\right)'$, $y = \left(y'_1, \dots, y'_N\right)'$, $\varkappa^{Lv} = \left(\varkappa_1^{Lv'}, \dots, \varkappa_N^{Lv'}\right)'$ and

$$\omega^{Lv} = \left(\frac{1}{N}\sum_{i=1}^{N} \varkappa_i^{Lv'}\varkappa_i^{Lv}\right)^{-1} \quad (12)$$

In other to compute the two-step level GMM estimator, the moment conditions are then weighted thus;

$$\omega_{(2)}^{Lv} = \left(\frac{1}{N}\sum_{i=1}^{N} \varkappa_i^{Lv'}\hat{e}_i\hat{e}'_i\varkappa_i^{Lv}\right)^{-1} \quad (13)$$

Given that $\hat{e}_i$ are the fitted residuals from level GMM estimator.

2.3 The System GMM Estimator

The system GMM estimator is an optimal combination of the moment conditions of differenced GMM and level GMM estimators. Sebastian (2019) stated that system GMM" can be seen as a system of a level equation and an equation in first differences. The system GMM enhances these GMM estimators by avoiding weak instruments and improving the efficiency of the estimator. In the execution of system GMM, a new set of stacked data is expanded from the original data in levels and another in difference. In constructing the system GMM estimator the moment conditions applied is given by;

$$E(\varkappa_i^{sy'}, e_i^{sy}) = 0, (sy\ is\ for\ identification\ of\ system) \quad (14)$$

Given that $e_i^{sy} = (\Delta e'_i, e'_i)'$ and $\varkappa_i^{sy}$ is a $2(T-2)\ X\ (T-2)(T+1)/2$ block diagonal matrix presented as;

$$\varkappa_i^{sy} = \begin{pmatrix} \varkappa_i^D & 0 \\ 0 & \varkappa_i^L \end{pmatrix} \quad (15)$$

Applying the moment conditions in equation (14), the one-step system GMM estimator is computed as given as: $\hat{\psi}^{Sy} = \left(y_{-1}^{sy'}\varkappa^{sy}\omega_{\not{f}}^{sy}\varkappa^{sy'}y_{-1}^{sy}\right)^{-1} y_{-1}^{sy'}\varkappa^{sy}\omega_{\not{f}}^{sy}\varkappa^{sy'}y^{sy}$ (16)

Where; $y_{-1}^{sy} = \left[\left(\Delta y'_{1,-1}, y'_{1,-1}\right), \dots, \Delta y'_{N,-1}, y'_{N,-1})\right]'$, $y^{sy} = \left[\left(\Delta y'_1, y'_1\right), \dots, \left(\Delta y'_N, y'_N\right)\right]'$, $\varkappa^{sy} = \left(\varkappa_1^{sy'}, \dots, \varkappa_N^{sy'}\right)'$ and $\omega_{\not{f}}^{sy} = \left(\frac{1}{N}\sum_{i=1}^{N} \varkappa_i^{sy'}\not{f}\varkappa_i^{sy}\right)^{-1}$ (17)

given that $\not{f} = \begin{pmatrix} D & 0 \\ 0 & I_{T-2} \end{pmatrix}$

Computing the two-step system GMM estimator, the moment conditions are then weighted thus;

$$\omega_{\not{f}(2)}^{sy} = \left(\frac{1}{N}\sum_{i=1}^{N} \varkappa_i^{sy'}\hat{e}_i^{sy}\hat{e}_i^{sy'}\varkappa_i^{sy}\right)^{-1} \quad (18)$$

Given that $\hat{e}_i$ are the fitted residuals from level system estimator.

The proposed model for the analysis is;

$GL_{it} = \psi GL_{i,t-1} + \beta_1 VL_{it} + \beta_2 VL_{it-1} + \delta_1 FP_{it} + \delta_2 FP_{it-1} + \xi_2 d_2 + \xi_3 d_3 + \xi_4 d_4 + \xi_5 d_5 + \upsilon_i + \eta_{it}$ (19)

Where i represents the states (cross sectional units) and *t* stands for current time and *t-1* is the lag, υ_i is unobserved individual heterogeneity effects and η_{it} is the idiosyncratic errors. β's are the effects of 'value of the loans' at current time (*t*) and the period before current time (*t-1*), δ's are the effects of 'fully paid loans' at current time (*t*) and the period before current time (*t-1*). Guaranteed loans (*GL)* represents the dependent variable where ψ is *GL* lag effect, The variables $d_2, \ldots, d_5$are time dummies with corresponding coefficients$\xi_2, \ldots, \xi_5$, the time period considered is 2017-2021. The aim is to estimate the lag parameter ψ and the coefficients of the independent variables $\beta's$ *and* $\delta's$ while controlling for (unobserved) time effects and accounting for unobserved individual-specific heterogeneity.

2.4 Over-identification test

The Hansen-J test for validity of the over-identifying restriction was used. Over-identification basically means that you have more instruments than necessary to estimate the model. The consistency of the system GMM estimator relies on the fact that, the set of instrumental variables must be valid, i.e. uncorrelated with the error terms. The j-test statistic is given by;

$$\mathcal{J}_i = n(\widehat{\mathfrak{R}}_2' \mathfrak{Z} \widehat{\omega}_2 \mathfrak{Z}' \widehat{\mathfrak{R}}_2) \qquad \mathcal{J}_i \sim asymptotically\ N(m,p)$$

The vector $\widehat{\mathfrak{R}}_2$denotes the two-step residuals, $\mathfrak{Z}$ is matrix that does not depend on parameter estimates, $\widehat{\omega}_2$ is the weighting matrix of the two-step GMM estimator, n is number of cross sections,p denotes the number of estimated coefficients and$m$ is number of sample moment conditions.

The hypothesis is as follows:

H_0: Instruments are valid

H_1: Instruments are not valid

2.5 Serial Correlation test

The serial correlation test of Arellano and Bond (1991) tries to find out if the departure of the covariance of the residuals of period 't' from the residuals of period $t-I$ is large enough show the presence of *i-th* order serial correlation in the idiosyncratic component. The corresponding test statistic is given by;

$$\vartheta_{mi} = \frac{\hat{r}_i}{\mathcal{S}_{\hat{r}_i}} \vartheta_{mi} \sim asymptotically\ N(0,1)$$

Where $\mathcal{S}_{\hat{r}_i}$is the standard error of the *i-th* order auto covariance of the residuals $\hat{r}_i$. The hypothesis is as stated below;

$H_0: \rho_0 = 0$ (No serial correlation)

$H_1: \rho_0 \neq 0$ (Presence of serial correlation)

2.6 Linear Hypothesis Test

The Wald test is used to test general linear hypotheses of the form H0 :Rθ = r, The Wald statistic is given by;

$$\mathrm{T} = n(\mathcal{G}\hat{\Theta} - \varpi)'\left(\mathcal{G}\hat{\phi}(\hat{\Theta})\mathcal{G}'\right)^{-1}\mathcal{G}\hat{\Theta} - \varpi \qquad \mathrm{T}\ asympotically \sim \chi^2(c)$$

Where Θ is a vector of population parameter, $\mathcal{G}$ is a *cxp* matrix that picks the parameters needed to indicate the left-hand side of the equations of the null hypothesis, ϖ is a *cx1* vector that indicates the right-hand side of the equations and $\hat{\phi}(\hat{\Theta})$is the covariance matrix.

3 RESULTS

Table 1: Descriptive Statistics

Variables	Mean	Std dev	min	max	skew	kurtosis
N_GUAR	880	994.34	0(Bauchi)	8875 (Adamawa State)	3.68	22.65
V_GUAR	132475	132527.01	0	825295(Adamawa State)	2.04	5.81
F_PAID	792	939.40	0	7279(Plateau State)	3.09	14.57

Table 1 shows that Adamawa had maximum number of guaranteed loans (8875) and that was in 2021, while the maximum number of fully paid loans is 7279 by Plateau state. Plateau state had a total of 7507 guaranteed loans and the paid offer 7279 by the year 2021. The data also showed that some states like Bauchi, Borno and Yobe did not have any guaranteed loans in certain years.

Table 2: Serial correlation and linear hypothesis test results for TSLMC

Model Parameters	Test Statistic (P-value)	Decision
Serial correlation	-1.3217 (0.1863)	No serial correlation
Coefficients	69.349 (1.4e-13*)	Has predictive power
Time-Dummy	7.6595 (0.0536)	Has no predictive power

Table 3: Dynamic linear panel estimation using TSLMC

Variables	Estimate	Std.error	z-value	p-value
L1_N_GUAR	6.955e-01	1.872e-01	3.715	0.0002*
V_GUAR	5.255e-03	1.895e-03	2.773	0.0055 *
L1_V_GUAR	-4.701e-03	1.593e-03	-2.952	0.0032 *
F_PAID	5.119e-02	1.085e-01	0.472	0.63693
L1_F_PAID	1.308e-01	7.700e-02	1.699	0.0893
2018	-1.727e-04	4.935e-05	-3.501	0.0005 *
2019	5.120e-04	1.311e-04	3.906	9e-05 *
2020	-3.680e-04	8.708e-05	-4.227	2e-05 *
2021	1.875e-04	6.317e-05	2.968	0.0030 *

Sig level 5% *

Table 2 and 3 shows results of the two-step method with linear moment conditions (TSLMC). The result show significance of the all the variables except for fully paid and its lag. The linear hypothesis test reveals that the significant coefficients have predictive power in the linear model while the time dummy coefficients though significant have no predictive power in the linear model. There is also no evidence of serial correlation. Hence it can be concluded from the model results that number of guaranteed loans is affected by its lag, value of the loans and lag of the value of the loans.

Table 4: Serial correlation and Linear hypothesis test results: for OSLMC

Model Parameters	Test Statistic (P-value)	Decision
Serial correlation	-0.001115 (0.999)	No serial correlation
Coefficients	1.2e+9	Predictive power
Time-Dummy	1.3e+8	Predictive power

Table 5: Dynamic linear panel estimation using OSLMC

Variables	Estimate	Std.error	z-value	p-value
L1_N_GUAR	6.805e-01	9.473e-02	7.184	< 2e-16 *
V_GUAR	6.129e-03	1.372e-03	4.467	1e-05 *
L1_V_GUAR	-5.617e-03	1.685e-03	3.334	0.0009 *
F_PAID	1.978e-02	9.112e-02	0.217	0.82821
L1_F_PAID	2.097e-01	8.927e-02	2.349	0.01882 *
2018	1.772e-04	2.905e-05	6.100	< 2e-16 *
2019	2.429e-05	1.269e-05	1.914	0.0556
2020	2.876e-05	5.495e-06	5.234	< 2e-16 *
2021	-1.341e-04	2.444e-05	-5.485	< 2e-16 *

Sig level 5% *

Table 4 and 5 shows the one-step method with linear moment conditions (OSLMC). The results show that all the coefficients are significant except fully paid and these coefficients has predictive power. The result also reveals significant time dummy variables except 2019, it went ahead to show that these time dummy variables have predictive power, which should not be, giving away an indication that the model is not portraying the true relationship.

Table 6: Serial correlation and linear hypothesis test results for TSNLMC

Model Parameters	Test Statistic (P-value)	Decision
Serial correlation	0.2487 (0.836)	No serial correlation
Coefficients	0.0531 (0.9968)	No predictive power
Time-Dummy	4.1014 (0.762)	No predictive power

Table 7: Dynamic linear panel estimation using TSNLMC

Variables	Estimate	Std.error	z-value	p-value
L1_N_GUAR	-4.016	4.452	-0.902	0.367
V_GUAR	-0.031	0.034	-0.916	0.360
L1_V_GUAR	-0.016	0.031	-0.515	0.607
F_PAID	-0.235	0.779	-0.303	0.762
L1_F_PAID	18.989	13.335	1.424	0.154
2018	0.038	0.002	20.221	<2e-16 *
2019	0.451	0.018	25.027	<2e-16 *
2020	-0.709	0.001	-1115.053	<2e-16 *
2021	0.310	0.002	188.955	<2e-16 *

Sig level 5% *

Table 6 and 7 shows results from the two-step method with nonlinear moment conditions (TSNLMC).The results show that all the coefficients are not significant; hence no predictive power but it shows that the time dummies are significant but they do not have predictive power. The result portrays that the model is not showing the true relationship between the models.

Table 8: Serial correlation and linear hypothesis test results for OSNLMC

Model Parameters	Test Statistic (P-value)	Decision
Serial correlation	-0.0009115 (0.9993)	No Serial correlation
Coefficients	1.6e+26 (2.2e-16)	Predictive power
Time-Dummy	2.6e+9 (2.2e-16)	Predictive power

Table 9: Dynamic linear panel estimation using OSNLMC

Variables	Estimate	Std.error	z-value	p-value
L1_N_GUAR	-3.672	2.237	-1.641	0.101
V_GUAR	-0.026	0.018	-1.496	0.135
L1_V_GUAR	-0.014	0.022	-0.619	0.536
F_PAID	-0.164	0.547	-0.299	0.765
L1_F_PAID	16.799	5.020	3.346	0.001 *
2018	0.038	0.001	44.665	< 2e-16 *
2019	0.450	0.001	847.489	< 2e-16 *
2020	-0.708	0.000	2617.413	< 2e-16 *
2021	0.309	0.000	1141.055	< 2e-16 *

Sig level 5% *

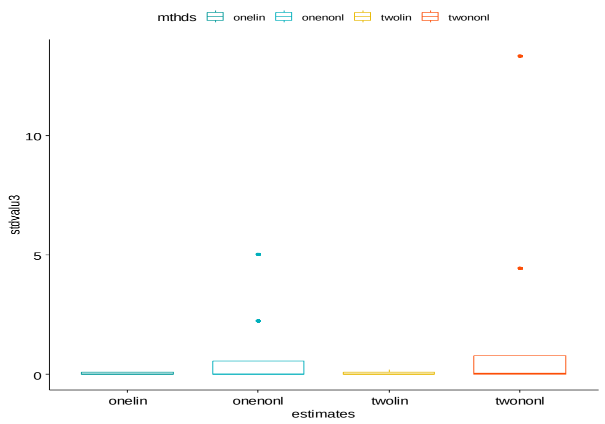
Table 8 and 9 shows the one-step method with nonlinear moment conditions (OSLMC). The results show that all the coefficients are not significant except lag of fully paid and the time dummy variables, therefore indicating that the lag of fully paid has a predictive power in the model as well as the time dummy variables which should not be. Hence it can be concluded that the model is not portraying the true relationship between the response and independent variables.

Table 10: Comparison of the methods based on the mean of the standard errors of their estimates and instrument validity

Methods	n	Mean (std. error)	Hansen J-test for instrument validity	
			Test Statistic (P-value)	Decision
Two-step with linear moments conditions (TSLMC)	**9**	**0.03**	**16.44 (0.3534)**	**Instruments are valid**
One-step with linear moments conditions (OSLMC)	9	0.871	4.9e+8 (<0.001*)	Instruments are not valid
Two-step with non-linear moments conditions (TSNLMC)	9	0.042	28.6 (0.0268*)	Instruments are not valid
One-step with non-linear moments conditions (OSNLMC)	9	2.07	6.7e+11 (<0.001*)	Instruments are not valid

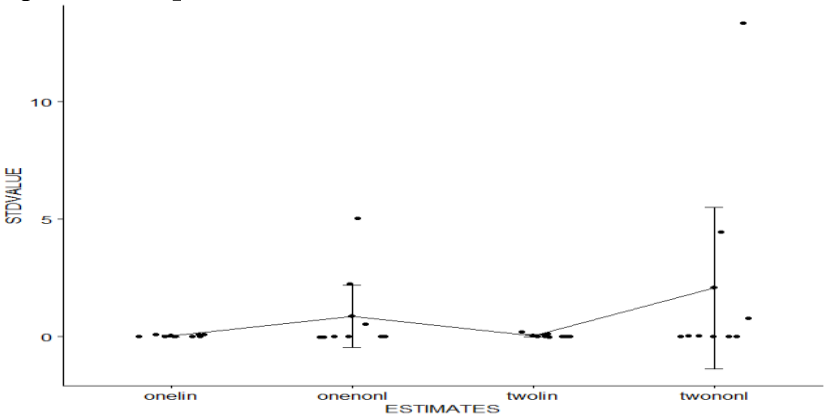
The results of the comparison of the methods reveals that the TSNLMC and OSNLMC have higher means hence shows evidence of higher standard errors in comparison to TSLMC and OSLMC, whereas the mean of standard errors of the TSLMC is lower than that of OSLMC. The results also reveal that only the instruments of TSLMC were valid, which is an indication that it is most preferred compared to the OSLMC, TSNLMC and OSNLMC.

Fig 1: Visualizing standard error of estimates using box plot



The fig 1 above shows that OSLMC and TSLMC methods produced standard errors of estimates that are very low and without visible difference in values, while OSNLMC and TSNLMC methods produced standard error of estimates that were more spread with some outliers (values that were way off the range).

Fig 2: Mean plots of the standard error of the estimates



The fig 2 visualizes the average of the standard errors from each method. It can be seen that the average standard errors of methods with linear moment conditions produced lower mean values hence lower standard errors compared to the methods with nonlinear methods. This plot confirms what the box plot in fig1showed.

Based on the results the TSLMC method is the most preferred model. Going with the results of TSLMC method in table 3, the model for this research is thus;

$$\widehat{GL}_{it} = \psi GL_{i,t-1} + \beta_1 VL_{it} + \beta_2 VL_{it-1} + \xi_2 d_2 + \xi_3 d_3 + \xi_4 d_4 + \xi_5 d_5$$

4. DISCUSSION

The research used a panel data on Nigerian loans given to all the 37 states of the federation, from 2017 to 2021, where “value of loans” (VL) and “fully paid loans” (FP) are the independent variables and “number of guaranteed loans” (GL) is dependent variable. The analysis employed the system generalized method of moments (GMM) proposed by Blundell and Bond (1998). The study investigated four different types of iterations of parameter estimation procedure namely; one-step with linear moment conditions (OSLMC), two-step with linear moment conditions (TSLMC), one-step with non-linear moment conditions (OSNLMC) and two step with non-linear moment conditions (TSNLMC). The analysis shows that under TSLMC all coefficients were significant with predictive power except for fully paid and its lag. Also the time dummy coefficients though significant have no predictive power in the linear model. There was also no evidence of serial correlation. Under the OSLMC all the coefficients were seen to be significant with predictive power except fully paid. The result also reveals significant time dummy variables with predictive power which should not be, giving away an indication that the model is not portraying the true relationship. The TSNLMC results reveal non-significant coefficients with significant time dummy variables but having no predictive power. TSNLMC method does not show any form of relationship between the variables, which is a wrong picture of the relationship between the variables. Lastly the OSNLMC methods results shows lag of fully paid loans and the time dummy variables as significant with predictive power which should not be. Hence OSNLMC model is not portraying the true relationship between the response and independent variables. It is observed that the one-step linear and nonlinear moment condition process, do not generally represent the true relationship between the variables due to the fact that the time-dummy coefficients were seen to have predictive powers in the model. Comparison of the four methods reveals that the

TSNLMC and OSNLMC shows evidence of higher standard errors in comparison to TSLMC and OSLMC, whereas the mean of standard errors of the TSLMC is lower than that of OSLMC. Among the four methods only the TSLMC had valid instruments with the least standard errors. The visual comparison of the standard errors confirms lower standard error of estimates of the linear moment conditions methods. We can then conclude that TSLMC method is most preferred compared to the OSLMC, TSNLMC and OSNLMC.

5. CONCLUSION

The research reveals no serial correlations. TSLMC and OSLMC had most of the coefficients significant with predictive power but the time-dummy coefficients of TSLMC did not have predictive power while the time-dummy coefficients of the OSLMC had predictive power (which is not supposed to be). The OSNLMC and TSNLMC did not have significant coefficients but the OSNLMC had its time dummy variables significant with predictive power. Hence we can say that both of the one stage linear and nonlinear methods do not represent the true relationship between the variables. It is also concluded that TSLMC method had the least standard error hence producing the best estimates in comparison to TSNLMC, OSNLMC and OSLMC. Also TSLMC had valid instruments with significant linear predictive powered coefficients and significant time-dummy coefficients without predictive power. It can be said that TSLMC method is most preferred method compared to the OSLMC, TSNLMC and OSNLMC. Based on the best preferred model (TSLMC) the research reveals that the number of guaranteed loans given to any state in Nigeria is dependent on the guaranteed loan given to the state in the previous year with the value of the loan in the previous year and the current value of the loan.

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