AN ASYMPTOTIC COMPARISON OF DYNAMIC PANEL DATA ESTIMATORS WITH AUTOCORRELATED ERROR TERMS

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ABSTRACT: This paper investigates properties of some dynamic panel data estimators including Ordinary Least Squares (OLS), the Anderson-Hsiao IV (AH), Arellano-Bond Generalized Method of Moment (GMM) first-step, Blundell- Bond System (SYS1) first-step, M and MM estimators in the presence of serial correlation. Absolute Bias and Root Mean Squares Error were used to evaluate finite properties of the estimators and revealed improving performances asymptotically under different sample sizes and varying degrees of autocorrelation. The results showed that in small and large sample situations, irrespective of time dimension, Anderson–Hsiao IV estimator (AH) outperforms all other estimators. Arellano-Bond Generalized Method of Moment (GMM) one-step proves to be relatively superior among the estimators when the time period (T) is small, though it may not be the best but performance improved drastically as the number of cross-sectional units increases. However, Ordinary Least Squares estimator has least performance among all the estimators considered in this study.

KEYWORDS: Dynamic Panel Data, Serial Correlation, Cross-Sections, Time Periods, Absolute Bias and Root Mean Squares Error.

1. INTRODUCTION

Panel data is a cross-section or group of entities that are surveyed periodically over a given time span. Panel data consist of repeated observations on some subjects at different occasions. It could be generated by pooling time-series observations across a variety of cross-sectional units. The units may be individuals, households, firms, regions or countries. Since the temporal dependencies for each unit could vary significantly, a dynamic parameter is desirable to relax the parametric constraints into the model. Dynamic panel data model postulates the lagged dependent variable as one of the explanatory variables to be included in the model. Just like in univariate time series analysis, modeling the dependency of the time series on its past value gives valuable insights on the temporal behavior of the series. [Bal05] noted that many economic relationships are dynamic in nature and the panel data allow the researcher to better understand the dynamics of structural adjustment exhibited by the data. The discussion of dynamic panel data modeling was opened by [ST85] and [BN66]. However, the number of existing estimators to estimate dynamic models has increased steadily. In fact, there still appears to be room for improvement as far as finite sample bias and efficiency is concerned. [See HM10a].

A number of techniques for modeling dynamic panel data have been proposed in the literature based on Instrumental Variable (IV) and Generalized Method of Moments (GMM) estimators. [Nic81, AH81, AH82, Kiv95, AB91, AS95, Isl98 among others]. However, the thrust of this work is to infuse serial correlation in a random effects one-way error component model and investigate the behaviours of the existing mainstream Instrumental Variable (IV) Generalized Method of Moments (GMM) estimators and other two robust estimators (M and MM) in the presence of serial correlation. Hence, various studies had been carried out using Monte Carlo simulations in small samples [See JO99, Hay08, Isl98, HM10b]. Therefore, this present study examines the performances of different estimators for dynamic panel data having serial correlation for small samples to large samples with different time dimensions.

2. MATERIALS AND METHODS

In this work, we considered one-way error component model with serial correlation injected via the individual-specific error component using random effects model type. Various levels of correlations ranging from 0.2 to 0.9 were considered. Our choice of method for injecting serial correlation is in agreement with [Isl98, JO99, HM10b] to mention but few. However, most of the previous works done on Dynamic panel data models ignored the possibility of serial correlation of disturbance term.

2.1 A Dynamic Panel Data Models

The dynamic panel data model is

$$y_{it} = \delta y_{i,t-1} + x'_{it}\beta + \mu_i + v_{it}, \quad i = 1,\ldots,N; t = 1,\ldots,T \qquad (1)$$

y_{it} is the dependent variable, $y_{i,t-1}$ is the lagged dependent variable, x'_{it} is a $(k-1)$x1 vector of exogenous regressors, μ_i is an individual specific fixed effects, δ is unknown parameters of lagged variable and β is unknown parameter vector of K explanatory variable, and v_{it} is a disturbance term which varies over the cross section and time, $i = (1,\ldots,N)$ is an index over the cross section and $t = (1,\ldots,T)$ denotes the time period. We assume that the explanatory variables are weakly exogenous variables with $\mathrm{E}(w_{it}x_{is}) \neq 0$ for $s \geq t$ and zero otherwise.

2.2 Brief overview of some estimators of dynamic panel data models considered

Ordinary Least Square estimators are applied to the equation (1) in level form. The OLS estimator may render the estimates biased and inconsistent for a number of reasons. First, y_{it} is a function of both the individual specific effects (μ_i). This then follows that $y_{i,t-1}$ is also of function of these effects. Thus, $y_{i,t-1}$ is correlated with the error term $(i.e\ \mathrm{E}(y_{i,t-1}v_{it}))$. This undoubtedly rendered the OLS estimator biased and inconsistent even if the error term v_{it} is not serially correlated. Therefore, Ordinary Least Squares estimator is given as

$$\hat{\beta}_{OLS} = (X'X)^{-1}X'y. \qquad (2)$$

[AH81] proposed an Instrumental Variable (IV) estimator that is consistent for fixed T and N tends to infinity. Anderson and Hsiao (IV) estimator is applied to the model in first-differenced form in equation (1) is given as

$$y_{it} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (x'_{it} + x_{i,t-1})\beta + v_{it} + v_{i,t-1} \quad (3)$$

Which cancelled the individual fixed effects assumed to possibly correlate with the exogenous variable $(\mathrm{E}(x'_{it} - \mu_i) \neq 0)$ and it results in the "loss" of one cross section from the actual estimation. They suggested the use of level instrument y_{t-2} or the lagged difference $y_{i,t-2} - y_{i,t-3}$ as an instrument for the differenced lagged endogenous regressor $y_{i,t-1} - y_{i,t-3}$.

Anderson-Hsiao estimator is given as

$$\hat{\gamma}^{AH} = (XPX)^{-1}X'Py$$
$$\text{where } P = Z(Z'Z)^{-1}Z \qquad (4)$$

The symbol l or d to represent the use of levels or differences as instruments $(\hat{\gamma}^{AH(l)}, \hat{\gamma}^{AH(d)})$. The AH estimator was found to be consistent but not efficient. [AB91] estimator is similar to the one suggested by Anderson-Hsiao but exploits additional moment restrictions, which enlarges the set of instrument. The equation (1) will be estimated in levels form where the individual effect μ_i is eliminated by differencing

$$y_{it} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (x'_{it} + x_{i,t-1})\beta + v_{it} + v_{i,t-1} \quad (5)$$

We now look for the instruments available for instrumenting the difference equation for each year. For t=3 the equation to be estimated is

$$y_{i3} - y_{i,2} = \delta(y_{i2} - y_{i1}) + (x'_{i3} - x'_{i,2})\beta + v_{i3} + v_{i2} \quad (6)$$

Where the instruments (again assuming x being at least predetermined) $y_{i,1}, x'_{i2}$ and x'_{i1} are available.
For t=4, the equation is

$$y_{i4} - y_{i5} = \delta(y_{i3} - y_{i2}) + (x'_{i4} - x'_{i3})\beta + v_{i4} - v_{i3} \quad (7)$$

The instruments $y_{i,1}, y_{i,2}, x'_{i1}, x'_{i2}$ and x'_{i3} are available.
Therefore, the first step GMM estimator makes use of a covariance matrix taking this autocorrelation into account

$$V = W'GW = \sum_{Ii=1}^{N} W'G_T W_i \qquad (8)$$

Arellano-Bond GMM estimator is given as

$$\hat{\gamma}^{ABGMM} = \left(XW\hat{V}^{-1}W'X\right)^{-1} X'W\hat{V}^{-1}W'y. \qquad (9)$$

[AB95] develops another estimator which was modified by [BB98] and called System Generalized Method of Moments estimator or Blundell and Bond estimator. When the instruments are weak the GMM estimator suggested by Arellano-Bover is known to be rather inefficient because making use of the information contained in differences only. Blundell-Bond suggests making use of additional level information beside the difference. The Blundell-Bond estimator is given as

$$\hat{\gamma}^{GMM-SSY} = \left(XW\hat{V}^{-1}W'X\right)^{-1} X'W\hat{V}^{-1}W'y \qquad (10)$$

The first step GMM estimator makes use of a covariance matrix taking this autocorrelation into account, enlarges for the level equations.

$$V = W'GW = \sum_{i=1}^{N} W'G_T W_i \qquad (11)$$

M-estimators were proposed by [Hub73]. M-estimation for regression is a relatively straightforward extension of M- estimation for location and scale. It represents one of the first attempts at a compromise between the efficiency of the Least Squares estimator and a resistance estimator - Least Absolute Value (LAV) estimators. Newton-Raphson and Iteratively Reweighted Least Squares (IRLS) are the two methods to the M-estimates nonlinear normal equations.

$$\sum_{i=1}^{n} \Psi\left(\frac{y_i - x'\beta_1}{s}\right) x_i = 0 \qquad (12)$$

IRLS express the normal equations as

$$X'WX\hat{\beta} = X'Wy \qquad (13)$$

where W is an n x n diagonal matrix of weights.
The initial vector of parameter estimates $\hat{\beta}_0$ are typically obtained from OLS,
M estimator is given as

$$\hat{\beta}_1 = \left(X'WX\right)^{-1} X'Wy \qquad (14)$$

MM estimation was introduced by [Yoh87] and it combines a high breakdown point with a good efficiency (approximately 95%) relative to the Ordinary Least Squares estimator under the Gauss-Markov assumptions. The MM refers to the fact that Multiple M-estimation procedure is used to calculate the final estimate. It has also become most common robust regression technique for linear regression.

2.3 Simulation study

Monte-Carlo experiments were carried out to compare the behaviours of six estimators namely; Ordinary Least Squares (OLS), Anderson-Hsiao IV (AH), Arellano-Bond Generalized Method of Moment (GMM) one-step, Blundell- Bond System (SYS1) one-step, M and MM when the error terms are serially correlated. The data generating process follows [Ner71] and [AB91] as shown below

$$y_{it} = \delta y_{i,t-1} + X^1{}_{it}\beta + \mu_i + v_{it} \qquad (15)$$

$$x_{it} = \lambda x_{i,t-1} + \varepsilon_t \qquad (16)$$

where $xit \approx u(-0.5, 0.5)$
For the random effects specification, we generate $u_{it} = \mu_i + v_{it}$ where $\mu_i \sim$ N (0, 1) and error term v_{it} is generated by

$$\text{AR (1):} \quad v_{it} = \rho v_{i,t-1} + w_{it} \qquad (17)$$

Or by the MA (1) process

$$v_{it} = w_{it} + \theta w_{i,t-1} \qquad (18)$$

Or by the ARMA (1, 1) process

$$v_{it} = \rho v_{i,t-1} + w_{it} + \theta w_{i,t-1} \qquad (19)$$

The parameter δ and β is given as $\gamma = (\delta, \beta)^1$ for the value of $\beta = 1$. The parameters that are varied in the simulation are autoregressive coefficients δ and λ and the autocorrelation coefficients ρ and θ. The chosen values of $\delta = (0.3, 0.5, 0.7)$, $\lambda = (0.3, 0.5, 0.7)$, $\rho = (0.2, 0.5, 0.9)$ and $\theta = (0.2, 0.5, 0.9)$ were used in the simulation. We choose cross sectional units N = (10, 20, 50, 100, 200) and time periods T = (5, 10, 15, 20). For each combination of N and T, we carried out 1000 iterations. The assessments of the various estimators considered in this work were based on the absolute bias and root mean square errors of parameter estimates. The whole Monte Carlo experiments were carried out in the environment of R statistical package which is downloadable freely on www.cran.org.

3. RESULTS AND DISCUSSIONS

The results of the performance of the estimators considered at various levels of autocorrelation were highlighted below. The estimators were ranked from 1 to 6 with rank 1 having lowest value of the absolute bias and root mean square error which are regarded as best estimator. A rank 2 is assigned to the second best estimator and rank 3 is assigned to the third best estimator and so on. Table 1 and 2 showed the summary result of the estimators of δ and β in terms of RMSE criteria for various combinations of N and T. The simulation result shows only the AR (1) in tables 1- 4 in order to save space and the other result can be released on request from authors.

Our simulation result for the estimate of δ, Anderson-Hsiao IV estimator performs better when T is small for all sample sizes (small and large) and when T is moderate, Anderson-Hsiao IV estimator also performs better except for when N=20 and 100 that Blundell-Bond System GMM performs better. But when T is large, Anderson-Hsiao IV estimator performs well except when N=10 and 50, Arellano-Bond GMM estimator performs better than all other estimators. For the estimate of β, Arellano-Bond GMM estimator performs better when T is moderate and large in terms of RMSE.

Table 1: The table for Best Estimator using RMSE Criterion at various combinations of N and T for δ

N	δ	ρ/T	5	10	15	20
10	0.3	0.2	AH(d)	AH(d)	AH(d)	ABGMM
		0.5	ABGMM	AH(d)	AH(d)	ABGMM
		0.9	AH(d)	AH(d)	AH(d)	ABGMM
	0.5	0.2	AH(d)	AH(d)	AH(d)	ABGMM
		0.5	ABGMM	AH(d)	AH(d)	ABGMM
		0.9	AH(d)	AH(d)	AH(d)	ABGMM
	0.7	0.2	AH(d)	AH(d)	AH(d)	ABGMM
		0.5	ABGMM	AH(d)	AH(d)	ABGMM
		0.9	AH(d)	AH(d)	AH(d)	ABGMM
20	0.3	0.2	AH(d)	SYS1	AH(d)	AH(d)
		0.5	AH(d)	SYS1	AH(d)	AH(d)
		0.9	AH(d)	SYS1	AH(d)	AH(d)
	0.5	0.2	AH(d)	SYS1	AH(d)	AH(d)
		0.5	AH(d)	SYS1	AH(d)	AH(d)
		0.9	AH(d)	SYS1	AH(d)	AH(d)
	0.7	0.2	AH(d)	SYS1	AH(d)	AH(d)
		0.5	AH(d)	SYS1	AH(d)	AH(d)
		0.9	AH(d)	SYS1	AH(d)	AH(d)
50	0.3	0.2	AH(d)	AH(d)	AH(d)	ABGMM
		0.5	AH(d)	AH(d)	AH(d)	ABGMM
		0.9	AH(d)	AH(d)	AH(d)	ABGMM
	0.5	0.2	AH(d)	AH(d)	AH(d)	ABGMM
		0.5	AH(d)	AH(d)	AH(d)	ABGMM
		0.9	AH(d)	AH(d)	AH(d)	ABGMM
	0.7	0.2	AH(d)	AH(d)	AH(d)	ABGMM
		0.5	AH(d)	AH(d)	AH(d)	ABGMM
		0.9	AH(d)	AH(d)	AH(d)	ABGMM
100	0.3	0.2	AH(d)	SYS1	SYS1	AH(d)
		0.5	AH(d)	SYS1	SYS1	AH(d)
		0.9	AH(d)	SYS1	SYS1	AH(d)
	0.5	0.2	AH(d)	SYS1	SYS1	AH(d)
		0.5	AH(d)	SYS1	SYS1	AH(d)
		0.9	AH(d)	SYS1	SYS1	AH(d)
	0.7	0.2	AH(d)	SYS1	SYS1	AH(d)
		0.5	AH(d)	SYS1	SYS1	AH(d)
		0.9	AH(d)	SYS1	SYS1	AH(d)
200	0.3	0.2	AH(d)	AH(d)	AH(d)	AH(d)
		0.5	AH(d)	AH(d)	AH(d)	AH(d)
		0.9	AH(d)	AH(d)	AH(d)	AH(d)
	0.5	0.2	AH(d)	AH(d)	AH(d)	AH(d)
		0.5	AH(d)	AH(d)	AH(d)	AH(d)
		0.9	AH(d)	AH(d)	AH(d)	AH(d)
	0.7	0.2	AH(d)	AH(d)	AH(d)	AH(d)
		0.5	AH(d)	AH(d)	AH(d)	AH(d)
		0.9	AH(d)	AH(d)	AH(d)	AH(d)

Table 2: The table for Best Estimator using RMSE Criterion at various combinations of N and T for β

N	δ	ρ/T	5	10	15	20
10	0.3	0.2	M	ABGMM	ABGMM	ABGMM
		0.5	ABGMM	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
	0.5	0.2	MM	ABGMM	ABGMM	ABGMM
		0.5	ABGMM	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
	0.7	0.2	MM	ABGMM	ABGMM	ABGMM
		0.5	ABGMM	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
20	0.3	0.2	ABGMM	ABGMM	ABGMM	ABGMM
		0.5	ABGMM	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
	0.5	0.2	ABGMM	ABGMM	ABGMM	ABGMM
		0.5	ABGMM	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
	0.7	0.2	OLS	ABGMM	ABGMM	ABGMM
		0.5	ABGMM	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
50	0.3	0.2	M	ABGMM	ABGMM	ABGMM
		0.5	MM	ABGMM	ABGMM	ABGMM
		0.9	MM	ABGMM	ABGMM	ABGMM
	0.5	0.2	MM	ABGMM	ABGMM	ABGMM
		0.5	MM	ABGMM	ABGMM	ABGMM
		0.9	MM	ABGMM	ABGMM	ABGMM
	0.7	0.2	MM	ABGMM	ABGMM	ABGMM
		0.5	MM	ABGMM	ABGMM	ABGMM
		0.9	MM	ABGMM	ABGMM	ABGMM
100	0.3	0.2	OLS	ABGMM	ABGMM	ABGMM
		0.5	OLS	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
	0.5	0.2	OLS	ABGMM	ABGMM	ABGMM
		0.5	OLS	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
	0.7	0.2	OLS	ABGMM	ABGMM	ABGMM
		0.5	OLS	ABGMM	ABGMM	ABGMM
		0.9	ABGMM	ABGMM	ABGMM	ABGMM
200	0.3	0.2	OLS	ABGMM	ABGMM	ABGMM
		0.5	OLS	ABGMM	ABGMM	ABGMM
		0.9	OLS	ABGMM	ABGMM	ABGMM
	0.5	0.2	OLS	ABGMM	ABGMM	ABGMM
		0.5	OLS	ABGMM	ABGMM	ABGMM
		0.9	OLS	ABGMM	ABGMM	ABGMM
	0.7	0.2	OLS	ABGMM	ABGMM	ABGMM
		0.5	OLS	ABGMM	ABGMM	ABGMM
		0.9	OLS	ABGMM	ABGMM	ABGMM

Table 3. RMSE of Various Estimators when N=10 and T=5

			AR(1) RMSE (δ) T=5, N=10					
λ	δ	ρ	OLS	ABGMM1	SYS 1	AH(d)	M-EST.	MM-EST.
0.3	0.3	0.2	0.390578	0.274066	0.548435	0.148394	0.33103	0.316731
		0.5	0.37267	0.253897	0.349828	0.127307	0.343493	0.317478
		0.9	0.363491	0.256259	0.240481	0.135672	0.351536	0.310558
	0.5	0.2	0.409019	0.271727	0.486112	0.145714	0.354622	0.328157
		0.5	0.390378	0.246969	0.317507	0.126903	0.365856	0.330681
		0.9	0.379828	0.245384	0.226372	0.13585	0.378163	0.324974
	0.7	0.2	0.425503	0.269078	0.429279	0.142545	0.374764	0.337593
		0.5	0.406193	0.240098	0.286414	0.128045	0.387059	0.350776
		0.9	0.394255	0.235287	0.211096	0.136124	0.39911	0.338526
0.5	0.3	0.2	0.401874	0.251233	0.379942	0.14223	0.333238	0.319855
		0.5	0.381131	0.238433	0.298317	0.192852	0.342782	0.320757
		0.9	0.364277	0.233751	0.216235	0.149117	0.349595	0.31335
	0.5	0.2	0.420505	0.249849	0.353878	0.140497	0.353468	0.330791
		0.5	0.398836	0.231872	0.272574	0.23107	0.363116	0.334843
		0.9	0.380878	0.223744	0.200572	0.149894	0.371768	0.327938
	0.7	0.2	0.437357	0.248175	0.326793	0.138059	0.37282	0.340971
		0.5	0.414892	0.22533	0.247496	0.408955	0.381355	0.348633
		0.9	0.395724	0.214646	0.18419	0.150732	0.392655	0.346069
0.7	0.3	0.2	0.410819	0.226003	0.28226	0.133645	0.333772	0.326292
		0.5	0.388604	0.218302	0.242219	0.603111	0.345284	0.321813
		0.9	0.365072	0.204307	0.177084	0.161817	0.349669	0.315022
	0.5	0.2	0.429685	0.225089	0.268036	0.13177	0.354097	0.337235
		0.5	0.406367	0.212426	0.224058	0.583106	0.364941	0.338065
		0.9	0.382484	0.198101	0.165656	0.163321	0.374072	0.328403
	0.7	0.2	0.446871	0.223944	0.253067	0.129377	0.371455	0.346949
		0.5	0.422641	0.206521	0.206074	0.473047	0.382946	0.352597
		0.9	0.398956	0.19485	0.156683	0.165154	0.395347	0.342564

Table 4. Bias of Various Estimators when N=10 and T=5

			AR(1) BIAS (δ)T=5, N=10					
λ	δ	ρ	OLS	ABGMM1	SYS 1	AH(d)	M-EST.	MM-EST.
0.3	0.3	0.2	0.047656	-0.01743	0.001584	-0.07247	0.006718	0.013961
		0.5	0.042466	-0.02312	0.018672	-0.00891	0.020523	0.041127
		0.9	0.040698	-0.03296	0.028485	-0.05041	0.050594	0.053034
	0.5	0.2	0.050202	-0.01743	-0.00757	-0.06737	0.010845	0.020835
		0.5	0.045067	-0.02273	0.013322	-0.00059	0.016723	0.042929
		0.9	0.04247	-0.03139	0.022473	-0.0508	0.063871	0.063938
	0.7	0.2	0.052018	-0.0174	-0.00957	-0.06078	0.01665	0.025838
		0.5	0.046916	-0.02232	0.009754	0.01766	0.013303	0.047996
		0.9	0.043508	-0.02989	0.017484	-0.05147	0.071098	0.074004
0.5	0.3	0.2	0.050078	-0.01299	0.000761	-0.06037	-0.0135	0.01712
		0.5	0.043932	-0.01843	0.009896	0.144753	0.047487	0.05667
		0.9	0.039629	-0.02635	0.015269	-0.07919	0.04715	0.059122
	0.5	0.2	0.052684	-0.01302	-0.00401	-0.05637	-0.01651	0.020307
		0.5	0.046685	-0.01826	0.00559	0.192809	0.029867	0.059176
		0.9	0.041528	-0.02508	0.011653	-0.08058	0.044989	0.06828
	0.7	0.2	0.054565	-0.01302	-0.00608	-0.05021	-0.02794	0.022407
		0.5	0.048692	-0.01803	0.003325	0.388648	0.011655	0.057165
		0.9	0.042679	-0.02389	0.009024	-0.08209	0.05405	0.077815
0.7	0.3	0.2	0.051772	-0.00964	-5.71E-05	-0.03767	-0.03173	0.017574
		0.5	0.045072	-0.01455	0.004092	-0.58948	0.058581	0.063209
		0.9	0.03859	-0.02023	0.00524	-0.10081	0.044386	0.055346
	0.5	0.2	0.054379	-0.00966	-0.00162	-0.03047	-0.03118	0.020318
		0.5	0.047901	-0.01454	0.001703	-0.56901	0.042687	0.062122
		0.9	0.040763	-0.01961	0.004202	-0.10317	0.040584	0.064908
	0.7	0.2	0.056254	-0.00968	-0.00232	-0.0176	-0.00926	0.020753
		0.5	0.049979	-0.01447	0.000632	-0.45558	0.031401	0.060111
		0.9	0.042485	-0.01929	0.003944	0.042485	0.056823	0.072579

In term of bias for the estimate of δ, Arellano-Bond GMM and Blundell-Bond System GMM estimator outperforms all other at T=5, 10, and 15 while Anderson Hsiao IV estimator and Arellano- Bond GMM estimator performs quite well at T=20 and the robust estimators also performs better in some cases. For estimate of β, Arellano-Bond GMM, Ordinary Least Square and the robust estimators performs better than Blundell-Bond System GMM and Anderson-Hsiao IV estimators.
The result of our findings also reveals that Anderson-Hsiao IV and Arellano-Bond GMM estimators performs better than all other estimators while the Ordinary Least Square estimator has the least performance.

5. CONCLUSIONS

In this paper, we investigate properties of some Dynamic Panel Data estimators in the presence of serial correlation. Absolute Bias and Root Mean Squares Error were used to evaluate finite properties of the estimators and revealed that in small and large sample situations, irrespective of time dimension, Anderson–Hsiao IV estimator (AH) outperforms all other estimators. Secondly, Arellano-Bond Generalized Method of Moment (GMM) one-step proves to be relatively Superior among the estimators when T is small, though it may not be the best but performance improved drastically as N increases. The result of our findings also show that, as to be expected all estimators (with the exception Blundell-Bond System GMM in few cases) generally perform better with smaller T and larger T. However, Arellano-Bond Generalized Method of Moment estimator seems to show the largest improvement as N and T increases.

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