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Testing for Periodicity Effects in a Panel Data Regression Model

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Abstract:
This research attempts to investigate the effect of periodicity usually occasioned by the presence of serial correlation in panel data, through the estimation of pooled ordinary least square estimator (POLS) of a specified audit fees PDRM. Other analytical techniques employed through derivation are Fixed Effect Least Square dummy variable (where all coefficient vary over time), and Random Effect estimator (REM). A conditional Lagrange multiplier test was developed via a two-way error components model, to examine the presence of serial correlation in the fitted POLS model while Hausman test was used to ascertain the suitability of the LSDV Model over Random effect model and vice-versa. The conditional LM test gave a value of 35.3806 with P-value of 0.0001075 which shows that there is presence of serial correlation among the residuals of the fitted Pooled OLS model, thereby rendered the estimator inconsistent. Both LSDV and RE models captured the goodness of fit better when compared to the Pooled OLS model. However, the hausman test revealed that fixed effect model will be a preferable model since its results support the rejection of null hypothesis.

1. Introduction:

A panel is a cross-section or a kind of data in which observations are obtained on the same set of entities at several periods of time (Frees, 1995; Gujarati and Porter, 2009; Hsiao, 2003; Kennedy, 2008 and Green, 2003). Panel data models examine individual-specific effect, time effect or both in order to deal with heterogeneity/serial correlation of individual effects that may or may not be observed. In this paper, our focus shall only reflect on the problems which affect the time series aspect of panel data, which is the problem imposed by serial correlation. This shall be looked into via a panel data regression model of audit fees.

The term serial correlation may be defined as "correlation between members of series of observations ordered in time (as in series data) or space (as in cross-sectional data), see (Gujarati and Porter, 2009 and Green, 2003) $i.e$ Cov $(U_{it}, U_{is} \ / \ x_{it}, x_{is})$ = E (U_{it}, U_{is}) $\neq$ 0, t $\neq$ s. The pioneering work of (Lillard and Willis, 1978) has given rise to further researches on the estimation of serial correlation effects in panel data. Prominent among these works are those of (Bhargava, Franzini and Narendranathan, 1983; Burke, Godfrey and Termayne,1990; Baltagi and Li, 1991,2008).

Lillard and Willis (1978) extended the error component model to take into account first-order serial correlation in the remainder disturbances of random effects model. Bhargava, Franzini and Narendranathan (1983) carried out the same work for fixed effects. Both studies considered the first order Autoregressive [AR (1)] specification on the remainder disturbances. In Baltagi and Li (2008), while considering first order moving average MA(1) as a viable alternative to AR(1), Baltagi and Li (1995) give a transformation which may be applied to certain serially correlated disturbances in an error components model to yield spherical disturbances. They derive the transformations for first order Autoregressive [AR(1)] and second order Autoregressive [AR(2)] cases. In furtherance to this theoretical paper, Baltagi and Li (2008) provide a simple estimation method for an error component regression model with q_{th} order Moving Average [MA(q)] remainder disturbances. Their estimation method utilizes the transformation derived by Baltagi and Li (1995) for an error component model with autoregressive remainder disturbances, and a standard orthogonalizing algorithm for the general MA(q) model. Comprehensively, Baltagi and Li (2008) combine their earlier works in Baltagi and Li (1991) and Baltagi and Li (1995) by testing AR(1) against MA(1) disturbances in an error component model. The authors derive three Lagrangian Multiplier (LM) statistics for an error component model with first-order serially correlated errors. The first LM statistic jointly tests for zero first-order serial correlation and random individual effects, second LM statistic tests for zero first-order serial correlation assuming fixed individual effects, and the third LM statistic tests for zero first-order serial correlation assuming random individual effects. In all the three cases, the authors find that the corresponding LM statistic is the same whether the alternative is AR (1) or MA (1). The tests are computationally simple requiring only OLS. Galbraith and Zinde-Walsh (1995) also considered orthogonalizing transformation for the error-component model with serially correlated disturbances in the general ARMA case. Their work involves generalizations of results obtained by the Baltagi and Li (1991) in the study of AR (1) or AR (2) error processes.

More recently, Filho, Salagado, Sato and Oliveira(2014) analysed panel data for the impact of wage premiums on the product market competition of major full service carriers and low fare carriers in the airline industry. The authors employed a fixed effects estimator for the demand (d), cost (C) and wage (w) equations. They assumed a composite-error structure of $\in_{jt}^{d}$, $\in_{jt}^{c}$, $\in_{jt}^{w}$ in their three monthly dummy variables model specified as a followed up to the work of Good, Nadri and Sickles (1991) in which Instrumental Variables was employed.

When POLS is used in the estimation of PDRM, the estimator $\hat{\beta}$ is only linear, unbiased as well as consistent and asymptotically normally distributed, but not efficient or best. That is, $\hat{\beta}$ is not BLUE (best, linear, unbiased estimator) in the presence of serial correlation. This implies that Var $(\hat{\beta}_H)$ = $\sum x_i^2 \sigma_i^2 / (\sum x_i^2)^2$ is obviously different from the usual variance formula obtained under the assumption of homoscedasticity and zero serial correlation, which is given as Var ($\hat{\beta}_{POLS}$) = $\sigma^2/\sum x_i^2$

This research therefore, intends to examine this opinion on a PDRM tagged Audit Fees Model.

Audit fees represent fees a company pays an external auditor in exchange for performing an audit. Prominent among authors who have worked on modelling of audit fees are Agunbiade and Adeboye (2012), El-Gammal (2012), Akinpelu, Omojola, Ogunseye and Bada (2013), Soyemi and Olowookere (2013) Hassan (2015), but they all conjectured differently from the background knowledge of the audit fees model specified in this research.

2. Material and Methods:

2.1 *Specification of Audit Fees Model*

This model employed the use of four (4) Pre-determined variables namely Profit before Tax (PBT), Total Assets (TA), Total Liability (TL) and Shareholders Fund (SHF) which shall be originated from panel data of published annual reports of sixteen (16) Nigerian Commercial Banks for periods of ten (10) years. The model as implied by the scope of auditor's work in CAMA (1990) is thus presented as:

$$AF = f(PBT, TA, TL, SHF) + \varepsilon \quad (1)$$

When the model is expressed in an explicit format, we have

$$AF_{it} = \beta_1 + \beta_2 PBT_{it} + \beta_3 TA_{it} + \beta_4 TL_{it} + \beta_5 SHF_{it} + \varepsilon_{it} \quad (2)$$

$$where \quad i = 1, 2, 3, \dots N \; and \; t = 1, 2, 3, \dots, T$$

β_1, β_2, β_3, β_4 and β_5 are parameters to be estimated and ε_{it} is a composite error term. Within the context of this research, $i = 1, 2, 3, \dots, 16 \; and \; t = 1, 2, 3, \dots, 10$

In the course of this research, we hope to demonstrate that that there is dependency over time for each of the operational activities. That is,

$$Cov(U_{it}, U_{is} \; / \; x_{it}, x_{is}) = E(U_{it}, U_{is}) \neq 0 \qquad t \neq s \quad (3)$$

Within the context of PDRM, both the parameters and error terms of equation (2) shall be varied based on time that will result into the following equations:

$$AF_{it} = \beta_{1i} + \beta_2 PBT_{it} + \beta_3 TA_{it} + \beta_4 TL_{it} + \beta_5 SHF_{it} + \varepsilon_{it} \quad (4)$$

In estimation, we employ the dummy variable technique (i.e. the differential intercept dummies) to account for the periodic effect. Thus the model becomes

$$AF_{it} = \lambda_0 + \lambda_1 D_1 + \lambda_2 D_2 + \cdots + \lambda_9 D_9 + \beta_2 PBT_{it} + \beta_3 TA_{it} + \beta_4 TL_{it} + \beta_5 SHF_{it} + \varepsilon_{it} \quad (5)$$

λ_0 is the intercept of the tenth year while $\lambda_1, \lambda_2 \dots, \lambda_9$ and $D_1, D_2, \dots, D_9$ are the intercepts and dummy variables of the remaining years respectively.

In a situation where all the coefficients are allow to vary over time, we extend equation (5) to gives

$$AF_{it} = \lambda_0 + \lambda_1 D_1 + \lambda_2 D_2 + \cdots + \lambda_9 D_9 + \beta_2 PBT_{it} + \beta_3 TA_{it} + \beta_4 TL_{it} + \beta_5 SHF_{it} + \psi_1 (D_1 \, PBT_{it}) + \psi_2 (D_1 \, TA_{it}) + \psi_3 (D_1 \, TL_{it}) + \psi_4 (D_1 \, SHF_{it}) + \dots + \psi_{33} (D_9 \, PBT_{it}) + \psi_{34} (D_9 \, TA_{it}) + \psi_{35} (D_9 \, TL_{it}) + \psi_{36} (D_9 \, SHF_{it}) + \varepsilon_{it} \quad (6)$$

It is pertinent to note that equation (5) shall be our focus model within the context of FEM.

Similarly, for the REM, we recalled equation (4) and instead of treating as fixed, we assume that it is a random variable with a mean value of β_1. Thus, the intercept value for the individual bank can be expressed as

$$\beta_{1i} = \beta_1 + u_i \quad , \quad i = 1, 2, \dots, N \quad (7)$$

The individual differences in the intercept values of each bank are reflected in the error term u_i. if we substitute equation (7) in (4), we have

$$AF_{it} = \beta_1 + \beta_2 PBT_{it} + \beta_3 TA_{it} + \beta_4 TL_{it} + \beta_5 SHF_{it} + u_i + \varepsilon_{it} \quad (8)$$

Equation (8) implies

$$AF_{it} = \beta_1 + \beta_2 PBT_{it} + \beta_3 TA_{it} + \beta_4 TL_{it} + \beta_5 SHF_{it} + \omega_{it} \quad (9)$$

Where $\omega_{it} = u_i + \varepsilon_{it}$

Thus, the composite error term ω_{it} consists of two components u_i(cross section error component) and ε_{it} which is the combined time series and cross-section error component.

1.2 Model Estimation Techniques:

Here, we provide brief theoretical overview of the three (3) techniques considered in this study.

(i) **Pooled OLS:** This technique pool the data over i and t into one nT observations, and estimates of the parameters are obtained by OLS using the model

$$\mathbf{y} = X'\beta + \omega \quad (10)$$

where $\mathbf{y}$ is an nT × 1 column vector of response variables, X is an nT × k matrix of regressors, β is a (k+1) × 1 column vector of regression coefficients, ω is an nT × 1 column vector of the combined error terms (i.e $\epsilon_i + u_{it}$). The Pooled estimator is given as

$$\hat{\beta}_{pooled} = (X'X)^{-1} X' y \quad (11)$$

(ii) **Fixed Effect Least Square Dummy Variable:** Let Y_i and X_i be the T observations for the i_{th} unit, i be a $T \; x \; 1$ column of ones, and let e_i be associated $T \; x \; 1$ vector of disturbances. Then

$$Y_i = X_i\beta + \mathbf{i}\alpha_i + e_i \quad (12)$$

Connecting these terms in matrix form gives

$$Y = [X \quad d_1 \quad d_2 \quad \dots \quad d_N] \begin{bmatrix}\beta \\ \alpha\end{bmatrix} + e_i \quad (13)$$

where d_i is a dummy variable indicating the i^{th} unit.

Let the NT x N matrix $D = [\, d_1 \quad d_2 \quad \dots \quad d_n]$ then, assembling all NT rows gives;

$$Y = X\beta + D\alpha + e_i \quad (14)$$

Estimating the equation using OLS gives an estimator

$$\hat{\beta} = [X' M_D X]^{-1} [X' M_D y] \quad (15)$$

$where\ D\ is\ the\ i^{th}\ dummy\ variable$, $M_D = -D(D'D)^{-1}D'$, $the\ transformed\ data\ X = M_D X\ and\ Y = M_D\, y$.

(iii) Random Effect Estimator: Consider a random effect model

$$Y_{it} = \beta_0 + \beta_i X_{it} + a_i + u_{it} \quad (16)$$

we employ GLS estimator by transforming model (16) into

$$\bar{Y}_{it} = \beta_0 + \beta_1 \bar{X}_{it} + \bar{V}_{it} \quad (17)$$

We then multiply equation (17) by λ and takes its difference from equation (16) to have

$$Y_{it} - \lambda\bar{Y}_{it} = \beta_0(1-\lambda) + \beta_1(X_{it} - \bar{X}_{it}) + v_{it} - \lambda\bar{V}_{it} \quad (18)$$

Thus, the GLS estimator for the slope parameter of (18) becomes

$$\hat{\beta}_{RE} = (X'\,\Omega^{-1}X)^{-1}(X'\,\Omega^{-1}y) \quad (19)$$

$where$

$$\Omega^{1/2} = \sigma_u^{-1}(I - T^{-1}\lambda i_T i_T') \quad (20)$$

And λ $(the\ key\ transformation\ parameter)\ is\ given\ as$

$$\hat{\lambda} = 1 - \left(\frac{\sigma_u^2}{\sigma_u^2 + \sigma_\varepsilon^2}\right)^{1/2} \quad (21)$$

Thus, equation (19) is the specific GLS estimator called Random effect estimator.

(iv) **Hausman Test:** This is employed to test for the consistency of the random effect and fixed effect estimator. The hypothesis for the Hausman test is stated as

$$H_0 : Cov(X_{it}, a_i) = 0$$
$$H_1 : Cov(X_{it}, a_i) \neq 0$$

Under the null hypothesis, both random and fixed effects are consistent i.e

$$\tilde{\beta}_{RE} \xrightarrow{\rho} \approx \beta, \qquad \tilde{\beta}_{FE} \xrightarrow{\rho} \approx \beta$$

Thus, we can expect that $\hat{\beta}_{RE} \approx \hat{\beta}_{FE}$

However, under H_1, only $\hat{\beta}_{FE}$ is consistent. Therefore, we reject H_0 if the difference between $\hat{\beta}_{RE}\ and\ \hat{\beta}_{FE}$ is large enough.

1.3 Model Testing:

Here, we shall employ a two-way error component model as earlier emphasized, to test for the violation of homoscedasticity assumption in our researched model.

Considering a two-way error component model stated as:

$$y_{it} = x_{it}\beta + u_{it}\ ,;\ i = 1,2,\dots,N\ \ t = 1,2,\dots,T \quad (22)$$

Within the context of two-way error component, the regression disturbances term u_{it} can be described by the equation

$$u_{it} = \mu_i + \lambda_t + v_{it} \quad (23)$$

With μ_i representing individual-specific effect, λ_t representing time-specific effect and v_{it} the idiosyncratic remainder disturbance term, which is usually assumed to be well-behaved and independent from both the regressors x_{it} and μ_i. The two-way error component model can be written in matrix form as

$$y = X\beta + u \quad (24)$$

The disturbance term u in equation (24) can be written in vector form as

$$u = (I_{NT} \otimes \iota_{NT})\upsilon + (I_N \otimes \iota_T)\mu + (I_T \otimes \iota_N)\lambda + V \quad (25)$$

Where I_{NT} is an identity matrix of dimension NT, I_N is an identity matrix of dimension N, I_T is an identity matrix of dimension T, ι_{NT} is a vector of ones of dimension NT, ι_T is a vector of ones of dimension T, ι_N is a vector of ones of dimension N, $\mu' = (\mu_1, \dots\ ,\mu_N)$, $\lambda' = (\lambda_1, \dots\ ,\lambda_T)$, V is the AR(1) covariance matrix of dimension T, $\otimes$ denotes the kronecker product and

$$Var(\mu_i) = \sigma_{\mu i}^2 = h\left(f_i'(\alpha)\right)\ \ ,i = 1, \dots,\ N \quad (26)$$

According to Breusch and Pagan (1980), the function $h(\cdot)$ is an arbitrary strictly positive twice continuously differentiable function, $\alpha\ is\ a\ P\ x\ 1$ vector of unrestricted parameters and f_i is a $P\ x\ 1$ vector of strictly exogenous regressors which determine the heteroscedasticity of the individual specific effects and the first element of f_i is one, and without loss of generality, $h(\alpha_1) = \sigma_\mu^2$.

Following Baltagi, Jung and Song (2010), the variance-covariance matrix of u can be written as

$$E(uu') = \Sigma = \sigma_u^2(I_N \otimes \iota_T\, \iota_T') + (I_T \otimes \iota_N\iota_N')\sigma_\lambda^2 + \sigma_v^2 I_{NT}\ \otimes V$$

$$= (I_N \otimes \iota_T) diag[h(f_i'\alpha)](I_N \otimes \iota_T)' + (I_T \otimes \iota_N\iota_N')\sigma_\lambda^2 + \sigma_v^2 I_{NT}\ \otimes V$$

$$= diag[h(f_i'\alpha)] \otimes J_T + (I_T \otimes \iota_N\iota_N')\sigma_\lambda^2 + \sigma_v^2 I_{NT}\ \otimes V \quad (27)$$

Where J_T is a matrix of ones of dimension T, $diag[h(f_i'\alpha)]$ is a diagonal matrix of dimension NxN and V can be expressed as

$$V = E(VV') = \sigma_v^2\left(\frac{1}{1-\rho^2}\right)V_1 \quad (28)$$

$where\ V_1$ is a symmetric matrix of order ρ^{T-N}

1.3.1 Conditional LM Test for $H_0 : \sigma_{\mu i}^2 = \sigma_\mu^2, \forall_i\ and\ \sigma_{\lambda t}^2 \neq 0\ but\ \sigma_{v_{it}}^2 \neq 0, \rho > 0$

Here, we derive a conditional LM test for a case of homoscedastic random individual in the presence of first order serial correlation by setting $\tilde{\theta}' = (\sigma_v^2, \sigma_\mu^2, \sigma_\lambda^2, \alpha')$. Under normality of the disturbances, the log-likelihood function, L of a Lagrange multiplier follows that of a multivariate normal distribution. Thus,

$$L(\beta, \theta) = \frac{-NT}{2}\ln(2\pi) - \frac{1}{2}ln|\Sigma| - \frac{1}{2}u'^{\Sigma^{-1}}u \quad (29)$$

$L(\beta, \theta)$ becomes$\left(\beta, \tilde{\theta}'\right)$ $and\ we\ set\ \eta = (\beta', \sigma_v^2, \sigma_\mu^2, \sigma_\lambda^2, \alpha')$. In order to obtain the conditional LM statistic, we need to obtain the score statistic $D(\theta) = \frac{\partial L}{\partial \theta}$ and the Information matrix $I(\theta) = -E[\frac{\partial L^2}{\partial\theta\partial\theta'}]$.

Under H_0, the variance covariance matrix of the disturbance term as given by equation (27) becomes

$$\Sigma = \sigma_\mu^2(I_N \otimes I_T) + \sigma_\lambda^2 I_N I_N' + \sigma_v^2(I_{NT} \otimes)V_\rho) \quad (30)$$

$where\ V_\rho = \left(\frac{1}{1-\rho^2}\right)V_1\ and\ V_1 is\ the\ AR(1) correlation\ matrix$

According to Baltagi et al. (2010), the inverse of Σ under H_0 becomes

$$\Sigma^{-1} = \frac{1}{\sigma_v^2}\left(I_N \otimes V_\rho^{-1}\right) - \left(\frac{\sigma_\mu^2}{\sigma_v^2\sigma_\lambda^2\lambda^2}\right)\left(I_N \otimes V_\rho^{-1} J_T V_\rho^{-1}\right) \quad (31)$$

Therefore,

$$\frac{\partial L}{\partial \alpha_k} = D(\hat{\alpha}_k) = -\frac{1}{2}tr\left[\Sigma^{-1}\left(\frac{\partial \Sigma}{\partial \sigma_\lambda^2}\right)\right] + \frac{1}{2}\left[\hat{u}'\Sigma^{-1}\left(\frac{\partial \Sigma}{\partial \sigma_\lambda^2}\right)\Sigma^{-1}\hat{u}\right]$$

$$= -\frac{1}{2}tr\left[\frac{h'(\hat{\alpha}_1)}{\hat{\sigma}_v^2}\left\{\left(diag(f_{ik})\otimes\hat{V}_\rho^{-1}J_T\right) - \left(\frac{\hat{\sigma}_\mu^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\right)\left(diag(f_{ik})\otimes\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}J_T\right)\right\}\right]$$

$$+\frac{1}{2}\hat{u}'\left[\frac{h'(\hat{\alpha}_1)}{\hat{\sigma}_v^4}\left\{\left(diag(f_{ik})\otimes\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}\right) - 2\left(\frac{\hat{\sigma}_\mu^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\right)\left(diag(f_{ik})\otimes\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}\right)\right\} + \left(\frac{\hat{\sigma}_\mu^4}{\hat{\sigma}_\lambda^4\hat{\lambda}^4}\right)\left(diag(f_{ik})\otimes\right.\right.$$

$$\left.\left.\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}\right)\hat{u}\right]$$

$$= -\frac{h'(\hat{\alpha}_1)}{2\hat{\sigma}_v^2}\left[\varphi^2(1-\hat{\rho})^2\sum_{i=1}^N f_{ik} - \frac{\hat{\sigma}_\mu^2\varphi^4(1-\hat{\rho})^4}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\sum_{i=1}^N f_{ik}\right]$$

$$+\frac{h'(\hat{\alpha}_1)}{2\hat{\sigma}_v^4}\left[\hat{u}'^{\sum_{i=1}^N f_{ik}}\otimes(\varphi^2(1-\hat{\rho})^2\hat{V}_\rho^{-1} - 2\frac{\hat{\sigma}_\mu^2\varphi^4(1-\hat{\rho})^4}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\hat{V}_\rho^{-1} + \frac{\hat{\sigma}_\mu^4\varphi^6(1-\hat{\rho})^6}{\hat{\sigma}_\lambda^4\hat{\lambda}^4}\hat{V}_\rho^{-1})\hat{u}\right]$$

$$= -\frac{h'(\hat{\alpha}_1)\varphi^2(1-\hat{\rho})^2}{2\hat{\sigma}_v^2}\left[1-\frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\right]\sum_{i=1}^N f_{ik}$$

$$+\frac{h'(\hat{\alpha}_1)(\varphi^2(1-\hat{\rho})^2}{2\hat{\sigma}_v^4}\left[\hat{u}'\hat{V}_\rho^{-1}(1-2\frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2} + \frac{\hat{\sigma}_\mu^4\varphi^4(1-\hat{\rho})^4}{\hat{\sigma}_\lambda^4\hat{\lambda}^4})\hat{u}\right]\sum_{i=1}^N f_{ik}$$

$$= \frac{h'(\hat{\alpha}_1)(\varphi^2(1-\hat{\rho})^2}{2\hat{\sigma}_v^4}\sum_{i=1}^N f_{ik}\left[\hat{u}'\hat{V}_\rho^{-1}\left(1-2\frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2} + \frac{\hat{\sigma}_\mu^4\varphi^4(1-\hat{\rho})^4}{\hat{\sigma}_\lambda^4\hat{\lambda}^4}\right) - \left(1-\frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\right)\right]$$

$$= \frac{h'(\hat{\alpha}_1)(\varphi^2(1-\hat{\rho})^2}{2\hat{\sigma}_v^4}\sum_{i=1}^N f_{ik}\left[\hat{u}'\hat{V}_\rho^{-1}\left(1-2\frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2} + \frac{\hat{\sigma}_\mu^4\varphi^4(1-\hat{\rho})^4}{\hat{\sigma}_\lambda^4\hat{\lambda}^4}\right)\hat{u} - 1 + \frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\right]$$

$$= \frac{h'(\hat{\alpha}_1)(\varphi^2(1-\hat{\rho})^2}{2\hat{\sigma}_v^4}\sum_{i=1}^N f_{ik}\left(\hat{u}_i'\hat{A}\hat{u}_i - 1 + \frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}\right), \qquad k = 1,\dots,p \tag{32}$$

Equation (32) is the solution obtained after maximization of the first order condition, where $\hat{A} = \hat{V}_\rho^{-1}\left(1 - 2\frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2} + \frac{\hat{\sigma}_\mu^4\varphi^4(1-\hat{\rho})^4}{\hat{\sigma}_\lambda^4\hat{\lambda}^4}\right)$, $\hat{u} = y - x\hat{\beta}_{GLS}$ is the maximum likelihood residuals under H_0, $\hat{\beta}, \hat{\sigma}_v^2$, $\hat{\sigma}_\mu^2$ and $\hat{\alpha}_1$ is the maximum likelihood estimates of $\beta, \sigma_v^2, \sigma_\mu^2, \sigma_\lambda^2$ *and* α_1 respectively.

All components of the above score test statistic $\frac{\partial L}{\partial \eta}(\cdot)$ evaluated at $\hat{\eta}$ are equal to zero except $\frac{\partial L}{\partial \alpha}$ (Kouassi et al., 2014). Also, $\hat{\sigma}_\mu^2$ is the value of $h(\hat{\alpha}_1)$ and $h'(\hat{\alpha}_1)$ is the evaluated value of $\partial h(f_i'\alpha)/\partial f_i'$ when $\alpha_1 = \alpha_1 = \cdots = \alpha_p = 0$. In addition, $tr\left(\hat{V}_\rho^{-1}J_T\right) = \varphi^2(1-\hat{\rho})^2$ and $tr\left(\hat{V}_\rho^{-1}J_T\hat{V}_\rho^{-1}J_T\right) = \varphi^4(1-\hat{\rho})^4$.

Thus, the partial derivatives under H_0 are expressed in vector form as

$$D(\hat{\eta}) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ D(\hat{\alpha}) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \frac{h'(\hat{\alpha}_1)\varphi^2(1-\hat{\rho})^2}{2\hat{\sigma}_v^4}F'g \end{pmatrix} \tag{33}$$

Where $D(\hat{\alpha}) = \left((\hat{\alpha}_1), D(\hat{\alpha}_2), \dots, D(\hat{\alpha}_p)\right)'$, $F = (f_1, \dots, f_N)'$ *and* $g = (g_1, \dots, g_N)$ where $g_i = \hat{u}_i'\hat{A}\hat{u}_i - 1 + \frac{\hat{\sigma}_\mu^2\varphi^2(1-\hat{\rho})^2}{\hat{\sigma}_\lambda^2\hat{\lambda}^2}$

Also, we obtain information matrix under the null hypothesis as follow

$$E\left[-\frac{\partial L^2}{\partial\eta\partial\eta'}\right] = \frac{1}{2}tr\left[\Sigma^{-1}\left(\frac{\partial\Sigma}{\partial\eta}\right)\Sigma^{-1}\frac{\partial\Sigma}{\partial\eta'}\right]$$

$$E\left[-\frac{\partial^2 L}{\partial\beta\partial\beta'}\right] = \frac{1}{2}tr[X'\Sigma^{-1}X]^2$$

$$= \frac{1}{2}tr[X'\Sigma^{-1}X\,X'\Sigma^{-1}X] = N\overset{lim}{\longrightarrow}\infty\left[\frac{X'\Sigma^{-1}X}{NT}\right] = I_{\beta\beta}(\hat{\eta})$$

$$E\left[-\frac{\partial^2 L}{\partial\beta\partial\sigma_v^2}\right] = \frac{1}{2}tr\left[X'\Sigma^{-1}X\frac{1}{\sigma_v^2}\left\{(I_N\otimes I_T) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N\otimes V_\rho^{-1}J_T\right)\right\}\right] = 0$$

$$\left(since\ E\left[-\frac{\partial^2 L}{\partial\beta\partial\sigma_v^2}\right]\xrightarrow{N,T\to\infty}0\right)$$

$$E\left[-\frac{\partial^2 L}{\partial\beta\partial\sigma_\mu^2}\right] = \frac{1}{2} tr\left[X'\Sigma^{-1}X\frac{1}{\sigma_v^2}\left\{\left(I_N \otimes V_\rho^{-1}J_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N \otimes V_\rho^{-1}J_T V_\rho^{-1}\right)\right\}\right] = 0$$

$$\left(since\ E\left[-\frac{\partial^2 L}{\partial\beta\partial\sigma_\mu^2}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$E\left[-\frac{\partial^2 L}{\partial\beta\partial\sigma_\lambda^2}\right] = \frac{1}{2} tr\left[X'\Sigma^{-1}X\frac{1}{\sigma_v^2}\left\{\left(I_N I_N' \otimes V_\rho^{-1}\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N I_N' \otimes V_\rho^{-1}J_T V_\rho^{-1}\right)\right\}\right] = 0$$

$$\left(since\ E\left[-\frac{\partial^2 L}{\partial\beta\partial\sigma_\lambda^2}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$\left[-\frac{\partial^2 L}{\partial\beta\partial\alpha_k}\right] = \frac{1}{2} tr\left[X'\Sigma^{-1}X\frac{h'(\alpha_1)}{\sigma_v^2}\left\{\left(diag(f_{ik}) \otimes V_\rho^{-1}J_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(diag(f_{ik}) \otimes V_\rho^{-1}J_T V_\rho^{-1}J_T\right)\right\}\right]$$

$$= 0\ \left(since\ E\left[-\frac{\partial^2 L}{\partial\beta\partial\rho}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_v^4}\right] = \frac{1}{2} tr\left[\frac{1}{\sigma_v^2}\left\{\left(I_N \otimes I_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N \otimes V_\rho^{-1}J_T\right)\right\}\right]^2$$

$$= \frac{NT}{2\hat\sigma_v^4} - \frac{N\hat\sigma_\mu^2\varphi^2(1-\hat\rho)^2}{\hat\sigma_\lambda^2\hat\lambda^2\hat\sigma_v^4} + \frac{N\hat\sigma_\mu^4\varphi^4(1-\hat\rho)^4}{2\hat\sigma_v^4\hat\sigma_\lambda^4\hat\lambda^4} = \frac{NT}{2\hat\sigma_v^4}\left(1 - 2\frac{\hat\sigma_\mu^2\varphi^2(1-\hat\rho)^2}{T\hat\sigma_\lambda^2\hat\lambda^2} + \frac{\hat\sigma_\mu^4\varphi^4(1-\hat\rho)^4}{T\hat\sigma_\lambda^4\hat\lambda^4}\right) = \frac{1}{2}(\hat\sigma)_v^4$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_v^2\partial\sigma_\mu^2}\right] = \frac{1}{2} tr\left[\frac{1}{\sigma_v^2}\left(\left(I_N \otimes I_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N \otimes V_\rho^{-1}J_T\right)\right)\frac{1}{\sigma_v^2}\left(\left(I_N \otimes V_\rho^{-1}J_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N \otimes V_\rho^{-1}J_T V_\rho^{-1}\right)\right)\right] = 0$$

$$\left(since\ E\left[-\frac{\partial^2 L}{\partial\sigma_v^2\partial\sigma_\mu^2}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_v^2\partial\sigma_\lambda^2}\right] = \frac{1}{2} tr\left[\frac{1}{\sigma_v^2}\left(\left(I_N \otimes I_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N \otimes V_\rho^{-1}J_T\right)\right)\frac{1}{\sigma_v^2}\left(\left(I_N I_N' \otimes V_\rho^{-1}\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N I_N' \otimes V_\rho^{-1}J_T V_\rho^{-1}\right)\right)\right]$$

$$= 0\ \left(since\ E\left[-\frac{\partial^2 L}{\partial\sigma_v^2\partial\sigma_\lambda^2}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$\left[-\frac{\partial^2 L}{\partial\sigma_v^2\partial\alpha_k}\right] = \frac{1}{2} tr\left[\frac{1}{\sigma_v^2}\left(\left(I_N \otimes I_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(I_N \otimes V_\rho^{-1}J_T\right)\right)\frac{h'(\alpha_1)}{\sigma_v^2}\left(\left(diag(f_{ik}) \otimes V_\rho^{-1}J_T\right) - \left(\frac{\sigma_\mu^2}{\sigma_\lambda^2\lambda^2}\right)\left(diag(f_{ik}) \otimes\right.\right.\right.$$

$$\left.\left.\left.V_\rho^{-1}J_T V_\rho^{-1}J_T\right)\right)\right] = \frac{h'(\hat\alpha_1)(\varphi^2(1-\hat\rho)^2}{2\hat\sigma_v^4}F\left(1 - \frac{\hat\sigma_\mu^2\varphi^2(1-\hat\rho)^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)^2 = 0\left(since\ E\left[-\frac{\partial^2 L}{\partial\sigma_v^2\partial\sigma_\lambda^2}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_\mu^4}\right] = \frac{1}{2} tr\left[\frac{1}{\hat\sigma_v^2}\left(\left(I_N \otimes \hat V_\rho^{-1}J_T\right) - \left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(I_N \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}\right)\right)\right]^2 = \frac{N\varphi^4(1-\hat\rho)^4}{2\hat\sigma_v^4}\left(1 - 2\frac{\hat\sigma_\mu^2\varphi^2(1-\hat\rho)^2}{\hat\sigma_\lambda^2\hat\lambda^2} + \frac{\hat\sigma_\mu^4}{\hat\sigma_\lambda^4\hat\lambda^4}\right) = \frac{1}{2}(\hat\sigma)_\mu^4$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_\mu^2\partial\sigma_\lambda^2}\right] = \frac{1}{2} tr\left[\frac{1}{\hat\sigma_v^2}\left(\left(I_N \otimes \hat V_\rho^{-1}J_T\right) - \left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(I_N \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}\right)\right)\frac{1}{\hat\sigma_v^2}\left(\left(I_N I_N' \otimes \hat V_\rho^{-1}\right) - \left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(I_N I_N' \otimes\right.\right.\right.$$

$$\left.\left.\left.\hat V_\rho^{-1}J_T\hat V_\rho^{-1}\right)\right)\right] = 0\ \left(since\ E\left[-\frac{\partial^2 L}{\partial\sigma_\mu^2\sigma_\lambda^2}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_\mu^2\partial\alpha_k}\right]\frac{1}{2} = tr\left[\frac{1}{\hat\sigma_v^2}\left(\left(I_N \otimes \hat V_\rho^{-1}J_T\right) - \left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(I_N \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}\right)\right)\frac{h'(\hat\alpha_1)}{\hat\sigma_v^2}\left(\left(diag(f_{ik}) \otimes \hat V_\rho^{-1}J_T\right) -\right.\right.$$

$$\left.\left.\left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(diag(f_{ik}) \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}J_T\right)\right)\right] = \frac{h'(\hat\alpha_1)\varphi^4(1-\hat\rho)^4}{2\hat\sigma_v^4}N\overset{lim}{\longrightarrow}\infty\left[\frac{I_N' F}{N}\right]$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_\lambda^4}\right] = \frac{1}{2} tr\left[\frac{1}{\hat\sigma_v^2}\left(\left(I_N I_N' \otimes \hat V_\rho^{-1}\right) - \left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(I_N I_N' \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}\right)\right)\right]^2 = \frac{N}{2\hat\sigma_v^4}\left(1 - \frac{\hat\sigma_\mu^2\varphi^2(1-\hat\rho)^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)^2 = \frac{1}{2}(\hat\sigma)_\lambda^4$$

$$E\left[-\frac{\partial^2 L}{\partial\sigma_\lambda^2\partial\alpha_k}\right] = \frac{1}{2} tr\left[\frac{1}{\hat\sigma_v^2}\left(\left(I_N I_N' \otimes \hat V_\rho^{-1}\right) - \left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(I_N I_N' \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}\right)\right)\frac{h'(\hat\alpha_1)}{\hat\sigma_v^2}\left(\left(diag(f_{ik}) \otimes \hat V_\rho^{-1}J_T\right) -\right.\right.$$

$$\left.\left.\left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(diag(f_{ik}) \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}J_T\right)\right)\right] = 0\left(since\ E\left[-\frac{\partial^2 L}{\partial\sigma_\lambda^2\partial\alpha_k}\right]\xrightarrow{N,T\to\infty} 0\right)$$

$$E\left[-\frac{\partial^2 L}{\partial\alpha_k\partial\alpha_k'}\right] = \frac{1}{2} tr\left[\frac{h'(\hat\alpha_1)}{\hat\sigma_v^2}\left(diag(f_{ik}) \otimes \hat V_\rho^{-1}J_T\right) - \left(\frac{\hat\sigma_\mu^2}{\hat\sigma_\lambda^2\hat\lambda^2}\right)\left(diag(f_{ik}) \otimes \hat V_\rho^{-1}J_T\hat V_\rho^{-1}J_T\right)\right]^2$$

$$= \frac{h'(\hat{\alpha}_1)^2}{2\hat{\sigma}_v^4} tr\left[\left(diag(f_{ik}f_{ik}) \otimes \hat{V}_\rho^{-1} J_T \hat{V}_\rho^{-1} J_T\right) - 2\left(\frac{\hat{\sigma}_\mu^2}{\hat{\sigma}_\lambda^2 \hat{\lambda}^2}\right)\left(diag(f_{ik}f_{ik}) \otimes \hat{V}_\rho^{-1} J_T \hat{V}_\rho^{-1} J_T \hat{V}_\rho^{-1} J_T\right) + \left(\frac{\hat{\sigma}_\mu^4}{\hat{\sigma}_\lambda^4 \hat{\lambda}^4}\right)\left(diag(f_{ik}f_{ik}) \otimes \hat{V}_\rho^{-1} J_T \hat{V}_\rho^{-1} J_T \hat{V}_\rho^{-1} J_T \hat{V}_\rho^{-1} J_T\right)\right] = \frac{h'(\hat{\alpha}_1)^2 \varphi^4 (1-\hat{\rho})^4}{2\hat{\sigma}_v^4} N \xrightarrow{lim} \infty \left[\frac{F'F}{N}\right]$$

Thus, information matrix under the null hypothesis can be obtained as a symmetric matrix of the form $I(\hat{\eta}) =$

$$\begin{pmatrix} I_{\beta\beta}(\hat{\eta}_2) & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{2}(\hat{\sigma})_v^4 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2}(\hat{\sigma})_\mu^4 & 0 & \frac{h'(\hat{\alpha}_1)\varphi^4(1-\hat{\rho})^4}{2\hat{\sigma}_v^4} N \xrightarrow{lim} \infty \left[\frac{I_N' F}{N}\right] \\ 0 & 0 & 0 & \frac{1}{2}(\hat{\sigma})_\lambda^4 & 0 \\ 0 & 0 & \frac{h'(\hat{\alpha}_1)\varphi^4(1-\hat{\rho})^4}{2\hat{\sigma}_v^4} N \xrightarrow{lim} \infty \left[\frac{I_N' F}{N}\right] & 0 & \frac{h'(\hat{\alpha}_1)^2\varphi^4(1-\hat{\rho})^4}{2\hat{\sigma}_v^4} N \xrightarrow{lim} \infty \left[\frac{F'F}{N}\right] \end{pmatrix} \quad (34)$$

Thus, a conditional LM statistic under the specified H_0 is given as

$$LM_{\alpha|\rho} = D(\hat{\alpha})'[(I_{NT}(I(\hat{\eta})))^{-1}|_{\alpha\alpha}]D(\hat{\alpha}) \quad (35)$$

Where $(I(\hat{\eta}))^{-1}|_{\alpha\alpha} = \frac{h'(\hat{\alpha}_1)^2\varphi^4(1-\hat{\rho})^4}{2\hat{\sigma}_v^4} N \xrightarrow{lim} \infty \left[\frac{1}{N} F'\left(I_N - \frac{I_N I_N'}{N}\right) F\right]$

Under H_0, LM statistic is asymptotically distributed as χ_p^2 $as\ N, T \to \infty$

2. Results and Discussion:

The results of the three models fitted from the analytical techniques discussed and that of the test carried out to showcase the periodicity effects as occasioned by the presence of serial correlation, on the predictive ability of POLS are presented and discussed in this section

Table 1: Presentation of Pooled OLS Results

Variables	Coefficients	Standard Error	t-value	Pr(>|t|)
Intercept	120,970	10,011	12.0840	0.0000
PBT	80,588	0.00027278	2.9543	0.0036
TA	-260,960	0.000012963	-2.0131	0.0458
TL	8,048,200	0.0000035418	2.2724	0.0244
SHF	25,419	0.00012246	2.0757	0.0396

Table 2: Conditional Lagrange Multiplier Test for serial correlation

Chi-Squared	Degree of Freedom	P-value
35.3806	10	0.0001075

Table 3: Presentation of LSDVM Results that Accounts for Only Time Effects

Variables	Coefficients	Standard Error	t-value	Pr(>|t|)
Intercept	42,820	23810	1.799	0.074138
PBT	-0.0003292	0.00001201	-2.741	0.006900
TA	0.0007216	0.0002691	2.681	0.008175
TL	0.00000668	0.000003255	2.055	0.041701
SHF	0.0007216	0.0002691	2.681	0.008175
YEAR- 2007	0.0002586	0.000115	2.249	0.026005
2008	0.0002628	0.0003391	0.775	0.439568
2009	0.0009526	0.0003445	2.765	0.006422
2010	0.0008981	0.0003379	2.658	0.008741
2011	0.00001142	0.0003398	3.362	0.000989
2012	0.0008981	0.000339	2.658	0.008741
2013	0.00001253	0.0003421	3.664	0.000347

2014	0.00001561	0.0003463	4.507	0.0000134
2015	0.00001613	0.0003615	4.461	0.0000162

Table 4: Presentation of Random Effect Model Results that Accounts for Both Individual and Time Effects (Twoways effects Model)

Effects	**Variance**	**Standard Dev**	**Shares**	**Theta (Lambda)**
idiosyncratic	5809000000	76210	0.746	-
individual	1894000000	43520	0.243	0.5155
time	85800000	9263	0.011	0.1006
Total	-	-	-	0.08774
Variables	**Coefficients**	**Standard Error**	**t-value**	**Pr(>|t|)**
Intercept	130400	130400	1.6386	0.0000
PBT	0.00061736	26438	2.3351	0.02082
TA	-0.000011315	0.000013033	0.8682	0.38664
TL	0.0000079030	0.000003179	2.4860	0.01398
SHF	0.000099058	0.00012030	0.8234	0.41152

Table 5: Presentation Hausman Test Results

Chi square	**Df**	**p-value**
1193.6	4	0.0000

The specified models for POLS, LSDVM and REM from tables 1-3 respectively are given as follows:

$$AF = 120{,}970 + 80{,}588PBT - 260{,}960TA + 8{,}048{,}200TL + 25{,}419SHF \quad (30)$$

$(R^2 = 0.2043, \bar{R}^2 = 0.2523, F = 13.6451, DF(4{,}155), P - value = 0.0000)$

$(se(\hat{\beta}_2) = 0.00027278, se(\hat{\beta}_3) = 0.000012963, se(\hat{\beta}_4) = 0.000035418, se(\hat{\beta}_5) = 0.00012246)$

$$AF = 42{,}820 - 0.0003292\ PBT + 0.0007216\ \ TA + 0.00000668TL + 0.0007216SHF \quad (31)$$

$(R^2 = 0.4395, \bar{R}^2 = 0.3896, F = 8.807, DF(13.146), P - value = 0.0000)$

$(se(\hat{\beta}_2) = 0.00001413, se(\hat{\beta}_3) = 0.000003303, se(\hat{\beta}_4) = 0.00002772, se(\hat{\beta}_5) = 0.00001289)$

$$AF = 130{,}400 + 0.000062PBT - 0.000011TA + 0.0000079TL + 0.000099SHF \quad (32)$$

$(R^2 = 0.15611, \bar{R}^2 = 0.15611, F = 7.16815, DF(4{,}155), P - value = 0.0000)$

$(se(\hat{\beta}_2) = 0.00001201, se(\hat{\beta}_3) = 0.00002691, se(\hat{\beta}_4) = 0.000003255, se(\hat{\beta}_5) = 0.00002691)$

The three specified models are statistically significant based on their P-values which are less than 0.05 while there coefficient of determination, R^2 indicates that our exogenous variables explained 20.43%, 43.95% and 15.61% variation in the audit fees of Nigerian banks for the years under review respectively for POLS, LSDVM and REM. Meanwhile, the standard errors of regression coefficients for the POLS model are a bit higher than that of LSDV and REM models. The POLS's standard errors was due to the inefficiency of POLS estimator as induced by the presence of serial correlation while that of LSDV was equally due to the same reason as well as loss of degree of freedom from 155 to 146 as a result of dummy variables put into used.

The fact that serial correlation is present in the POLS estimator was established through the conduct of LM test. The LM result is chi squared distributed with value of 35.3806 and a P-value of 0.0001075, which is far less than the critical value of 0.05. This result prompts the rejection of our null hypothesis and thereby validates the presence of serial correlation in the POLS residual i.e $Corr(\eta_{it}, \eta_{is}) \neq 0$.

The LSDVM seems to be a better model to explain the specified audit fees model as a result of its lower standard errors and higher coefficient of determination, and this is further confirmed by its preference based on Hausman test.

3. Conclusion:

Various results obtained in this work generally showed that the behaviours of the three estimators investigated for modeling audit fees vary due to violation of serial correlation assumption. The efficiency of these methods for estimating audit fees model with violation of serial correlation assumptions has been addressed.

Failure of the serial correlation assumption makes the POLS estimators to be biased and imprecise. For POLS to be accurately used in estimating the parameters of panel data models, errors have to be independent and homoscedastic. These conditions are so atypical and mostly unrealistic in many real life situations that would have warranted the use of POLS for modeling panel data efficiently.

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