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COMPARING SOME PANEL DATA ESTIMATORS IN THE PRESENCE OF AUTOCORRELATION

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ABSTRACT
In this work, panel data that were characterized by features of no first order autocorrelation was modelled using three estimation models: Pool Regression, Fixed Effect, Random Effect models. Panel data like other aspects of econometrics, exploits regression analysis as one of the statistical tools to formulate and illustrate models. The regression analysis requires some assumptions which, if violated, results to one problem or the other. In such case, the Pooling method of estimation remains linear, unbiased and normally distributed but might not be efficient as the estimates of the parameters might become indeterminate, the confidence intervals may be too wide and the standard errors might become large. Simulation studies were carried out at different panel structures and autocorrelation level. The experiment was repeated for 10,000 times and Root Mean Square Error (RMSE) was used to judge the performance of the models. The results from this work showed that for small sample panel structure N = 25, T = 5 and n = 5, irrespective of autocorrelation levels, fixed effect model is preferable at all level. But when moderate for N = 50, T = 10, n = 5, irrespective of autocorrelation level, random effect model is preferred, while for large panel structure for N = 450, T = 30, n = 15, irrespective of autocorrelation level, random effect model is preferred.

Keywords: Pooled Regression, Fixed Effect, Random Effect, Autoregression

INTRODUCTION
A panel dataset is one where there are repeated observations on the same units. The units may be individuals, households, firms, regions or countries. Panel data have the combination of the features of both time-series and cross-sectional data. Hence, one of the problem that naturally afflict time-series data is autocorrelation is inherited by panel data and therefore need to be addressed while analyzing such data. Many distinctive features usually characterize panel data as abound in many econometrics settings, thus, the use of classical ordinary least squares (OLS) estimator for modelling such data becomes grossly inefficient. One of the critical assumptions of the classical linear regression model (CLRM) is that the error terms in the model are independent. If this assumption is violated, then serial correlation (or autocorrelation) is suspected $(\text{i.e}\ \text{cov}\ u_{it}, u_{is}) \neq 0, \text{for}\ t \neq s)$ Garba et al (2015).
Adenomon et al (2015) examined Short Term Forecasting Performances of Classical VAR and Sims-Zha Bayesian VAR Models for Time Series with Collinear Variables and Correlated Error Terms Forecasts they worked short term forecast because of the problem of limited data or time series data that often encounter in time series analysis. The simulation studied considers the performances of the classical VAR and Sims-Zha Bayesian VAR for short term series at different levels of collinearity and correlated error terms. The results from 10,000 iteration reveal that the BVAR models are excellent for time series length of T = 8 for all levels of collinearity while the classical VAR is effective for time series length of T = 16 for all collinearity levels except when ρ = −0.9 and ρ = −0.95. Therefore, we recommend that for effective short term forecasting, the time series length, forecasting horizon and the collinearity level should be considered.
Olajide et al (2017) Studied Dynamic Panel Data (DPD) model estimation that has been limited by two major problems; autocorrelation resulting from the inclusion of a lagged dependent variable among the explanatory variables and the unobserved main effects and interaction effects characterizing the heterogeneity among the individuals which may lead to invalid parameter estimate. Their investigated the performance of some Generalized Method of Moment (GMM) estimators of DPD models in the presence of autocorrelated disturbance term. One-way error component model (ECM) of a random effects dynamic model with one exogenous variable was considered using a Monte Carlo experiment with 500 replications when cross-section dimension (N) is large and time series dimension (T) is finite for varying degrees of autocorrelated disturbance terms. The bias and root mean square error (RMSE) criterions were used to assess the performance of the estimators. The result of Simulation revealed that Blundell-Bond System (SSY) GMM estimator performed better when T is small while Arelano-Bond (AB) GMM estimator performed better when T is large.
Badi et al (2003) worked on spatial panel data regression model with serial correlation on each spatial unit over time as well as spatial dependence between the spatial units at each point in time. In addition, the model allows for heterogeneity across the spatial units using random effects. The result derived several Lagrange Multiplier tests for panel data regression model including a joint test for serial correlation, spatial autocorrelation and random effects. The tests draw upon two strands of earlier work. The first is the LM tests for the spatial error correlation model and the second is the LM tests for the error component panel data model with serial correlation. Hence the joint LM test derived in their work encompasses those derived in both strands of earlier works. In fact, in the context of the general model, the earlier LM tests become marginal LM tests that ignore either serial correlation over time or spatial error correlation. Their derived conditional LM and LR tests that do not ignore these correlations and contrast them with their marginal LM and LR counterparts. The small sample performance of these tests is investigated using Monte Carlo experiments. As expected, ignoring any correlation when it is significant can lead to misleading inference.
Tobechukwu and Azubuike (2020) examined some panel data estimators in the presence of serial and spatial autocorrelation with panel heteroscedasticity. The study was done using two different

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sets of data simulated separately with ρ=0.95 and 0.50. For each set of simulations, short and long panels were considered for different sample sizes. The analysis considered two settings were rho is considered to be panel-specific (ρi) and where rho is considered to be common for all panels (ρ). The estimators were examined based on bias, overconfidence and relative efficiency. The results revealed evidence that the size of the autocorrelation coefficient ρ affects the general performance of an estimator. Comparison of the estimators showed that Panel Corrected Standard Error Estimator (PCSE) produced better results than the other estimators considered in their work. But it was seen to do very well in small samples and short panels. In terms of relative efficiency Park-Kmenta estimator was found to be more efficient that PCSE and PWLS (Panel Weighted Least Square Estimator). The results also show that the size of rho at the long run has an impact on the performance of the estimators, while at small size of rho tends to increase overconfidence.

Badi (2008) considered a panel data regression model with heteroskedastic as well as serially correlated disturbances, and derives a joint LM test for homoskedasticity and no first order serial correlation. The restricted model is the standard random individual error component model. It also derives a conditional LM test for homoskedasticity given serial correlation, as well as, a conditional LM test for no first order serial correlation given heteroskedasticity, all in the context of a random effects panel data model. Monte Carlo results show that these tests along with their likelihood ratio alternatives have good size and power under various forms of heteroskedasticity including exponential and quadratic functional forms

Benjamin and Jorg (2010) investigated three new tests for serial correlation in the disturbances of fixed effects panel data models with a small number of time periods. First, modify the panel Durbin-Watson statistic such that it has a standard normal limiting distribution for fixed T and N → ∞. The second test was based on LM statistic and the third test employs an unbiased estimator for the autocorrelation coefficient. The first two tests are robust against cross-sectional but not time dependent heteroskedasticity and the third statistic is robust against both forms of heteroskedasticity. Furthermore, all test statistics can be easily adapted to unbalanced data. Monte Carlo simulations suggest that our new tests have good size and power properties compared to the popular Wooldridge-Drukker test. This study will compare the simulation performances using Pooled Regression, Fixed effect and Random effect models and to find the best estimator among three models using root mean squared errors (RMSE) of parameter estimates.

Mohammed et al (2013) the work investigates the efficiency of four methods of estimating panel data models (Pooling (OLS), First-Differenced (FD), Between (BTW) and Feasible Generalized Least Squares (FGLS)) when the assumptions of homoscedasticity, no autocorrelation and no collinearity are jointly violated. Monte-Carlo studies were carried out at different sample sizes, at varying degrees of heteroscedasticity, different levels of collinearity and autocorrelation all at different time periods. The results from this work revealed that in small sample situation, irrespective of number of time length, FGLS estimator is efficient when heteroscedasticity is severe regardless of levels of autocorrelation and multicollinearity. However, when heteroscedasticity is low or mild with moderate autocorrelation level, both FD and FGLS are efficient, while BTW performs better only when there is no autocorrelation and low degree of heteroscedasticity. However, in large sample with short time periods, both FD and BTW could be used when there is no autocorrelation and low degree of heteroscedasticity, while FGLS is preferred elsewise. Meanwhile, pooling estimator performs better when the assumptions of homoscedasticity, independent of error terms and orthogonality among the explanatory variables are justifiably valid.

MATERIALS AND METHODS

This work considers Pooled Regression, Fixed Effect and Random Effect models with three exogenous and one endogenous variables. The autocorrelation work done by Lillard and Wallis (1978), Bhargava et al (1983) and Garba et al (2015) to mention but a few. Most of the earlier works on autocorrelated disturbances focused on single exogenous variable and two exogenous variables. We, however, considered three exogenous variables with the possibility of existence of collinearity between them and this effects with respect to stability while efficiency of the estimation methods for panel data models were examined

Pooled Regression model

The pooled model does not differ from the common regression equation. It regards each observation as unrelated to the others ignoring panels and time. No panel information is used. A pooled model can be expressed as:

$$y_{it} = B_0 + B_1x_{1,it} + B_2x_{2,it} + \ . \ . \ . + B_kx_{k,it} + \varepsilon_{it} \qquad 1$$

A pooled model is used under the assumption that the individuals behave in the same way, where there is homoscedasticity and no autocorrelation. Only then OLS can be used for obtaining efficient estimates from the model in equation (1)

Fixed effects model

One of the advantages of using panel data as mention in equation 1 above is that models like the fixed effects model can deal with the unobserved heterogeneity. The fixed effects model for k factors can be expressed in the following way:

$$y_{it} = \alpha_0 + B_1x_{1,it} + B_2x_{2,it} + \ . \ . \ . + B_kx_{k,it} + \varepsilon_{it} \qquad 2$$

There is no constant term in the fixed effects model. Instead of the constant term B_0 in pooled model (1), now we have an individual-specific component α_i that determines a unique intercept for each individual. However, the slopes (the β parameters) are the same for all individuals

Random effects model

In the random effects model the individual-specific component α is not treated as a parameter and it is not being estimated. Instead, it is considered as a random variable with mean μ and variance $\sigma^2{}_u$. The random effects model can thus be written as:

$$y_{it} = \mu + B_1x_{1,it} + B_2x_{2,it} + \ . \ . \ . + B_kx_{k,it} + (\alpha_i - \mu) + \varepsilon_{it} \qquad 4$$

Where μ is the average individual effect, Let $\mu_{it} = (\alpha_i - \mu) + \varepsilon_{it}$ and (3) can be rewritten as:

$$y_{it} = \mu + B_1x_{1,it} + B_2x_{2,it} + \ . \ . \ . + B_kx_{k,it} + \varepsilon_{it} \qquad 5$$

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Simulation Procedure

The dataset used for this study were simulated using Monte Carlo experiment in the environment of R statistical package which the dependent variable (y) had different level of autocorrelation

Step 1: Generate $X{\sim}N(N, O, 1)$

Step 2: Given $y = 50 + 25x + \varepsilon_t$ such that $\varepsilon_t = \rho v_{t-1} + v_t$

Such that $\rho = 0.5, 0.7, 0.9$ and 0.99

Step 3: Data was generated for different panel data structure

(i) N = 25, T = 5, n = 5
(ii) N = 50, T = 10, n = 5
(iii) N = 100, T = 10, n = 10
(iv) N = 450, T = 30, n = 15

Step 4: The experiment was repeated for 10,000 times and Root Mean Square Error (RMSE) was used judge the performance of the models

$$RMSE = \sqrt{\frac{\sum(\beta_i - \hat{\beta}_i)^2}{10000}} \quad \text{Where I = 1, 2, . . . 10000}$$

The model with the smallest RMSE is preferred among the competing models

Analysis on simulation for autocorrelation

In this chapter we shall be concerned with the analysis and interpretation of simulation data analysis

RESULTS AND DISCUSSION

Table 1 RMSE of Fixed Effect model in the presence of autocorrelation

	Autocorrelation levels							
	0.5		0.7		0.9		0.99	
Panel Structure/Model parameter	B_0	B_1	B_0	B_1	B_0	B_1	B_0	B_1
N=25 T=5 n=5		4.494095		4.577057		4.63345		4.703941
N=50 T=10 n=5		3.292825		3.794922		5.427457		7.766143
N=100 T=10 n=10		2.316926		2.649991		3.903451		6.966257
N=450 T=30 n=15		1.092535		1.285989		2.073846		5.34133

Table 1 above shows that as autocorrelation level (ρ) is increases for N =25, T = 5, and n =5 the Root Mean Square Error increases, as (ρ) is increases for N =50, T = 10, and n =5 the Root Mean Square Error increases, as (ρ) is increases for N = 100, T = 10, and n = 10 the Root Mean Square Error increases, as (ρ) is increases for N =450, T = 30, and n = 15 the Root Mean Square Error increases while as sample size increases for (ρ) = 0.5 the Root Mean Square Error decreases, as sample size increases for ρ = 0.7 the Root Mean Square Error decreases, as sample size increases for (ρ) = 0.9 the Root Mean Square Error decreases, as sample size increases for (ρ) = 0.99 the Root Mean Square Error decreases, therefore for fixed effect model the autocorrelation level for (ρ) = 0.5 is preferred.

Table 2: Random Effect model in the presence of autocorrelation

	Autocorrelation Levels							
Panel Structure/Model parameter	0.5		0.7		0.9		0.99	
	B_0	B_1	B_0	B_1	B_0	B_1	B_0	B_1
N=25 T=5 n=5	7.866705	4.498928	12.59654	4.65496	31.81468	4.782513	137.6591	4.959946
N=50 T=10 n=5	5.635049	3.233015	9.113077	3.741035	25.00935	5.383944	130.0881	7.797073
N=100 T=10 n=10	3.975798	2.271486	6.538878	2.657743	19.29517	3.871417	120.6523	7.049415
N=450 T=30 n=15	1.892743	1.09352	3.142597	1.296383	9.278448	2.06625	83.05061	5.344232

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Table 2 above shows that as autocorrelation level (ρ) is increases for model parameter (β_0), the N =25, T = 5, and n =5 the Root Mean Square Error increases. As autocorrelation level (ρ) is increases for model parameter (β_1), N =25, T = 5, and n =5 then the Root Mean Square Error increases. As autocorrelation level (ρ) is increases for model parameter (β_0), the N =50, T =10, and n =10 the Root Mean Square Error increases, as autocorrelation level (ρ) is increases for model parameter (β_1), the N =50, T = 10, and n =10 the Root Mean Square Error increases, as autocorrelation level (ρ) is increases for model parameter (β_0) the N =100, T =10, and n =10 the root mean square error increases, as autocorrelation level (ρ) is increases for model parameter (β_1) the N =100, T = 10, and n =10 then Root Mean Square Error increases, as autocorrelation level (ρ) is increases for model parameter (β_0), the N = 450, T =30, and n =15 the Root Mean Square Error increases, as autocorrelation level (ρ) is increases for model parameter (β_1) the N =450, T = 30, and n =15 the Root Mean Square Error increases, while as panel structures increases for autocorrelation level (ρ) = 0.5 the model parameter β_0 for Root Mean Square Error decreases and as panel structures increases for autocorrelation level (ρ) = 0.5 the model parameter β_1 for Root Mean Square Error also decreases. As panel structures increases for autocorrelation level (ρ) = 0.7 the model parameter β_0 for Root Mean Square Error decreases and as panel structures increases for autocorrelation level (ρ) = 0.7 the model parameter β_1 for Root Mean Square error also decreases. As panel structures increases for autocorrelation level (ρ) = 0.9 the model parameter β_0 for Root Mean Square Error decreases and as sample size increases for autocorrelation level (ρ) = 0.9 the model parameter β_1 for Root Mean Square Error also decreases. As panel structures increases for autocorrelation level (ρ) = 0.99 the model parameter β_0 for Root Mean Square Error decreases and as panel structures increases for autocorrelation level (ρ) = 0.99 the model parameter β_1 for Root Mean Square Error also decreases. Therefore random effect model revealed that for autocorrelation level (ρ) = 0.5 for β_0 and β_1 are preferred

Table 3: Pooled Regression coefficient in the presence of autocorrelation

	Autocorrelation Levels							
Panel Structure/Model parameter	0.5		0.7		0.9		0.99	
	B0	B1	B0	B1	B0	B1	B0	B1
N=25 T=5 n=5	7.884728	4.697757	12.58496	5.435414	32.14336	7.058388	136.21	8.666858
N=50 T=10 n=5	5.668887	3.297746	9.188777	3.920675	25.76089	5.514255	131.2184	8.176125
N=100 T=10 n=10	3.980144	2.310056	6.608478	2.784635	18.87223	4.307665	122.4245	7.532492
N=450 T=30 n=15	1.877821	1.086536	3.103326	1.323327	9.432464	2.144578	82.90519	5.395957

From table 3 above shows that as autocorrelation level (ρ) is increases for model parameter (β_0), the N =25, T = 5, and n =5 the Root Mean Square Error increases, as autocorrelation level (ρ) is increases for model parameter (β_1), N =25, T = 5, and n =5 then the Root Mean Square Error increases. As autocorrelation level (ρ) is increases for model parameter (β_0), the N = 50, T = 10, and n = 5 the Root Mean Square Error increases, as autocorrelation level (ρ) is increases for model parameter (β_1), N = 50, T = 10, and n =5 then the Root Mean Square Error increases. As autocorrelation level (ρ) is increases for model parameter (β_0), the N = 100, T = 10, and n =10 the Root Mean Square Error increases, as autocorrelation level (ρ) is increases for model parameter (β_1), N = 100, T = 10, and n =10 then the Root Mean Square Error increases. As autocorrelation parameter (ρ) is increases for model parameter (β_0), the N = 450, T = 30, and n = 15 the Root Mean Square Error increases, as autocorrelation parameter (ρ) is increases for model parameter (β_1), N = 450, T = 30, and n = 15 then the Root Mean Square Error increases. While as panel structures increases for autocorrelation level (ρ) = 0.5 the model parameter β_0 for Root Mean Square Error decreases and as panel structures increases for autocorrelation parameter (ρ) = 0.5 the model parameter β_1 for Root Mean Square Error also decreases. As panel structures increases for autocorrelation level (ρ) = 0.7 the model parameter β_0 for Root Mean Square Error decreases and as panel structures increases for autocorrelation level (ρ) = 0.7 the model parameter β_1 for Root Mean Square Error also decreases. As panel structures increases for autocorrelation level (ρ) = 0.9 the model parameter β_0 for Root Mean Square Error decreases and as panel structures increases for autocorrelation level (ρ) = 0.9 the model parameter β_1 for Root Mean Square Error also decreases. As panel structures increases for autocorrelation level (ρ) = 0.99 the model parameter β_0 for Root Mean Square Error decreases and as panel structures increases for autocorrelation level (ρ) = 0.99 the model parameter β_1 for Root Mean Square Error also decreases. Therefore pooled regression model revealed that for autocorrelation level (ρ) = 0.5 for β_0 and β_1 are preferred. Therefore the implication is that as panel structures increases the estimated parameter close to actual parameter

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Table 4: β_i summary for fixed effect, random effect and pooled regression

	Autocorrelation Levels											
Panel Structure/ Model parameter	0.5			0.7			0.9			0.99		
	FE(β_i)	RE(β_i)	PR(β_i)	FE(β_i)	RE(β_i)	PR(β_i)	FE(β_i)	RE(β_i)	PR(β_i)	FE(β_i)	RE(β_i)	PR(β_i)
N=25 T=5 n=5	4.494095	4.498928	4.697757	4.577057	4.65496	5.435414	4.63345	4.78251	7.058388	4.703941	7.058388	8.666858
N=50 T=10 n=5	3.292825	3.233015	3.297746	3.794922	3.741035	3.920675	5.427457	5.38394	5.514255	7.766143	5.514255	8.176125
N=100 T=10 n=10	2.316926	2.271486	2.310056	2.649991	2.657743	2.784635	3.903451	3.87141	4.307665	6.966257	4.307665	7.532492
N=450 T=30 n=15	1.092535	1.09352	1.086536	1.285989	1.296383	1.323327	2.073846	2.06625	2.144578	5.34133	2.144578	5.395957

Table 4 above revealed that, for autocorrelation level ρ = 0.5, the sample size for N = 25, T = 5, n = 5 fixed effect model is preferred, for autocorrelation level ρ = 0.5, the sample size for N = 50, T = 10, n = 5 random effect model is preferred, for autocorrelation level ρ = 0.5, the sample size for N = 100, T = 10, n = 10 random effect model is preferred, for autocorrelation level ρ = 0.5, the sample size for N = 450, T = 30, n = 15 pooled regression model is preferred, therefore for small sample size fixed effect model performed better, for average sample size random effect model performed better while for large sample size pooled regression model performed better. For autocorrelation level ρ = 0.7, the sample size for N = 25, T = 5, n = 5 fixed effect model is preferred, for autocorrelation level ρ = 0.7, the sample size for N = 50, T = 10, n = 5 random effect model is preferred, for autocorrelation level ρ = 0.7, the sample size for N = 100, T = 10, n = 10 fixed effect model is preferred, for autocorrelation level ρ = 0.7, the sample size for N = 450, T = 30, n = 15 fixed effect model is preferred, therefore for small sample size fixed effect model performed better, for average sample size random effect model performed better while for large sample size fixed effect model performed better. For autocorrelation level ρ = 0.9, the sample size for N = 25, T = 5, n = 5 fixed effect model is preferred, for autocorrelation level ρ = 0.9, the sample size for N = 50, T = 10, n = 5 random effect model is preferred, for autocorrelation level ρ = 0.9, the sample size for N = 100, T = 10, n = 10 random effect model is preferred, for autocorrelation level ρ = 0.9, the sample size for N = 450, T = 30, n = 15 random effect model is preferred, therefore for small sample size fixed effect model performed better, for average sample size random effect model performed better and for large sample size random effect model performed better. For autocorrelation level ρ = 0.99, the sample size for N = 25, T = 5, n = 5 fixed effect model is preferred, for β_1 = 0.99, the sample size for N = 50, T = 10, n = 5 random effect model is preferred, for autocorrelation level ρ = 0.99, the sample size for N = 100, T = 10, n = 10 random effect model is preferred, for autocorrelation level ρ = 0.99, the sample size for N = 450, T = 30, n = 15 random effect model is preferred, Therefore, for small sample size N = 25, T = 5 and n = 5 fixed effect model performed better at all level of autocorrelation level, also for N = 50, T = 10, n = 5 random effect model performed better at all level of autocorrelation level and for large sample size N = 450, T = 30 and n = 15 random effect model performed better at all level of autocorrelation level as agreed with Garba et al 2015

Conclusion

The various results obtained in this work showed that the behaviours of the three estimators investigated for modeling various panel data vary as the violations are varied.

The efficiency of three methods of estimating panel data models with violations of no autocorrelation assumptions is addressed in this work. Our findings from experiments for several combinations of violations revealed that for fixed effect model the autocorrelation parameter (ρ) = 0.5 is preferred. Also, random effect model revealed that for autocorrelation parameter (ρ) = 0.5 for β_0 and β_1 are preferred. While pooled regression model revealed that for autocorrelation parameter (ρ) = 0.5 for β_0 and β_1 are preferred. Furthermore, for small sample size N = 25, T = 5 and n = 5 fixed effect model performed better at all level of autocorrelation parameter, also for N = 50, T = 10, n = 5 random effect model performed better at all level of autocorrelation parameter and for large sample size N = 450, T = 30 and n = 15 random effect model performed better at all level of autocorrelation parameter

Finally, As a general remark, given the various results obtained in this study, it is always necessary to assess the degree level of autocorrelation while developing panel data models in order to ensure efficient results.

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