

Modeling Panel Data in The Presence of Autocorrelation, Heteroscedasticity and Collinearity: A Monte Carlo Study

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Abstract

In this work, panel data that were characterised by features of autocorrelation, heteroscedasticity and collinearity were modelled using four estimation methods: Pooling (OLS), First-Differenced (FD), Between (BTW) and Feasible Generalized Least Squares (FGLS). Panel data like other aspects of econometrics, exploits regression analysis as one of the statistical tools to formulate, illustrate and appraise models. The regression analysis requires some assumptions which, if violated, results to one problem or the other. In such situation, the Pooling method of estimation which is the naive approach remains linear, unbiased and asymptotically normally distributed but might not be efficient as the estimates of the parameters might become indeterminate, the associated confidence intervals may be too wide and the standard errors might become infinitely large. Monte-Carlo studies were carried out at different sample sizes and time periods, varying degrees of heteroscedasticity and levels of autocorrelation and collinearity. The results from this work showed that in small sample situations, irrespective of number of time periods, FGLS is preferable when heteroscedasticity is severe regardless of levels of autocorrelation and multicollinearity. But when heteroscedasticity is low or mild with moderate autocorrelation level, both FD and FGLS are preferred, while BTW performs better only when there is no autocorrelation and low degree of heteroscedasticity. However, in large samples with little time periods, both FD and BTW could be used when there is no autocorrelation and low degree of heteroscedasticity, while FGLS is preferred if otherwise.

Keywords: *Panel data, autocorrelation, collinearity, heteroscedasticity*

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Introduction

Panel data is a kind of data in which observations are obtained on the same set of entities over some periods of time. 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, problems that naturally afflict time-series data (i.e. autocorrelation) and cross-sectional data (i.e. heteroscedasticity) are inherited by panel data and therefore need to be addressed while analyzing such data. Many distinctive features usually characterise 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 (i.e. $cov(u_{it}, u_{is}) \neq 0$, for $t \neq s$). Also, the error terms are expected to have the same variance. If this is unfulfilled, there is heteroscedasticity (i.e. $var(u_{it}) = \sigma_i^2$). (See Schmidt, 2005; Greene, 2008; Maddala, 2008; Creel, 2011; Wooldridge, 2012). Multicollinearity ensues when the assumption of “no linear dependencies in the explanatory variables” is not satisfied. (See Chatterjee, 2006; Maddala, 2008; Gujarati & Porter, 2009). When multicollinearity is present in a model, there will be deterministic relationship among the exogenous variables such that one of the variables can be expressed as a linear function of at least one of the other variables.

Furthermore, multicollinearity could render the estimates of the parameters indeterminate and there would be contradicting inferences between the overall fitness of the model and the significance tests for the parameters of the model. For the cases where the estimates of the parameters are obtained, the associated confidence intervals tend to be too wide and the standard error becomes infinitely large, an indication of inherent inconsistency in the estimated parameters.

In the presence of both autocorrelation and heteroscedasticity, the usual OLS estimators, although linear, unbiased, and asymptotically normally distributed, are no longer having minimum variance among all linear

unbiased estimators. See Greene (2008), Baltagi et al. (2008), and Olofin et al. (2010). Thus, the OLS estimator is not efficient relative to other linear and unbiased estimators under such situations

A number of works on the methodologies and applications of panel data modelling have appeared in the literature (Li and Stengos, 1994; Roy, 2002; Baltagi et al., 2005, 2008; Bresson et al., 2006; and Olofin et al., 2010). Situations where all the necessary assumptions underlying the use of classical linear regression methods are satisfied are rarely found in real life situations. Consequently, most of the studies that discussed panel data modelling considered the violation of each of the classical assumptions separately. For instance, Lillard and Wallis (1978), Bhargava et al. (1983), Baltagi and Li (1995), Galbraith and Zinde-Walsh (1995) and Roy (1999; 2002) did appreciable works on panel data with autocorrelated disturbances. Also, the studies of Mazodier and Trognon (1978), Rao et al. (1981), Magnus (1982), Baltagi and Griffin (1988) and Wansbeek (1989) focused on the existence of heteroscedasticity in panel data modelling. Notable among the works that considered the joint violation of the assumptions of homoscedasticity and no autocorrelation are those of Baltagi et al. (2008) and Olofin et al. (2010). The major distinction in their studies is that Baltagi et al. (2008) considered one-way error component model while Olofin et al. (2010) considered two-way error component model.

In this study, the methodologies of panel data modelling when the assumptions of no serial correlation, no multicollinearity and homoscedasticity are jointly violated are examined. The efficiency of four methods of estimating panel data models is studied. The best estimator among those considered that is robust to the violations of the basic assumptions highlighted above is determined using absolute biases, variances and root mean squared errors (RMSE) of parameter estimates. Results from this work would serve as useful guides to econometricians and other allied researchers while modelling panel data that are characterised by the structure conjectured here.

Materials and Methods

This work considers one-way error component model with two exogenous and one endogenous variables. Heteroscedasticity was implanted into the model via the individual-specific error component. This is in line with the works of Mazodier and Trognon (1978), Baltagi and Griffin (1988), Roy (2002) and many others. We considered first-order serial correlation as done by Lillard and Wallis (1978) and Bhargava et al (1983) to mention but a few. Most of the earlier works on panel data with autocorrelated disturbances and heteroscedasticity focused on single exogenous variable. We, however, considered two 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.

A Classical Panel Data Model

A general panel data model is given as

$$Y_{it} = \alpha_i + X'_{it} \beta + u_{it} \quad . \quad (1)$$

$i = 1, 2, \dots, n$ and $t = 1, 2, \dots, T$

where Y_{it} is the response for unit i at time t , α_i is the individual-specific intercept, vector X'_{it} contains k regressors for unit i at time t , vector β contains k regression coefficients to be estimated and u_{it} is the error component for unit i at time t .

Specifically, we considered the panel data model that has two exogenous and one endogenous variables as shown below:

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it} \quad . \quad (2)$$

where $\alpha_i = \alpha + \varepsilon_i$

The individual-specific intercept (α_i) captures the effects of those variables that are peculiar to the i^{th} individual and that are time-invariant.

The model becomes $Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \varepsilon_i + u_{it}$ (3)

where ε_i is the individual-specific error component and u_{it} is the combined time-series and cross-section error component with variances σ_ε^2 and σ_u^2 respectively.

Suppose we let $w_{it} = \varepsilon_i + u_{it}$, the model then becomes

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + w_{it} \quad (4)$$

Brief Overview of Some Estimators of Panel Data Models Considered

In this section, we provide brief theoretical formulations of the four estimators of panel data models as considered in this study.

i. **Pooled Estimator (OLS):** This Estimator stacks the data over i and t into one long regression with NT observations, and estimates of the parameters are obtained by OLS using the model

$$y = X'\beta + w \quad (5)$$

where y is an nT by 1 column vector of response variables

X is an nT by k matrix of regressors

β is a $(k+1)$ by 1 column vector of regression coefficients

w is an nT by 1 column vector of the combined error terms (i.e $\varepsilon_i + u_{it}$)

The Pooled estimator is given as $\hat{\beta}_{\text{pooled}} = (X'X)^{-1}X'y \quad (6)$

ii. **Between Estimator (BTW):** This regresses the group means of Y on the group means of X 's in a regression of n observations. It uses cross-sectional variation by averaging the observations over period t . Explicitly, it converts all the observations into individual-specific averages and performs OLS on the transformed data.

Averaging model (7) above over t gives

$$\bar{Y}_i = \alpha + \beta_1 \bar{X}_{1i} + \beta_2 \bar{X}_{2i} + \bar{w}_i \quad (7)$$

$$\text{where } \bar{Y}_i = T^{-1} \sum_t Y_{it}, \bar{X}_{ji} = T^{-1} \sum_t X_{jit} \text{ and } \bar{w}_i = T^{-1} \sum_t w_{it}$$

$$\text{for } i = 1, 2, 3, \dots, n \text{ and } j = 1, 2,$$

iii. **First-Differenced Estimator (FD):** This is the ordinary least squares estimation of the difference between the original model and its one-period-lagged model. The FD model is given as

$$\Delta Y_{it} = \beta_1 \Delta X_{1it} + \beta_2 \Delta X_{2it} + \beta_3 \Delta X_{3it} + \dots + \beta_k \Delta X_{kit} + \Delta w_{it} \quad (8)$$

where $\Delta Y_{it} = Y_{it} - Y_{i, t-1}$; $\Delta X_{1it} = X_{1it} - X_{1i, t-1}$; $\Delta X_{2it} = X_{2it} - X_{2i, t-1}$; and $\Delta w_{it} = w_{it} - w_{i, t-1}$.

for $i = 1, 2, \dots, n$ and $t = 2, 3, \dots, T$.

iv. **Feasible Generalized Least Squares Estimator (FGLS):** The generalized least squares estimator for the model parameters is obtained from the OLS estimation of the transformed model as shown below:

$$\mathbf{y}_{it}^* = \alpha_i^* + \mathbf{X}_{it}'^* \boldsymbol{\beta} + \mathbf{w}_{it}^* ; \quad (9)$$

for $i = 1, 2, \dots, n$ and $t = 1, 2, \dots, T$

where $y_{it}^* = y_{it} - \lambda \bar{y}_i$; $X_{it}^* = X_{it} - \lambda \bar{X}_i$; $w_{it}^* = \lambda \bar{w}_i$ and $\alpha_i^* = 1 - \lambda$

$$\text{and } \lambda = 1 - \sqrt{\sigma_u^2 / \{\sigma_u^2 + T\sigma_\varepsilon^2\}}$$

The term λ gives a measure of the relative sizes of the within and between unit variances.

Which is compactly written as $\tilde{\boldsymbol{\beta}}_{GLS} = (\mathbf{X}^* \boldsymbol{\Omega}^{-1} \mathbf{X}^*)^{-1} \mathbf{X}^* \boldsymbol{\Omega}^{-1} \mathbf{y}^*$ (10)

Since $\boldsymbol{\Omega}$ is often unknown, FGLS is more frequently used rather than GLS.

In using FGLS to estimate the parameters of the model, we first estimate λ

$$\text{using } \hat{\sigma}_u^2 \text{ and } \hat{\sigma}_\varepsilon^2 \text{ such that } \lambda = \sqrt{\frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2 + T\hat{\sigma}_\varepsilon^2}}$$

The $\hat{\sigma}_u^2$ is derived from the SSE of the within effects or from the derivations of residuals from group means of residuals while the $\hat{\sigma}_\varepsilon^2$ comes from the between effects model (i.e group mean regression). See Hsiao (2002), Arellano (2003), Baltagi (2005), Greene (2008), Creel (2011), Wooldridge (2012).

Simulation Scheme

The datasets used for this work were simulated using Monte Carlo experiments in the environment of R statistical package which is downloadable www.cran.org. Two sizes of cross-sectional units (50 and 250), three time periods (10, 40, and 100), five levels of autocorrelation ($\rho = \pm 0.9, \pm 0.5, 0$), five levels of collinearity ($r = \pm 0.9, \pm 0.5, 0$) and three degrees of heteroscedasticity (low, mild and severe) were used for simulation. Each of the combinations was iterated 1000 times and the assessments of the various estimators considered in this work were based on the absolute bias, variance and RMSE of parameter estimates.

The absolute bias (AB) of parameter $\hat{\beta}_k$ estimated over r replicates is defined by

$$AB(\hat{\beta}_k) = \frac{1}{r} \sum_{j=1}^r |\hat{\beta}_{kj} - \beta_k| \quad (11)$$

The variance of the estimator $\hat{\beta}_k$ is given by

$$\text{Var}(\hat{\beta}_k) = \frac{1}{r} \sum_{j=1}^r (\hat{\beta}_{kj} - \bar{\beta}_k)^2 \quad (12)$$

while its root mean square error is given by

$$\text{RMSE}(\hat{\beta}_k) = \sqrt{\frac{1}{r} \sum_{j=1}^r (\hat{\beta}_{kj} - \beta_k)^2} \quad (13)$$

where $\hat{\beta}_k$ indicates the k^{th} parameter being estimated for $j = 1, 2, 3, \dots, r$ (number of iterations).

After the estimators were evaluated based on the above criteria, they were all being ranked according to their relative performances to one another. A test of significance was carried out to test if the sums of ranks of other estimators are actually significantly different from that of the estimator proclaimed best. Since the ranks are on ordinal scale of measurements, a non-parametric statistical test developed by Milton Friedman (1939) was employed to perform this task. *M. K. Garba et al*

Thereafter, the pair-wise comparison test between a pair of estimators, say p and q , was performed using the least significant difference (LSD) with the test statistic given by:

$$LSD = t_{(n-1)(k-1), \alpha} \sqrt{2\{n \sum_i^k \sum_j^n r_{ij}^2 - \sum_i^k R_i^2\} \div (n-1)(k-1)} \quad (14)$$

where k is the number of estimators, n is the number of repetitions (levels of collinearity), R_i is the sum of ranks for each estimator and r_{ij}^2 is the square of the rank for each estimator at each level of multicollinearity.

Based on this formulations, any two estimators, p and q , are declared to be significantly different in terms of their performances at a chosen type I error rate α , if the absolute difference of their ranks is greater than the estimated LSD value.

1. Results and Discussion

The results of the performances of the estimators considered at various levels of autocorrelation, multicollinearity, and heteroscedasticity considered in this work are presented and discussed here. The four estimators were assessed based on each of the criteria stated in section 2.3.

These estimators were ranked using the ranks 1, 2, 3 and 4 with rank 1 assigned to the best estimator that has the lowest value of the absolute bias, variance and root mean squared error. A rank of 2 is assigned to the second best estimator and so on.

For instance, the performances of the estimators using variance criterion when we have 50 cross-sectional units and 10 time periods at all levels of autocorrelation and multicollinearity and degrees of heteroscedasticity are presented in the following table

Table 1: Ranks of the Estimators Using Variance Criterion when N = 50 and T = 10

Auto	Estimator	Multi = -0.9			Multi = -0.5			Multi = 0			Multi = 0.5			Multi = 0.9		
		Heteroscedasticity			Heteroscedasticity			Heteroscedasticity			Heteroscedasticity			Heteroscedasticity		
		Low	Mild	Sev	Low	Mild	Sev	Low	Mild	Sev	Low	Mild	Sev	Low	Mild	Sev
-0.9	OLS	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	FD	2	2	2	1	1	2	1	1	1	1	1	2	2	2	2
	BTW	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	FGLS	1	1	1	2	2	1	2	2	2	2	2	1	1	1	1
-0.5	OLS	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	FD	1	1	2	2	1	1	2	2	1	2	1	1	1	1	2
	BTW	2	3	3	1	2	3	1	1	3	1	2	3	2	3	3
	FGLS	3	2	1	3	3	2	3	3	2	3	3	2	3	2	1
0	OLS	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	FD	2	3	1	2	2	3	2	2	3	2	2	3	2	3	1
	BTW	1	1	2	1	1	1	1	1	1	1	1	1	1	1	2
	FGLS	3	2	3	3	3	2	3	3	2	3	3	2	3	2	3
0.5	OLS	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	FD	1	1	2	2	1	1	2	2	1	2	1	1	1	1	2
	BTW	2	3	3	1	2	3	1	1	3	1	2	3	2	3	3
	FGLS	3	2	1	3	3	2	3	3	2	3	3	2	3	2	1
0.9	OLS	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	FD	2	2	2	1	1	2	1	1	1	1	1	2	2	2	2
	BTW	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	FGLS	1	1	1	2	2	1	2	2	2	2	2	1	1	1	1

The ranks for each of the estimators were summed for all levels of multicollinearity to determine an estimator with lowest sum of ranks at each

of the autocorrelation levels and degrees of heteroscedasticity. Here, the effects of multicollinearity are repressed to assess the upshots of autocorrelation and heteroscedasticity which are respectively the problems that are peculiar to time-series and cross-sectional data that are brass tacks of panel data.

Table 2 below has sum of ranks resulting from Table 1 for the four estimators considered in the study.

Table 2: Sum of Ranks of the Estimators Using Variance Criterion when N = 50 and T = 10

Autocorrelation	Estimator	Heteroscedasticity		
		Low	Mild	Severe
-0.9	OLS	20	20	20
	FD	7	7	9
	BTW	15	15	15
	FGLS	8	8	6
-0.5	OLS	20	20	20
	FD	8	6	7
	BTW	7	11	15
	FGLS	15	13	8
0	OLS	20	20	20
	FD	10	12	11
	BTW	5	5	7
	FGLS	15	13	12
0.5	OLS	20	20	20
	FD	8	6	7
	BTW	7	11	15
	FGLS	15	13	8
0.9	OLS	20	20	20
	FD	7	7	9
	BTW	15	15	15
	FGLS	8	8	6

The preference of these estimators at different sample sizes, different levels of autocorrelation and varying degrees of heteroscedasticity for each of the sample sizes used are presented in Table 3.

Table 3: Preference of the Estimators for each of the Sample Sizes

Sample Size	Degree of Heteroscedasticity	Autocorrelation Level		
		± 0.9	± 0.5	0
N = 50 T = 10	Low	FD/FGLS	BTW/FD	BTW
	Mild	FGLS/FD	FD	BTW
	Severe	FGLS/FD	FD/FGLS	BTW
N = 50 T = 40	Low	FGLS	FD	BTW
	Mild	FGLS	FD	BTW/FD
	Severe	FGLS	FD/FGLS	FD/BTW
N = 50 T = 100	Low	FGLS	FGLS	FGLS
	Mild	FGLS	FGLS	FGLS
	Severe	FGLS	FGLS	FGLS
N = 250 T = 10	Low	FGLS	FD	FD
	Mild	FGLS	FGLS	FD
	Severe	FGLS	FGLS	FD
N = 250 T = 40	Low	FGLS	FD	BTW
	Mild	FGLS	FGLS	FD
	Severe	FGLS	FGLS	FD
N = 250 T = 100	Low	FGLS	FGLS	FGLS
	Mild	FGLS	FGLS	FGLS
	Severe	FGLS	FGLS	FGLS

It can be deduced from Table 3 that at $N = 50$; $T = 10$ and at high level of autocorrelation (± 0.9) irrespective of degree of heteroscedasticity, the performances of FD and FGLS estimators are not significantly different from each other. Therefore, each of them is efficient for this scenario. Meanwhile, for moderate autocorrelation level (± 0.5), any of FD and BTW estimators could be used at low degree of heteroscedasticity. The FD estimator is preferred when there is mild heteroscedasticity, while under severe heteroscedasticity, the FD and FGLS estimators performed better. But at no autocorrelation, BTW estimator which regresses the group means of the dependent variable on the group means of independent variables using OLS is efficient irrespective of the degree of heteroscedasticity for sample size $N = 50$; $T = 10$. The efficient estimators for other sample sizes are presented accordingly in Table 3 above.

Conclusion

Various results obtained in this work generally showed that the behaviours of the four estimators investigated for modeling various panel data vary as the violations are varied. Failure of the orthogonality assumption makes the OLS estimators to be biased and imprecise. For OLS 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 OLS for modeling panel data efficiently.

The efficiency of four methods of estimating panel data models with violations of homoscedasticity, no autocorrelation and no collinearity assumptions is principally and thoroughly addressed in this work. Our findings from Monte Carlo experiments for several combinations of violations show that in small samples, irrespective of number of time periods, FGLS is preferable when heteroscedasticity is severe regardless of autocorrelation level. But when heteroscedasticity is low or mild with moderate autocorrelation level, both FD and FGLS are preferred, while BTW performs better only when there is no autocorrelation and low degree of heteroscedasticity. That is, in large samples with little time periods, both

FD and BTW could be used when there is no autocorrelation and low degree of heteroscedasticity. Also when the degree of heteroscedasticity is mild and there is no autocorrelation in large samples with little time periods, any of the FD and FGLS would produce efficient results. Finally, when severe degree of heteroscedasticity is present and autocorrelation is apparent in large samples regardless of time periods, FGLS is superior. Meanwhile, both FD and FGLS are suitable when there is low heteroscedasticity despite the existence of autocorrelation and multicollinearity.

As a general remark, given the various results obtained in this study, it is always necessary to assess the degree of heteroscedasticity and level of autocorrelation while developing panel data models in order to ensure efficient results. In case there is more than one predictor in the model, the strength of relationship between or among the predictors needs to be examined for possible presence of multicollinearity in the data as to avoid erroneous inferences that may arise from the use a wrong method for estimating the model.

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