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Research Article

On the Performance of Some Estimation Methods in Models with Heteroscedasticity and Autocorrelated Disturbances (A Monte-Carlo Approach)

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Abstract

The proliferation of panel data studies has been greatly motivated by the availability of data and capacity for modelling the complexity of human behaviour than a single cross-section or time series data and these led to the rise of challenging methodologies for estimating the data set. It is pertinent that, in practice, panel data are bound to exhibit autocorrelation or heteroscedasticity or both. In view of the fact that the presence of heteroscedasticity and autocorrelated errors in panel data models biases the standard errors and leads to less efficient results. This study deemed it fit to search for estimator that can handle the presence of these twin problems when they co- exists in panel data. Therefore, robust inference in the presence of these problems needs to be simultaneously addressed. The Monte-Carlo simulation method was designed to investigate the finite sample properties of five estimation methods: Between Estimator (BE), Feasible Generalized Least Square (FGLS), Maximum Estimator (ME) and Modified Maximum Estimator (MME), including a new Proposed Estimator (PE) in the simulated data infected with heteroscedasticity and autocorrelated errors. The results of the root mean square error and absolute bias criteria, revealed that Proposed Estimator in the presence of these problems is asymptotically more efficient and consistent than other estimators in the class of the estimators in the study. This is experienced in all combinatorial level of autocorrelated errors in remainder error and fixed heteroscedastic individual effects. For this reason, PE has better performance among other estimators.

Keywords

Modified, Method, Panel, Estimator, Simulations

1. Introduction

Panel data model have become increasingly popular in the past decades with the increased availability of cross country data sets. [15], were the first set of scholars to work on panel data. Panel data describes the number of individuals across a sequence of time periods. There are several key advantages of using panel data over a single time series or cross-section data set. This combination of time series with cross-section can enhance the quality and quantity of data in ways that would be possible using only one of these two dimensions. To realize the potential value of the information contained in a panel data, see [3, 4, 6, 9, 11, 27, 28].

Panel data typically contains some form of heteroscedas-

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ticity, serial correlation and /or spatial correlation. Therefore, robust inference in the presence of heteroscedasticity and serial correlation is an important problem in spatial data analysis, [14].

The essence of these two problems is that, in many econometrics studies, including panel study, the assumption of constant variance for the disturbance term is unrealistic. This, then calls for a restrictive assumptions for panel, where, in practice, the cross-sectional units may be of varying size and as a result exhibit different variation.

It was observed that some scholars, consider cases where one accounts for heteroscedasticity and ignores the possibility of serial correlation problems in the model and vice-versa [10, 12, 13, 16, 17-20, 22-26]. Few authors that consider both problems include [1-3, 7, 8, 21]. Of these authors, Baltagi et al, as well as both derived test for joint occurrence of heteroscedasticity and autocorrelation in one way and two-way error components respectively [3, 21]. The difference between this work and that of [3] is that it focuses on the development of a new estimator and estimation of the parameters not testing for the presence of autocorrelation and heteroscedasticity in the context of a panel data regression model.

Furthermore, this study explicitly decomposes error term as the sum of two elements; capturing individual heterogeneity and autocorrelation in the remainder error term. By so doing, the data is then generated from the error component model with serial correlation and heteroscedasticity with the help of Monte-Carlo Simulation method.

The study was mainly targeted at investigating finite sample properties of five estimation methods of panel data models in the presence of autocorrelation and heteroscedasticity in one-way error component model. The estimation methods are BE, FGLS, M, MM and PE.

The inclusion of M and MM estimators in this study is due to their performance in the various work [29].

2. Methodology

2.1. Model Specification

Consider the following panel data model:

$$y_{it} = X_{it}^{1}\beta + u_{it,} \quad i = 1, \cdots, N; \quad t = 1, \cdots, T. \tag{1}$$

where: β is K × 1 vector of regression coefficient.

y_{it} represent the response variable;

x_{it} represent the regressors;

u_{it} represent disturbance term

The disturbance follow one-way error component model

$$u_{it} = \mu_i + v_{it} \tag{2}$$

$\mu_i \sim IID(0, \sigma_{\mu i}^2)$ and v_{it} follows AR(1) i.e.

$$v_{it} = \rho v_{i,t-1} + \varepsilon_{it} \tag{3}$$

Where $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$.

2.2. Monte-Carlo Experiment

This work present a Monte-Carlo experiment that studied the finite sample properties of the five estimation methods; Between estimator (BE), Feasible Generalized Least Square (FGLS), Maximum estimator (M), Modified Maximum estimator (MM) and Proposed estimator (PE) applied to panel data model.

The Root Mean Square Error (RMSE) were used as criterion to assess the performances of these estimators.

The set- up in the experiment in this study was based on both individual- specific effect and remainder disturbance simultaneously with joint assumptions of heteroscedasticity and AR(1); generating contaminated data.

2.3. Data Generating Scheme

The design of Monte- Carlo experiments in this study uses the following information to generate infected data.

Consider the following panel model:

$$y_{it} = \beta_0 + \beta_1 X_{it} + \mu_i + V_{it} \tag{4}$$

where $X_{it} = \omega_{it} + 0.5\omega_{i,t-1}, \sim \omega_{it} \sim \cup(0.2)$. The parameters were assigned as. $\beta = (\beta_0, \beta_1, \beta_2) = 1$

The cross- sections and time periods was chosen as N= 25,100,200 and T= 5, 10. For each combinations of N and T; 5000 replications were considered.

The autocorrelation coefficient values and heteroscedasticity used are specified as ρ varies as 0.3, 0.5, 0.8 and $\sigma_\mu^2(1 + \lambda\bar{x}_i)$. $\lambda = 1$.

The variance of individual effects, remainder error and error term is one. i.e. $\sigma_\mu^2 = \sigma_v^2 = \sigma_\varepsilon^2 = 1$

2.4. Derivation of a New Proposed Panel Data Estimator

Consider the likelihood function of the normal distribution as follows;

$$L = \frac{1}{(2\pi)^{\frac{n}{2}}|V|^{1/2}} e^{\frac{-1}{2}U`V^{-1}U} \tag{5}$$

where $U = Y - X\beta$

Therefore

$$L = \frac{1}{(2\pi)^{\frac{n}{2}}|V|^{1/2}} e^{\frac{-1}{2}(Y-X\beta)`V^{-1}(Y-X\beta)} \tag{6}$$

Assume that there exist, linear restriction $R\,\beta$, binding the regression coefficients vector of β, where R is a row vector of ones defined as $\frac{1}{K}(1,1 \cdots 1)$

(6) is transformed, subject to constraint Rβ, as follows:

$$l = (2\pi)^{-n/2} |v|^{-\frac{1}{2}} e^{\frac{-1}{2}(Y-X\beta)^{`}V^{-1}(Y-X\beta)-R\beta} \quad (7)$$

Taking natural logarithm of (7), we have,

$$log_e\, l = -{}^{n}/_{2}\, log_e\,(2\pi) - {}^{1}/_{2}\, log_e\,|V| - \tfrac{1}{2}(Y - X\beta)^1 V^{-1}(Y - X\beta) - \mathrm{R}\beta. \quad (8)$$

$$log_e\, l = -{}^{n}/_{2}\, log_e\,(2\pi) - {}^{1}/_{2}\, log_e\,|V| - \tfrac{1}{2}[Y^1 V^{-1}Y\text{-}Y^1V^{-1}X\beta - \beta^1X^1 V^{-1}Y + \beta^1X^1V^{-1}X\,\beta] - R\beta$$

$$log_e\, l = -{}^{n}/_{2}\, log_e\,(2\pi) - {}^{1}/_{2}\, log_e\,|V| - \tfrac{1}{2}[Y^1 V^{-1}Y\text{-}2X^1V^{-1}Y\beta + \beta^1X^1V^{-1}X\beta] - R\beta$$

$$log_e\, l = -{}^{n}/_{2}\, log_e\,(2\pi) - {}^{1}/_{2}\, log_e\,|V| - \tfrac{1}{2}[Y^1 V^{-1}Y\text{-}2X^1V^{-1}Y\beta + \beta^1X^1V^{-1}X\beta + 2R\beta]$$

By maximizing the log- likelihood function, therefore,
Let $log_e l = A$

$$\frac{\partial A}{\partial \beta} = -{}^{1}/_{2}\,[-2X^1V^{-1}Y + 2(X^1V^{-1}X)\beta + 2R]$$

$$\frac{\partial A}{\partial \beta} = X^1V^{-1}Y - (X^1V^{-1}X)\beta - R$$

Setting $\frac{\partial A}{\partial \beta} = 0$
It implies that:

$$0 = X^1V^{-1}Y - (X^1V^{-1}X)\beta - R$$

Therefore,

$$(X^1V^{-1}X)\beta = X^1V^{-1}Y - R$$

Pre-multiply by $(X^1V^{-1}X)^{-1}$, it results into:

$$\beta_P = (X^1V^{-1}X)^{-1}X^1V^{-1}Y - R(X^1V^{-1}X)^{-1} \quad (9)$$

$$\mathrm{Var}(\beta_p) = E[(\beta_P - \beta)(\beta_P - \beta)^1]$$

From (9),

$$\beta_P = (X^1V^{-1}X)^{-1}X^1V^{-1}(X\beta + U) - R(X^1V^{-1}X)^{-1} \quad (10)$$

$$\beta_P = (X^1V^{-1}X)^{-1}X^1V^{-1}\mathrm{X}\beta + (X^1V^{-1}X)^{-1}X^1V^{-1}U - R(X^1V^{-1}X)^{-1}$$

$$\beta_P = \beta + (X^1V^{-1}X)^{-1}X^1V^{-1}U - R(X^1V^{-1}X)^{-1} \quad (11)$$

$$\beta_P - \beta = (X^1V^{-1}X)^{-1}X^1V^{-1}U - R(X^1V^{-1}X)^{-1} \quad (12)$$

Therefore,

$$\mathrm{Var}(\beta_P)=\mathrm{E}[(X^1V^{-1}X)^{-1}X^1V^{-1}U - R(X^1V^{-1}X)^{-1}][(X^1V^{-1}X)^{-1}X^1V^{-1}U - R(X^1V^{-1}X)^{-1}]^1$$

$$\mathrm{Var}(\beta_P)= (X^1V^{-1}X)^{-1}X^1V^{-1}E(UU^1)X(X^1V^{-1}X)^{-1} + R(X^1V^{-1}X)^{-1}(X^1V^{-1}X)^{-1}R^1$$

$$\mathrm{Var}(\beta_P)=\sigma^2(X^1V^{-1}X)^{-1} + R(X^1V^{-1}X)^{-1}(X^1V^{-1}X)^{-1}R^1 \quad (13)$$

$$Bias\lfloor\hat{\beta}\rfloor = E\lfloor\hat{\beta}\rfloor - \beta = E\lfloor\hat{\beta} - \beta\rfloor \tag{14}$$

$$E(\beta_P - \beta) = E[(X^1V^{-1}X)^{-1}X^1V^{-1}U - R(X^1V^{-1}X)^{-1}]$$

$$E(\beta_P - \beta) = [(X^1V^{-1}X)^{-1}X^1V^{-1}E(U) - R(X^1V^{-1}X)^{-1}]$$

Recall: $E(U) = 0$

$$E(\beta_P - \beta) = -R(X^1V^{-1}X)^{-1} \tag{15}$$

$$\text{ABias }(\beta) = |E(\beta_P - \beta)| = R(X^1V^{-1}X)^{-1}. \tag{16}$$

3. Results

In this analysis, attention is focused on the asymptotic behaviour of five estimators in panel data infected with autocorrelated error terms of low, moderate and high levels and heteroscedastic structure. Monte-Carlo experiment is used to generate infectious data. 5000 replications are performed on combination of cross section, N=25,100 and 200 and time periods, T=5 and 10 for different degrees of autocorrelation and heteroscedastic structure (0.3, 0.5, and 0.8). R- Package is used for the analysis.

***Table 1**. Root Mean Square Error in the Presence of Heteroscedasticity and Low Autocorrelation.*

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
25	BE	0.00436	0.13246	0.11342	0.17371	0.03544	0.22084
	FGLS	0.04683	0.22915	0.61354	0.11077	0.77631	0.01124
	ME	0.00437	0.13246	0.11343	0.17371	0.03544	0.22084
	MME	0.06349	0.0681	0.24825	0.0499	0.03942	0.22238
	PE	0.00021	0.00031	0.00078	0.00399	0.00011	0.00356
100	BE	3.72E-06	3.82E-08	0.03066	0.00037	0.00011	0.01132
	FGLS	0.00075	0.00662	0.04158	0.0002	0.00785	0.05017
	ME	3.70E-06	0.00394	0.03066	0.00037	0.00011	0.01132
Ugkl;	MME	0.01193	0.00961	0.05442	0.00866	0.00712	0.03283
	PE	5.29E-06	0.00019	0.00047	0.000017	1.02E-04	0.00039
200	BE	0.00018	5.37E-05	0.00566	0.00031	0.00244	0.00098
	FGLS	0.0001	0.00393	0.02509	0.00422	0.01802	0.00233
	ME	0.00018	5.37E-05	0.00566	0.00031	0.00244	0.00098
	MME	0.00569	0.00457	0.02635	0.00604	0.00592	0.02736
	PE	0.000002	6.1E-07	0.00019	5.15E-06	0.000042	0.000027

Proposed estimator outperforms other estimators.

Table 2. Root Mean Squared Error in the Presence of Heteroscedasticity and Moderate Autocorrelation.

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
25	BE	0.0013093	0.0397366	0.0340263	0.0521136	0.0106306	0.066251
	FGLS	0.0140494	0.0687456	0.1840608	0.0332317	0.2328942	0.003373
	ME	0.0013095	0.0397381	0.03403	0.0521136	0.0106306	0.066251
	MME	0.0190483	0.0204296	0.0744744	0.0149688	0.0118272	0.066713
	PE	0.000064	0.0000936	0.000235	0.0119883	0.0000358	0.001069
100	BE	1.11E-06	1.14E-08	0.0091979	0.0001101	3.22E-05	0.003396
	FGLS	0.0002264	0.0019866	0.012474	6.11E-05	0.0023553	0.015052
	ME	1.11E-06	0.0011827	0.0091981	0.0001101	3.22E-05	0.003396
	MME	0.0035777	0.0028833	0.0163271	0.0025988	0.0021363	0.009848
	PE	3.29E-06	0.0000084	0.0002032	5.32E-06	3.37E-05	0.000117
200	BE	5.51E-05	1.61E-05	0.0016978	9.25E-05	0.0007306	0.000294
	FGLS	3.05E-05	0.0011776	0.007526	0.001265	0.0054075	0.000699
	ME	5.51E-05	1.61E-05	0.0016978	9.25E-05	0.0007306	0.000294
	MME	0.0017085	0.0013696	0.007906	0.0018133	0.0017767	0.008208
	PE	2.66E-06	1.8E-07	0.0000086	1.55E-06	0.0000028	0.000008

Proposed estimator outperforms other estimators.

Table 3. Root Mean Squared Error in the Presence of Heteroscedasticity and High Autocorrelation.

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
25	BE	0.0034915	0.10596432	0.0907368	0.1389696	0.0283483	0.176669
	FGLS	0.0374651	0.1833216	0.4908288	0.0886178	0.6210512	0.008994
	ME	0.0034921	0.10596821	0.0907466	0.1389696	0.0283483	0.176669
	MME	0.0507954	0.05447904	0.1985984	0.0399168	0.0315392	0.177901
	PE	0.000234	0.00196221	0.0001235	0.0000068	0.0007244	0.000015
100	BE	2.97E-06	3.05E-08	0.0245277	0.0002937	8.59E-05	0.009055
	FGLS	0.0006037	0.0052976	0.033264	0.0001629	0.0062807	0.040139
	ME	2.96E-06	0.00315392	0.0245281	0.0002937	8.59E-05	0.009055
	MME	0.0095406	0.00768891	0.0435389	0.00693	0.0056968	0.026261
	PE	1.55E-04	0.00070211	0.0000962	0.0000029	3.12E-04	0.000055
200	BE	0.0001468	4.29E-05	0.0045276	0.0002466	0.0019482	0.000785
	FGLS	8.147E-05	0.00314034	0.0200694	0.0033732	0.0144199	0.001863
	ME	0.0001469	4.29E-05	0.0045274	0.0002466	0.0019484	0.000785
	MME	0.0045559	0.00365226	0.0210826	0.0048356	0.0047378	0.021888

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
	PE	4.9E-07	1.56E-04	0.00000412	3.8E-07	0.0000022	0.0000004

Proposed estimator outperforms other estimators.

Table 4*. Absolute Bias in the Presence of Heteroscedasticity and Low Autocorrelation.*

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
25	BE	0.052136	0.287336	0.265776	0.329084	0.148666	0.371028
	FGLS	0.170912	0.378084	0.618576	0.262836	0.6958	0.084084
	ME	0.0521752	0.2874144	0.265972	0.329182	0.1486856	0.371224
	MME	0.235396	0.216188	0.415912	0.178752	0.161504	0.378672
	PE	0.003269	0.003945	0.006256	0.014119	0.002439	0.013334
100	BE	0.0304388	0.308504	0.2765364	0.0302604	0.0163621	0.168033
	FGLS	0.043708	0.129164	0.325556	0.02254	0.139944	0.35378
	ME	0.003038	0.0003136	0.276556	0.0302624	0.016366	0.168031
	MME	0.17248	0.15484	0.36848	0.147	0.13328	0.28616
	PE	0.0002320	0.000061	0.013233	0.005950	0.001557	0.008829
200	BE	0.0302428	0.01636208	0.1680308	0.0392134	0.1102108	0.069952
	FGLS	0.02254	0.139944	0.35378	0.14504	0.29988	0.1078
	ME	0.0302624	0.016366	0.1680308	0.0392196	0.1102304	0.069972
	MME	0.16856	0.15092	0.3626	0.173656	0.171892	0.36946
	PE	0.000595	0.0003038	0.008829	0.001433	0.007553	0.00333

Proposed Estimator is asymptotically consistent.

Table 5*. Absolute Bias in the Presence of Heteroscedasticity and Moderate Autocorrelation.*

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
25	BE	0.0156408	0.0862008	0.0797328	0.0987252	0.0445998	0.111308
	FGLS	0.0512736	0.1134252	0.1855728	0.0788508	0.20874	0.025225
	ME	0.0156526	0.08622432	0.0797916	0.0987546	0.0446057	0.111367
	MME	0.0706188	0.0648564	0.1247736	0.0536256	0.0484512	0.113602
	PE	0.0009807	0.0011835	0.0068769	0.0042359	0.0007319	0.004000
100	BE	0.0091316	0.0925512	0.0829609	0.0090781	0.0049086	0.05041
	FGLS	0.0131124	0.0387492	0.0976668	0.006762	0.0419832	0.106134

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
	ME	0.0009114	0.00009408	0.0829668	0.0090787	0.0049098	0.050409
	MME	0.051744	0.046452	0.110544	0.0441	0.039984	0.085848
	PE	0.0000696	0.00001835	0.003970	0.001785	0.000467	0.002648
200	BE	0.0090728	0.00490862	0.0504092	0.011764	0.0330632	0.020986
	FGLS	0.006762	0.0419832	0.106134	0.043512	0.089964	0.03234
	ME	0.0090787	0.0049098	0.0504092	0.0117659	0.0330691	0.020992
	MME	0.050568	0.045276	0.10878	0.0520968	0.0515676	0.110838
	PE	0.000038	0.000091	0.002648	0.000430	0.0002659	0.000999

Proposed estimator is more asymptotically consistent than Modified Maximum Estimators.

Table 6. Absolute Bias in the Presence of Heteroscedasticity and High Autocorrelation.

N		T=5			T=10		
		β_0	β_1	β_2	β_0	β_1	β_2
25	BE	0.0417088	0.2298688	0.2126208	0.2632672	0.1189328	0.296822
	FGLS	0.1367296	0.3024672	0.4948608	0.2102688	0.55664	0.067267
	ME	0.0417402	0.22993152	0.2127776	0.2633456	0.1189485	0.296979
	MME	0.1883168	0.1729504	0.3327296	0.1430016	0.1292032	0.302938
	PE	0.0026154	0.00315607	0.005005	0.0112958	0.0019518	0.010667
100	BE	0.024351	0.2468032	0.2212291	0.0242084	0.0130897	0.134426
	FGLS	0.0349664	0.1033312	0.2604448	0.018032	0.1119552	0.283024
	ME	0.0024304	0.00025088	0.2212448	0.0242099	0.0130928	0.134425
	MME	0.137984	0.123872	0.294784	0.1176	0.106624	0.228928
	PE	0.000185	0.00004892	0.0048714	0.0476045	0.0012456	0.007063
200	BE	0.0241942	0.01308966	0.1344246	0.0313707	0.0881686	0.055962
	FGLS	0.018032	0.1119552	0.283024	0.116032	0.239904	0.08624
	ME	0.0242099	0.0130928	0.1344246	0.0313757	0.0881843	0.055978
	MME	0.134848	0.120736	0.29008	0.1389248	0.1375136	0.295568
	PE	0.000076	0.0002431	0.0020635	0.001146	0.0060424	0.002664

Proposed estimator is more asymptotically consistent than Modified Maximum Estimator.

4. Discussion

The following results are obtained when there exists combination of different level of autocorrelation and heteroscedasticity irrespective of cross-section and time period.

1) The study came up with a proposed estimator;
2) Proposed estimator (PE) is asymptotically efficient and consistent;
3) PE is a more suitable technique for both small and large sample size than other existing estimators in this study.

5. Implication to Research and Practice

The implication of this work is that it will assist the firms, government, social and behavioral scientists in their decision making in order to minimize the effect of one-way error component on the parameter estimates.

6. Conclusion

This study considers a case of heteroscedastic individual random when first order serial correlation is present in the context of a panel data regression model. This is in contrary to the usual econometrics literature that deals with heteroscedasticity ignoring serial correlation or vice versa. The results of the Monte-Carlo experiment showed that PE outperforms other methods of estimation for it is asymptotically efficient and consistent in the presence of autocorrelation and heteroscedasticity. Therefore, it is more robust than the existing estimators in this study.

Future Research

The study can further be extended to non-linear panel data of balanced and unbalanced type. Bayesian inference can also be looked into for possible robust estimation.

Conflicts of Interest

The authors declare no conflicts of interest.

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