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An Estimation Method for Panel Data Model with Heteroscedasticity, Serial and Spatial Correlations

Edokpayi, A.A, Abiodun, A.A

ABSTRACT - The kernel based nonparametric HAC estimation methods have been suggested as alternative to PCSE for panel data with heteroscedasticity, serial and spatial correlations, But the two commonly used kernel functions –the truncated and Bartlett functions for kernel based HAC estimations are too restrictive and that they yield negative bias and that such bias could be substantial in finite samples In this study, the error structure of the PCSE was modified with the introduction of two new kernel functions -.the Parzen kernel and Turkey-Hannings kernel functions and a non-linear weight was defined for them. Using simulated data for varied levels of heteroscedasticity, serial and spatial correlations, varying spatial weight matrix specification and different cross-sectional and time dimensions, the performances of these two new kernel functions were compared with Bartlett kernel ,the truncated kernel functions and the PCSE' Using absolute bias (AB), residual variance (RVar) and the root mean squares error (RMSE) as assessment criteria, the performances of these estimators were determined The results from the study showed that the kernel based nonparametric approach performed better than the PCSE and that the Bartlett kernel, the Turkey-Hanning kernel and the Parzen performed better in the presence of heteroscedasticity, serial and spatial correlations . However, the Tukey-Hannings kernel was generally more preferred for small sample sizes, narrow spatial weight matrix specifications and for short panels N>T), while the Parzen kernel estimator performed better for long panels (N<T) and wider spatial weight matrix specifications .The Bartlett kernel functions however, performed better than the Turkey-Hanning and Parzen kernels generally for large sample sizes, wider spatial weight matrix specifications. From the results the study concludes that the performances of the different estimators were generally influenced by the type of panel data, the size of the cross-sectional and time dimensions and the spatial weight matrix specifications

KEYWORD: **Panel Data, heteroscedasticty, serial correlation, spatial Dependence, kernel Estimators**

I. INTRODUCTION

Panel data are data sets that consists of repeated measures of the same variable, taken from the same set of units over time (Woodridge, 2002, Baltagi, *et al.,* 2008, and Gujarati, 2009) .The cross-section units may consist of individuals, firms, states, regions or countries, while the time units may be years, months, days or any other time expression such as hours, minutes or seconds (Baltagi, 2013).. Panel data therefore involves both the cross sectional and time dimensions and therefore combines the characteristics of both cross sectional and time series data. (Baltigi, *et al.,,* 2008, Greene, 2012..However, due to the presence of these two complementary dimensions,, panel data typically provide sufficient observations and consequently more sample variability, decrease collinearity problems among the explanatory variables and increase in degree of freedom (Hsiao 2003, Baltagi and Li, 2004).

However, despite the advantages and wide use of panel data for empirical research, heteroscedasticity and serial correlation have long been identified as potential problems Baltagi,, *et al.,* 2005 and Garba, *et al.,* 2014,). But in recent times, there is the growing concern among panel data researchers that panel data may also contain some form of spatial dependence (Anselin, 1988, Elhorst, 2003). Thus while some panel data researchers are concerned with the problems of heteroscedasticity and serial correlation, some others are strictly restricted to the problem of spatial dependence with little or no considerations for the simultaneous presence heteroscedasticity, serial and spatial correlations.

Just like the presence of heteroscedasticity and serial correlation or spatial dependence, in the face of heteroscedasticity, serial and spatial correlations,, the assumptions of identical and independent distributions of the errors is violated . In that case, the error terms across the cross – sectional units are no longer uniform or constant, and also no longer independence over time and across the cross - sectional units. The implications of this is that the standard panel data estimation procedures may be invalid and could lead to serious bias and inefficiency in the estimation methods.

But available estimation methods are either robust to heteroscedasticity and serial correlation on the one hand or robust to spatial dependence with no estimation methods available to directly accounts for heteroscedasticity, serial correlation and spatial dependence .However, two procedures are available in the literature for resolving this challenge. The first approach makes use of the generalized least square (GLS) estimator (see Park, 1970). Though the GLS procedure produces coefficient and standard error estimates that are efficient and unbiased respectively, but this approach is only appealing if the covariance structure is correctly specified and the elements of the error covariance matrix are known (Beck and Katz, 1995). However, in most cases, the form of the error structure is unknown or the true value for the variance-covariance is unknown, thus making this approach very unappealing (Reed and Ye, 2009)

The second approach is the standard error approach .This approach is appealing because estimating panel data models using conventional panel data estimators generate inefficiency in coefficient estimation and bias standard errors. For accurate inference in such models, it is essential to use covariance matrix estimators that can consistently estimate the covariance of the model parameters. This approach required an adjustment of the standard error in other to obtain an unbiased standard errors of OLS in the presence of heteroscedasticty, serial correlation and spatial dependence is obtained. The most popular of these robust standard error approach or covariance matrix estimators are the Huber (1967),, Eicker, (1967), White, (1980) and Newey and West 1987) estimators developed to addressed the problems of heteroscedasticity (HC) in cross sectional settings and heteroscedasticity and serial correlation (HAC) in time series settings .But for panel data settings with heteroscedasticity and serial correlation as well as spatial correlation, Beck and Katz (1995) suggested the use of OLS coefficient estimates in combination with the panel structure of the data called the panel corrected standard error (PCSE). Though, the PSCE is widely used and performs well when the number of time periods (T) is close to, or equal to the number of cross-sections (N), but the PCSE underperforms with substantial loss in efficiency when T > N). The PCSE is said to be also biased, hence statistical inferences based on them are invalid (Hoechle, 2007).

However, Driscoll and Kraay (1997) has proposed a class of nonparametric method based on kernel which is said to be applicable when parametric description of the data is not sufficiently adequate. This kernel based procedures attends to nonzero covariance between the cross-sectional units and unequal variance by weighting through a kernel smoother function where the weights are determined by the kernel function and bandwidth (Millo, 2017). Though a range of kernel functions are available in the literature, but the truncated kernel, the Bartlett kernel, the Parzen kernel, the Turkey-Hanning kernel and the Quadratic spectral kernel are more desirable for HAC procedures because of their properties which are symmetric and guarantee positive semi-definiteness. (Andrew1991) .

Even though the truncated kernel, the Bartlett kernel, the Parzen kernel, the Turkey-Hanning kernel and the Quadratic spectral kernel are more desirable for HAC procedure, but the Truncated kernel and Bartlett kernel functions are the two most commonly used kernel function for the HAC procedures.. White, (1980) and Arellano (1987) for instance assigns unit or constant weights using truncated kernel. to all autocovariances up to the lag truncation point while Newey and West (1987) and Drisscoll and Kraay (1998) respectively assigned a decreasing weight to all autocovariances using Bartlett kernel

However, the Truncated and Bartlett kernel does not ensure a positive semi-definite covariance matrix and that they are too restrictive and yield negative bias that such bias could be substantial in finite samples (Andrew, 1991). Andrew and Monahan (1992.) therefore, suggested the need for larger class of kernel estimator for an improved HAC estimation .In this study, the error structure of a panel corrected standard was modified with a kernel function .Two new kernel functions were introduced and a non-linear weight matrix defined for the two kernel functions. The performances of the new kernel function in comparison with the widely used kernel functions were assessed. Secondly, the effects of different cross-sectional and time dimensions on the performance of the different kernel HAC estimators were determined and finally the effects of different spatial weight matrix specifications on the performance of the different kernel HAC estimators were also assessed since a distance measure in the cross-section is needed to implement this kernel base approach (Kin, 2010).

II. SOME ESTIMATION METHODS FOR PANEL DATA MODEL WITH HETEROSCEDASTICITY, SERIAL AND SPATIAL CORRELATIONS

2.1: Standard Panel Data Estimators

A diversity of estimation methods are available in the literature for estimating panel data (Reed and Ye, 2007). The Ordinary Least Square (OLS) for instance exhibit an important downward bias and have the worst performance when compared to the other estimators in the presence of heteroscedasticity, serial correlation and spatial dependence (Vogelsang, 2012).

For heteroscedasticity and serial correlation in panel data Baltagi, *et.al,* (2007), Olofin,*et al*,.(2010) and Garba, *et.al*, (2014) concluded the fixed and random effects estimators are invalid and lead to serious bias and inefficient . Similarly, in the presence of spatial dependence, Baltagi*, et al.* (2012) revealed that in the presence of large spatial coefficient, the ordinary panel data estimators' leads to misleading inferences. However, a major weakness with these common panel data model estimation methods is that they performed poorly in the presence of heteroscedasticity, serial correlation and spatial dependence

2.2: The Feasible generalized least square (FGLS)

In an earlier attempt to account for heteroscedasticity, serial correlation and spatial dependence in the residuals, Park (1967) proposed a feasible generalized least square (FGLS). This procedure is in two steps. Firstly the serial correlation is eliminated after which the spatial correlation is eliminated. The process obtains residual from the OLS estimates; this residual is then used to estimate the panel specific correlation coefficient which in turn is used to transform the model into one with serial independent errors. Secondly the residuals from these estimates are then used to estimate the spatial correlation coefficient which again is transformed to allow for OLS estimation with independent errors that have constant variance.

However, the Park (FGLS) method is infeasible if the panel's time dimension (T) is smaller than its cross-sectional dimension (N) because the associated error variance-covariance matrix (EVCM) cannot be inverted, that is, the problem of singularity. Secondly, Beck and Katz (1995) show that the Park method tends to produce unacceptable small standard errors. Therefore, to get reliable estimates of the sample population, the need to consider the standard error which helps to examine the accuracy of the estimates have become necessary.

2.3: Panel Corrected Standard Errors Estimator (PCSE)

Beck and Katz (1995) introduced the panel corrected standard errors (PCSE) and suggested estimating panel data by OLS .They proposed a sandwich type estimator of the covariance matrix of the estimated parameter which they called Panel-corrected standard errors (PCSE) that is robust to non-spherical errors (Bailey and Katz, 2011). Beck and Katz considered a panel model of the form:

$$Y_{1t} = \beta_{1t} + X_{1t}\beta + \varepsilon_{1t}\left(t = 1,\ldots T = 1,\ldots N\right) \quad (1)$$

and

$$\varepsilon_{1t} = \rho M_{1t}\varepsilon_{1t} + \mu \qquad |\rho| < 1 \quad (2)$$

Where M and ρ are weight matrix and scalar autoregressive parameter respectively? $\in_{it} \sim i.i.d\left(0, \Omega_{NT}\right)$.

Back and Katz (1995) original formulation of panel data model consists of (i) heteroscedasticity; (ii) serial correlation and (iii) spatial dependence.

The variance was expressed as,

$$Var\left(\hat{\beta}\right) = \left(X'X\right)^{-1} X'\left(\Omega_{NT}\right)X\left(X'X\right)^{-1} \quad (3)$$

While the error component Ω_{NT} was modeled to be of the form:

Where $$\Omega_{NT} = \sum \otimes \prod \quad (4)$$

Where

$$\sum = \begin{bmatrix} \sigma_{\in 11} & \sigma_{\in 12} & \cdots & \sigma_{\in 1N} \\ \sigma_{\in 21} & \sigma_{\in 22} & \cdots & \sigma_{\in 2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\in N1} & \sigma_{\in N2} & \cdots & \sigma_{\in NN} \end{bmatrix}, \quad \prod = \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & \rho & \cdots & \rho^{T-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \cdots & 1 \end{bmatrix} \quad (5)$$

Where, Σ caters for heteroscedasticity and serial correlation and ρ is scalar autoregressive parameter which cater for the spatial correlations. Though, the PCSE is popular and widely used for panel data model with heteroscedasticity, serial correlation and spatial dependence. However, the panel corrected standard error (PCSE) are biased hence statistical inferences based on them are invalid (Hoechle, 2007). Therefore to improve the standard errors and correct for the problems of heteroscedasticity, serial correlation and spatial dependence, Driscoll and Kraay (1997) proposed a class of nonparametric method based on kernel.

2.4: Kernel-Based (HAC) procedures for heteroscedasticity, serial and spatial correlations

Newey and West (1987) were the first to introduce the kernel function to address the problems of heteroscedasticity and serial correlation in time series settings.

The variance of the time series model with heteroscedasticity and serial correlation as expressed by Newey-West (1987) is as presented below

$$X\hat{\Omega}X = \left(\sum_{i=1}^{N}\sum_{i=1}^{T} \varepsilon_4^1 x_4^1 x_4^1 - 1\sum_{i-1}^{N}\sum_{t-1}^{N}\sum_{t-1}^{T}\left(1-\frac{m}{m+1}\right)\hat{\varepsilon}_{it}\varepsilon_{it-m}\left(x_{1t}^1 x_{1t-m} + x_{1t-m}^1 x_{1t}\right)\right) \quad (6)$$

Where $1-\frac{m}{m+1}$ is the weight and m is i the maximum lag. M +1 is the bandwidth and m is the maximum lag specifically, as m gets larger (and thus father from t, we give the correlation between e_t and e_{t-1} less weight. The bandwidth parameter defines the weight, and thus determines the degree of smoothing applied to the data.

Newey-West (1987) assigns a weight using the Bartlett kernel function.

The Bartlett kernel function is define as

$$K\left(x\right) = \begin{cases} 1-|x|/a, & if\ x \le 0 \\ 0 & Otherwise \end{cases} \quad (7)$$

Where :x is the distance from the kernel center and a is the bandwidth parameter that determines the range of the kernel function that assigns a weight to each data point based on its distance from a target point. But Newey and West (1987) kernel based procedure was restricted only to problems of heteroscedasticity and serial correlation in time series settings.

In panel data setting, White-Arellano, (1987) developed a consistent HAC estimator using the cluster standard errors

with truncated kernel to smoothing out serial correlation and spatial correlation (Vogelsang, 2012).
The variance was expressed as,

$$\hat{V}_{avc(t)} = T\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{X}_{1t}\tilde{X}_{1t}\right)^{-1}\left(\sum_{i=1}^{m}\hat{\Omega}_i\right)\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{X}_{1t}\tilde{X}_{1t}\right)^{-1} \quad (8)$$

While the variance –covariance matrix is as expressed below

$$\Sigma = \therefore \Omega_{NT} = T^{-1}\sum_{t=1}^{T}\sum_{S=1}^{T}K_{ts}V_{1t}U_{1S} \quad (9)$$

where

$$Kst = K\left(\frac{1t - s1}{M}\right) \quad (10)$$

Is the kernel function
White-Arellano (1987) assign weights using truncated kernel and is reported to be the simplest method that yields constant estimates of the spectral density.
The truncated kernel is defined as;

$$K_{TR}(x) = \begin{cases} 1 & for\ |x| \le 1 \\ 0 & otherwise \end{cases} \quad (11)$$

The truncated kernel function assigns weights of unity on all auto-covariance up to the lag truncation point.

Unfortunately, the lag truncated kernel does not necessary yields a positive semi-definite which therefore limits its usefulness

Driscoll and Kraay (1998) adapted the Newey-West estimator to a panel data context, where not only serial correlation between residuals from the same individual in different time periods is taken into account, but also cross-serial correlation between different individuals in different times and, within the same period,.
They express the variance as

$$\hat{V}_{HACSE} = T\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{X}_{1t}\tilde{X}_{1t}\right)^{-1}\hat{\Omega}\left(\sum_{j=1}^{n}\sum_{t=1}^{T}\tilde{X}_{1t}\tilde{X}_{1t}\right)^{-1} \quad (12)$$

while the variance –covariance matrix is as expressed as

$$\Sigma = \therefore \Omega_{NT} = T^{-1}\sum_{t=1}^{T}\sum_{S=1}^{T}K_{ts}V_{1t}U_{1S} \quad (13)$$

Where K is expressed as

$$W\ell = 1 - \frac{\ell}{L+1} \quad (14)$$

Driscoll and Kraay (1998) the Bartlett kernel function (K) with a linearly decaying weight.. Unfortunately, the Bartlett kernel on the other hand is reported to yield negative bias and such bias could be substantial in finite samples (Andrew, 1991).Therefore the need for an alternative kernel function becomes necessary

III. MATERIALS AND METHODS

3.1: Methodology

Adopting Beck and Katz (1995) original formulation of panel data model which consists of (i) heteroscedasticity; (ii) serial correlation and (iii) spatial dependence with an error component Ω_{NT} modeled in the form:

Where $\Omega_{NT} = \sum \otimes \prod$

Where

$$\sum = \begin{bmatrix} \sigma_{\in,11} & \sigma_{\in,12} & \cdots & \sigma_{\in,1N} \\ \sigma_{\in,21} & \sigma_{\in,22} & \cdots & \sigma_{\in,2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\in,N1} & \sigma_{\in,N2} & \cdots & \sigma_{\in,NN} \end{bmatrix}, \quad \prod = \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & \rho & \cdots & \rho^{T-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \cdots & 1 \end{bmatrix}$$

The modified error structure consists of (1) heteroscedasticity (2) serial correlation (3) spatial correlation and (4) kernel function. Two new kernel functions were introduced- the Parzen kernel and the Turkey-Hanning kernel functions
The Parzen kernel function is expressed as;

$$K_{pz}(x) = \begin{cases} 1 \quad -6x^2 + 6|x|^3 & for\ 0 \\ 2 \quad (1-|x|^3 & for\ \tfrac{1}{2} \le |x| \le 1 \\ 0 & otherwise \end{cases} \quad (15)$$

And the Tukey-Hannings kernel function is defined mathematically as:

$$K_{TH} = \begin{cases} \dfrac{1+\cos \pi x}{2} & for\ |x| \le 1 \\ otherwise \end{cases} \quad (16)$$

Therefore, the modified error component Ω_{NT} was modeled to be of the form

$$\Omega_{NT} = \Sigma \otimes \prod \otimes K \quad (17)$$

Equation (17) can be further expressed as

$$\sum = \begin{bmatrix} \sigma_{\in 11} & \sigma_{\in 12} & \cdots & \sigma_{\in 1N} \\ \sigma_{\in 21} & \sigma_{\in 22} & \cdots & \sigma_{\in 2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\in N1} & \sigma_{\in N2} & \cdots & \sigma_{\in NN} \end{bmatrix}, \otimes \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & \rho & \cdots & \rho^{T-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \cdots & 1 \end{bmatrix} \otimes K \quad (18)$$

Where the structure Σ, $\prod$, $\otimes$ is as defined above and K is expressed as kernel function . Since the kernel (K) determines the weighting scheme, a generalized weight for K as suggested by Andrew (1991) was adopted

According Andrew (1991)

Let K = $W\ell = k\left(\frac{\ell}{\beta}\right)$ (19)

Equation (19) was adjusted to a non-linearly weight as expressed below for Parzen kernel and Tukey-Hanning kernel functions respectively as

$$Wl = 1 - \frac{1}{(L+1)^{1/2}} \quad (20)$$

And

$$Wl = 1 - \frac{1}{(L+1)^{2}} \quad (21)$$

Recall the variance of PCSE

$$Var(\hat{\beta}) = (X'X)^{-1} X'(\Omega_{NT}) X (X'X)^{-1}$$

Where the variance –covariance matrix is

$$\Omega_{NT} = \sum \otimes \prod$$

While the new variance-covariance matrix is as expressed bolow

Where $\Omega_{NT} = \Sigma \otimes \prod \otimes K$

$$\Omega_{NT} = \Sigma \otimes \prod \otimes K_{\text{PARZ}} \quad (22)$$

While equation (22) is the variance-covariance matrix for Parzen kernel

$$\Omega_{NT} = \Sigma \otimes \prod \otimes K_{\text{TUK}} \quad (23)$$

And equation (23) is the variance-covariance matrix for the Tukey-Hanning kernel

3.2: Data used for the Study

Monte-Carlo studies were carried out at different sample sizes (10, 50, 150), 3 different spatial weight matrices (distance bands and k nearest neighbourhood; for k = 10 and *k* = 50), five different levels of spatial dependence (±0.5, 0, ±0.9); five different levels of serial correlation (±0.5, 0, ±0.9) and varying degree of spatial heterogeneity (low, mild and severe); all at different time periods (20, 40).

The data generating process follows from the model below

$$y_{1t} = X_{1t}^{1}\beta + a_i + u_{1t} \quad i = 1,2,\ldots n, \; t = 1, 2$$

(24)

where y is a $[N \times 1]$ vector representing the exogenous variable, X is a $[N \times N]$ matrix of spatially correlated explanatory variables, β is a $[N \times 1]$ vector of regression co-efficient, ε is the individual-specific error component represented as $[N \times 1]$ vectors of error terms and μ_{it} is the combined time-series and cross-section error component with variances σ_{ε}^2 and σ_{μ}^2 respectively. For the spatial autoregressive parameters, we employ combinations of ρ = (0.9; 0.5; 0; -0.5; -0.9) to allow for weak and strong spatial interactions. To generate the heteroskedastic errors, we follow Kelejian and Prucha (2010) and consider small group interactions structure for the spatial weight matrix to allow for an expansive drift across the dataset; and for serial correlation, first-order serial correlation AR (1) was used to implant serial correlation into the model as did by Lillard and Wallis (1978), Bhargava *et al*. (1983) e.t.c. Following the recommendations of Kelejian and Prucha (2010), spatial heterogeneity was simulated by applying a cholesky transformation on the weighted matrix `**W**` into the simulated spatial dependence covariates in the presence of an unobserved covariate (random noise), $\varepsilon \sim N(0, \sigma I_n)$.

The final model is represented as:

$$y_{in} = X_{in}\beta_i + \lambda W_n y_n + \mu_n \quad (25)$$

$$\mu_n = \rho M_n u_n + \varepsilon_n \quad (26)$$

where y_n is the $n \times 1$ vector of observations on the dependent variable, X_n is the $n \times k$ matrix of observations on k exogenous variables, W_n and M_n are $n \times n$ spatial weighting matrices of known constants, β is the $k \times 1$ vector of regression parameters, λ and ρ are scalar autoregressive parameters, μ_n is the $n \times 1$ vector of regression disturbances, and ε_n is an $n \times 1$ vector of innovations. The variables $W_n y_n$ and $M_n \mu_n$ are typically referred to as spatial lags of y_n and μ_n respectively..

Estimation methods used for the study

The following estimation methods was used for the simulated data: (1) Panel Corrected Standard Error (PCSE) (2) Truncated kernel (3) Bartlett kernel (4) Parzen kernel (5) Turkey-Hanning kernel functions

Testing for the presence of heteroscedasticity, serial correlation and spatial dependence in the simulated data

Breusch-Pagan test was used to test the presence of heteroscedasticity, Serial correlation was tested for using Durbin-Watson test statistic to test while Spatial-autocorrelations among the model residuals were assessed using both global and local Moran coefficients (Anselin 1988).

Criteria for assessing the performance of the Estimators

The Absolute Bias, the Variance and Root mean square error were used to assess the performance of the Estimators

IV. RESULTS AND DISCUSSION

Table 1: shows results of the test statistic to detect the presence of heteroscedasticity, serial correlation and spatial dependence in the simulated data

	Heteroscedasticity	**Serial correlation**	**Spatial dependence**
	(p-value)	**(p-value)**	**(p-value)**
N ,T	**BPErr**	**DW**	**Moran 1**
N=50 T=20	**8.0169 (0.01826)**	**0.95816 (2.2e-16)**	**8.6731 (0.000969)**
N=150 T=40	**5.01816 ((0.00532)**	**0.53741 (1.4e-3)**	**7.53744 (0.00069)**
N=50, T=20,K=10	**7.35303 (0.00619**	**0.83338 (2.2e-16)**	**12.47383 (0.03745)**
N=50,T=20,K=50	**4.53042 (0.04054)**	**0.58733 (0.0054)**	**9.53901 (0.00347)**
N=150,T=40,K =10	**8.33821 (0.00622**	**0.39392 (0.0045**	**4.68992 (0.000969)**
N=150,T=40,K =50	**3.22453 (0.02453)**	**0.13724 (0.0463)**	**7.16829 (0.0069)**
N=10, T=40	**7.35782 (0.0453)**	**0.57208 (0.056)**	**20.6383 (000 .0969)**
N=10, T=40, k=10	**5.24261 (0.07i74)**	**0.22445 (0.0055**	**5.72020 (0.000969)**
N=50, T=20, k=50	**6.53292 (0.00335**	**0.22439 (0.006**	**11.6380. 000969)**

Table 1 shows the results of various tests conducted show a BP value of 8.0169 and a p – value of 0.01816. Since this 0.01816 < 0.05, this confirmed the presence of heteroscedasticity in the simulated data. The DW value reported was 0.95816 and since this value is between 0 < d < 4, it shows the presence of serial correlation in the data. Finally, the p- values for the spatial dependence was 0.001107 and this was far below the threshold value of < 0.05, thus indicating the presence of spatial dependence in the data. The results of the tests statistics therefore confirmed the presence of heteroscedasticity, serial correlation and spatial dependence in the panel data sets.

Tables 2 -10 shows the results of the performances of the different estimators at the different levels of heteroscedasticity, serial correlation and spatial dependence, and across the different spatial weight matrices and cross-sectional and time dimensions using the simulated data. The estimators were ranked using the ranks 1, 2, 3, 4 and 5 with rank 1 assigned to the best estimator. A rank of 2 is assigned to the second best estimator and so on. . To determine the rank of the best estimator with highest occurrence of lowest value(s) of Absolute bias, Var, and RMSE were ranked in ascending order as best estimators.

Table 2: Preferred Estimator at different levels of heterogeneeity, serial correlation and spatial dependence, when N = 50, T = 20 (Distance Bands Weight Matrix)

		Serial Correlation				
SD	**HT**	**0.9**	**0.5**	**0**	**-0.5**	**-0.9**
0.9	Low	BAT	TUK	TRU	TUK	TUK
	Mild	TUK	BAT	TRU	BAT	TUK
	Severe	TUK	TUK	PAZ	BAT	TUK
0.5	Low	TUK	TUK	TRU	TUK	TUK
	Mild	TUK	TUK	TRU	TUK	TUK
	Severe	BAT	BAT	PAZ	BAT	TUK
0	Low	TRU	TRU	TRU	PSE	TRU
	Mild	PSE	PSE	TRU	PSE	TRU
	Severe	PSE	PSE	TRU	PSE	PSE
-0.5	Low	TUK	TUK	TRU	TUK	TUK
	Mild	TUK	TUK	TRU	BAT	TUK
	Severe	BAT	BAT	PSE	TUK	BAT
-0.9	Low	TUK	TUK	TRU	BAT	TUK
	Mild	TUK	TUK	PSE	TUK	TUK
	Severe	BAT	TUK	TRU	TUK	BAT

Panel Corrected Standard Error (PSE),Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

Table 2 shows the performance of the different estimators for the different levels of heteroscedasticity, serial correlation and spatial dependence for (50, 20) cross-sectional and time dimensions and the Distance Band Weight (DBW) matrix specifications. The results shows that the Bartlett kernel and The Turkey-Hannings kernel performed better than other estimators across the different combinations of heteroscedasticity, serial correlation and spatial dependence and irrespective the signs .However, the Turkey-Hannings kernel dominated the Bartlett kernel at more of the combinations of heteroscedasticity, serial correlation and spatial dependence.

Table 3: Preferred Estimator at different levels of heterogeneity, serial correlation and spatial dependence, when *N* = 150, *T* = 40 (*Distance Bands Weight Matrix*)

		Serial Correlation				
SD	HT	0.9	0.5	0	-0.5	-0.9
0.9	Low	BAT	TUK	TRU	TUK	BAT
	Mild	TUK	BAT	PSE	BAT	BAT
	Severe	BAT	BAT	PAZ	TUK	BAT
0.5	Low	TUK	BAT	TRU	TUK	TUK
	Mild	BAT	TUK	TRU	TUK	BAT
	Severe	BAT	BAT	PAZ	BAT	BAT
0	Low	PSE	PSE	TRU	PSE	PSE
	Mild	PSE	TRU	TRU	PSE	TRU
	Severe	PSE	PSE	PSE	PSE	PAZ
-0.5	Low	TUK	TUK	PSE	TUK	BAT
	Mild	BAT	TUK	TRU	TUK	TUK
	Severe	BAT	BAT	PSE	TUK	BAT
-0.9	Low	BAT	BAT	PSE	TUK	BAT
	Mild	BAT	BAT	PSE	TUK	BAT
	Severe	BAT	TUK	TUK	TUK	BAT

Panel Corrected Standard Error (PSE), Truncated (TRU)Bartlett (BAT), Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

For the different levels of heteroscedasticity, serial correlation and spatial dependence across for (150, 40) cross-sectional and time dimensions and the Distance Band Weight (DBW) matrix specifications (Table .3) The Bartlett kernel and the Turkey-Hannings kernel were the dominant estimators. However, for positive spatial dependence and positive serial correlation and also for negative spatial dependence and positive serial correlation, the Bartlett kernel dominated the Turkey-Hanning kernel in more of the combinations of heteroscedasticity, serial correlation and spatial dependence.

Table 4: Preferred Estimator at different levels of spatial dependence, spatial heterogeneity and serial correlation N = 50, T = 20 and k = 10 (*10-nearest Neighbour Spatial Weight Matrix*)

		Serial Correlation				
SD	Hetero	0.9	0.5	0	-0.5	-0.9
0.9	Low	TUK	BAT	PSE	TUK	BAT
	Mild	TUK	TUK	TRU	TUK	TUK
	Severe	TUK	TUK	PAZ	TUK	TUK
0.5	Low	BAT	TUK	TRU	TUK	BAT
	Mild	TUK	BAT	TRU	TUK	TUK
	Severe	TUK	TUK	PAZ	BAT	TUK
0	Low	PSE	TRU	TRU	PSE	PSE
	Mild	TRU	TRU	TRU	PSE	PAZ
	Severe	PSE	TRU	PSE	TRU	TRU
-0.5	Low	TUK	BAT	PSE	TUK	TUK
	Mild	BAT	BAT	TRU	TUK	BAT
	Severe	TUK	TUK	PSE	TUK	TUK
-0.9	Low	TUK	TUK	PSE	TUK	BAT
	Mild	TUK	TUK	PSE	TUK	TUK
	Severe	TUK	BAT	TUK	TUK	TUK

Panel Corrected Standard Error (PSE),Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

From (Table 4), the results shows that for different combinations of heteroscedasticity, serial correlation and spatial dependence and across the (50, 20) cross-sectional and time dimensions with K =10 spatial weight matrix specifications, the Bartlett kernel and the Turkey-Hannings kernel were the dominant estimators. The Turkey-Hannings kernel dominated the Bartlett kernel for more of this combination of serial correlation and spatial dependence in respective of their signs and degree of heteroscedasticity

Table 5: Preferred Estimator at different levels of heterogeneity, serial correlation and spatial dependence, spatial N = 150, T = 40 and k = 10 (*10-nearest Neighbour Spatial Weight Matrix*)

		Serial Correlation				
SD	Hetero	0.9	0.5	0	-0.5	-0.9
0.9	Low	BAT	BAT	PSE	BAT	BAT
	Mild	TUK	BAT	TRU	BAT	BAT
	Severe	BAT	BAT	PAZ	TUK	BAT
0.5	Low	TUK	BAT	TRU	TUK	TUK
	Mild	BAT	TUK	TRU	TUK	BAT
	Severe	BAT	BAT	PAZ	BAT	BAT
0	Low	TRU	PSE	PAZ	TRU	PSE
	Mild	PAZ	PSE	TRU	TRU	PAZ
	Severe	PSE	PSE	TRU	TRU	TRU
-0.5	Low	BAT	TUK	TRU	BAT	BAT
	Mild	BAT	TUK	TRU	TUK	TUK
	Severe	BAT	BAT	PSE	BAT	BAT
-0.9	Low	BAT	BAT	PSE	BAT	BAT
	Mild	BAT	BAT	PSE	BAT	BAT
	Severe	BAT	BAT	TUK	BAT	TUK

Panel Corrected Standard Error (PSE) Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

Table (5) shows **of** performances of the different estimators for different combinations of heteroscedasticity, serial correlation and spatial dependence for the (150, 40) cross-sectional and time dimension and for K=10 spatial weight matrix specifications. The results showed that the Bartlett kernel and the Turkey-Hannings kernel were the dominant estimators, but the Bartlett kernel dominated the Turkey-Hannings kernel for more of the combinations of serial correlation and spatial dependence in respective of the degree of heteroscedasticity and signs.

Table 6: Preferred Estimator at different levels of spatial dependence, spatial heterogeneity and serial correlation N = 50, T = 20 and k = 50 (*50-nearest Neighbour Spatial Weight Matrix*)

		Serial Correlation				
SD	**Hetero**	**0.9**	**0.5**	**0**	**-0.5**	**-0.9**
0.9	Low	BAT	BAT	PSE	BAR	BAT
	Mild	TUK	BAT	TRU	BAR	BAT
	Severe	BAT	BAT	PAZ	TUK	BAT
0.5	Low	TUK	BAT	TRU	TUK	TUK
	Mild	BAT	TUK	TRU	TUK	BAT
	Severe	BAT	BAT	PAZ	BAR	BAT
0	Low	TRU	PSE	PAZ	TRU	PSE
	Mild	PAZ	PSE	TRU	TRU	PAZ
	Severe	PSE	PSE	TRU	TRU	TRU
-0.5	Low	BAT	TUK	TRU	BAT	BAT
	Mild	BAT	TUK	TRU	TUK	TUK
	Severe	BAT	BAT	PSE	BAT	BAT
-0.9	Low	BAT	BAT	PSE	BAT	BAT
	Mild	BAT	BAT	PSE	BAT	BAT
	Severe	BAT	BAT	TUK	BAT	TUK

Panel Corrected Standard Error (PSE) Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

The results on (Table 6) shows that for the different combinations of heteroscedasticity, serial correlation and spatial dependence and for the (50, 20) cross-sectional and time dimensions and K =50 spatial weight matrix specifications, the Bartlett kernel and the Turkey-Hannings kernel were the dominant estimators irrespective of the signs combinations However, the Bartlett kernel performed better than the Turkey-Hanning kernel for more of the combinations of spatial dependence and serial correlation irrespective of the degree of heteroscedasticity and combinations of the signs.

Table 7: Preferred Estimator at different levels of heterogeneity, serial correlation and spatial dependence, spatial N = 150, T = 40 and k = 50 (*50-nearest Neighbour Spatial Weight Matrix*)

		Serial Correlation				
SD	**Hetero**	**0.9**	**0.5**	**0**	**-0.5**	**-0.9**
0.9	Low	BAT	BAT	PSE	BAT	BAT
	Mild	TUK	BAT	TRU	BAT	BAT
	Severe	BAT	BAT	PAZ	TUK	BAT
0.5	Low	TUK	BAT	TRU	TUK	TUK
	Mild	BAT	TUK	TRU	TUK	BAT
	Severe	BAT	BAT	PAZ	BAT	BAT
0	Low	TRU	PSE	PAZ	TRU	PSE
	Mild	PAZ	PSE	TRU	TRU	PAZ
	Severe	PSE	PSE	TRU	TRU	TRU
-0.5	Low	BAT	TUK	TRU	BAT	BAT
	Mild	BAT	TUK	TRU	TUK	TUK
	Severe	BAT	BAT	PSE	BAT	BAT
-0.9	Low	BAT	BAT	PSE	BAT	BAT
	Mild	BAT	BAT	PSE	BAT	BAT
	Severe	BAT	BAT	TUK	BAT	TUK

Panel Corrected Standard Error (PSE) Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

For the different combinations of heteroscedasticity, serial correlation and spatial dependence and the (150, 40) cross-sectional and time dimension and K = 50 spatial weight matrix specifications (Table 7). The results revealed that the Bartlett kernel and the Turkey-Hannings kernel were the dominated other estimators irrespective of the signs and combinations, However, the Bartlett kernel performed better than the Turkey-Hanning kernel for more of the combinations of serial correlation and spatial dependence irrespective of the degree of heteroscedasticity.

Table 8: Preferred Estimator at different levels of heterogeneity, serial correlation and spatial dependence, when *N* =10, *T* = 40 (*Distance Bands Weight Matrix*)

		Serial Correlation				
SD	**HT**	**0.9**	**0.5**	**0**	**-0.5**	**-0.9**
0.9	Low	BAT	PAZ	TRU	BAT	BAT
	Mild	BAT	PAZ	TRU	BAT	BAT
	Severe	BAT	BAT	TRU	BAT	PAZ
0.5	Low	PAZ	BAT	TRU	PAZ	PAZ
	Mild	BAT	BAT	TRU	PAZ	PAZ
	Severe	BAT	PAZ	TRU	BAT	PAZ
0	Low	TRU	TRU	TRU	TUK	TRU
	Mild	TRU	TRU	TRU	TRU	TRU
	Severe	TRU	TRU	TRU	TRU	TUK
-0.5	Low	PAZ	BAT	TRU	PAZ	PAZ
	Mild	PAZ	BAT	TRU	PAZ	PAZ
	Severe	BAT	PAZ	PSE	BAT	PAZ
-0.9	Low	BAT	PAZ	PSE	BAT	BAT
	Mild	BAT	BAT	TRU	BAT	BAT
	Severe	BAT	BAT	TRU	BAT	BAT

Panel Corrected Standard Error (PSE) Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

Table 8) shows the results of the performance of the different estimators for the different combinations of heteroscedasticity, serial correlation and spatial dependence for the (10, 40) cross-sectional and time dimension with Distance weight matrix specifications. From the results , the Bartlett kernel and the Parzen kernel were the dominant estimators for more combinations of heteroscedasticity, serial correlation and spatial dependence and also the for the different sigh combinations .However, the Bartlett kernel dominated the Parzen kernel in more of the combinations of spatial dependence and serial correlations irrespective of the degree of heteroscedasticity and signs combinations.

Table 9: Preferred Estimator at different levels of heterogeneity, serial correlation and spatial dependence, spatial when N = 10 and T = 40, k = 10 (*10-Nearest Neighbourhood Matrix*)

		Serial Correlation				
SD	**HT**	**0.9**	**0.5**	**0**	**-0.5**	**-0.9**
0.9	Low	PAZ	BAT	PSE	BAT	PAZ
	Mild	BAT	PAZ	TRU	PAZ	BAT
	Severe	BAT	PAZ	TRU	BAT	PAZ
0.5	Low	BAT	PAZ	TRU	BAT	BAT
	Mild	PAZ	BAT	PSE	BAT	PAZ
	Severe	PAZ	PAZ	PSE	PAZ	PAZ
0	Low	TRU	TRU	PSE	TRU	TRU
	Mild	TRU	PSE	TRU	TRU	PSE
	Severe	TRU	PSE	TRU	TRU	TRU
-0.5	Low	PAZ	PAZ	TRU	PAZ	PAZ
	Mild	PAZ	BAT	TRU	PAZ	BAT
	Severe	PAZ	PAZ	PSE	PAZ	PAZ
-0.9	Low	PAZ	BAT	PSE	PAZ	BAT
	Mild	PAZ	PAZ	TRU	PAZ	PAZ
	Severe	PAZ	PAZ	TRU	PAZ	BAT

Panel Corrected Standard Error (PSE) Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

From (Table 9), the results revealed that the Bartlett kernel and the Parzen kernel were the dominant estimators for the different combinations of heteroscedasticity, serial correlation and spatial dependence for the (10, 40) cross-sectional and time dimensions with K =10 spatial weight matrix specifications irrespective of the sign combinations. But the Parzen kernel performed better than the Bartlett kernel for more of the combinations of spatial dependence and serial correlation irrespective of the degree of heteroscedasticity and sigh combinations.

Table 10: Preferred Estimator at different levels of heterogeneity serial correlation and spatial dependence, when N = 10 and T = 40, k = 50 (*50-Nearest Neighbourhood Matrix*

		Serial Correlation				
SD	**Hetero**	**0.9**	**0.5**	**0**	**-0.5**	**-0.9**
0.9	Low	PAZ	PAZ	PSE	PAZ	PAZ
	Mild	PAZ	PAZ	TRU	BAT	BAT
	Severe	BAT	PAZ	TRU	PAZ	PAZ
0.5	Low	PAZ	BAT	TRU	PAZ	PAZ
	Mild	BAT	PAZ	TRU	BAT	BAT
	Severe	PAZ	BAT	TRU	BAT	BAT
0	Low	TRU	PAZ	TRU	PSE	PSE
	Mild	PSE	PAZ	TRU	PSE	TUK
	Severe	PSE	TRU	PSE	TRU	TRU
-0.5	Low	PAZ	PAZ	PSE	PAZ	BAT
	Mild	PAZ	PAZ	TRU	PAZ	PAZ
	Severe	BAT	PAZ	PSE	BAT	BAT
-0.9	Low	PAZ	BAT	PSE	PAZ	PAZ
	Mild	PAZ	BAT	PSE	PAZ	PAZ
	Severe	PAZ	PAZ	PAZ	BAT	BAT

Panel Corrected Standard Error (PSE) Truncated (TRU)Bartlett (BAT),Parzen (PAZ) Turkey-Hanning (TUK) Kernel functions

The performance of the different estimators for the different combinations of heteroscedasticity, serial correlation and spatial dependence for the (10, 40) cross-sectional and time dimensions with K =50 spatial weight matrix specifications is presented in (Table10). From the results, the Bartlett kernel and the Parzen kernel were adjudged better than the other estimators irrespective of the signs combinations .But, the Parzen kernel performed better than the Bartlett kernel for more of the combinations of spatial dependence and serial correlation irrespective of the degree of heteroscedasticity and the sigh combinations.

V. CONCLUSION AND RECOMMENDATIONS

For panel data model with heteroscedasticity, serial correlation and spatial dependence, in respective of the signs and magnitude of the error combinations, cross-sectional and time dimensions, and specifications of the spatial weight matrix, the Turkey-Hannings kernel, the Bartlett kernel and the Parzen kernel were the dominant estimators The Turkey-Hanning kernel and the Bartlett kernel were observed to have performed better for short panel (N > T) but the Turkey-Hannings kernel (TUK) was more preferred for small sample sizes (50, 20), with narrow spatial weight matrix specifications (Distance band weight, K =10) while the Bartlett (BART) kernel on the other hand performed better generally for large sample sizes ((150, 40) and wider spatial weight matrix specifications (K = 50). The Bartlett kernel and the Parzen kernel were the dominant estimators for long panel data (N < T). While the Bartlett (BART) kernel performed better for narrower spatial weight matrix specifications (Distance band weight). .The Parzen kernel estimator on the other hand was observed to have performed better with wider spatial weight matrix specifications (K = 50). Generally, the truncated kernel and the PCSE were dominant were either serial correlation was absence or where spatial dependence was absence or where both serial correlation and spatial dependence ware absence . However, the performance of the different estimators were influenced by the different panel type, different cross-sectional and time dimensions and different specifications of the spatial weight matrix

The study therefore recommends that either the Turkey-Hannings kernel, the Bartlett kernel or the Parzen kernel could be used for panel data model with data with heteroscedasticity, serial correlation and spatial dependence but that considerations should be given to the panel type, cross-sectional and time dimensions as well as under different the specifications of the spatial weight in the choice of any estimator

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EDOKPAYI, A.A [1], ABIODUN, A.A [2]

1 Statistics Division, Nigerian Institute for Oilpalm Research (NIFOR) Benin City

2 Departments of Statistics, University of Ilorin, Ilorin, Nigeria