Estimation of Dynamic Panel Data Models with Autocorrelated Disturbance Term: GMM Approach

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***Abstract*— Dynamic Panel Data (DPD) model estimation has been limited by two major problems; autocorrelation resulting from the inclusion of a lagged dependent variable among the explanatory variables and the unobserved main effects and interaction effects characterizing the heterogeneity among the individuals which may lead to invalid parameter estimate. This study investigates the performance of some Generalized Method of Moment (GMM) estimators of DPD models in the presence of autocorrelated disturbance term. A one-way error component model (ECM) of a random effects dynamic model with one exogenous variable was considered using a Monte Carlo experiment with 500 replications when cross-section dimension, N is large and time series dimension, T is finite for varying degrees of autocorrelated disturbance terms. The bias and root mean square error (RMSE) criterions were used to assess the performance of the estimators. Simulation revealed that Blundell-Bond System (SSY) GMM estimator performed better when T is small while Arelano-Bond (AB) GMM estimator performed better when T is large. Therefore, SSYGMM estimator is most appropriate for small T and ABGMM appropriate when T is large.**

Keywords- *Exogenous variable, GMM estimators, Heterogeneity, Random effects model, Parameter.*

I. INTRODUCTION

A repeated measurement on statistical units over a given period of time is called the Panel Data (PD) [1]. The standard error component panel data model assumes that the disturbances have homoscedastic variances and constant serial correlation through the random individual effects (see [2] and [3]). According to [2], it is only by taking proper account of selectivity and heterogeneity biases in the panel data that one can have confidence in the results obtained. Often, however, researchers ignore the existence of these problems when carrying out panel data analysis. This is not unconnected with the fact that a standard panel data model assumes that regression disturbances are homoscedastic with the same variance across time and individuals (thereby ignoring the possibility of selectivity and heterogeneity biases). The standard error components model has been extended to take into account serial correlation by [3], [4], [5], [6], [7], [8] and [9].

Panel data models can be specified as a static or dynamic panel. The inclusion of a lagged dependent variable on the right-hand side of the equation of a PD model leads to a dynamic panel model. Among social and behavioural science researchers, panel data is increasingly becoming popular and exhibiting phenomenal growth [10]. It is now widely used to estimate dynamic econometric models.

Estimation of dynamic panel models is unfortunately problematic. For the Fixed Effects (FE) specification, the problem arises as a consequence of relatively short time series component, typical of most panel data sets. Thus, the usual Hurwicz type bias is instigated into Ordinary Least Squares (OLS) estimation of a FE dynamic panel model [11]. In the random effects (RE) specification, traditional (feasible) Generalized Least Squares (GLS) estimators are similarly biased due to a correlation between the equations disturbance terms (via the individual effect) and the lagged variable [12]. Inference in Dynamic Panel (DP) model is limited by the presence of autocorrelation of the error terms which often leads to bias and inconsistent parameter estimates

The most favoured form of consistent estimation (of both FE and RE specification) is that of Instrumental Variables (IV). Extending this approach leads to the more general area of Generalized Method of Moments (GMM). GMM estimation has spawned much interest in attempting to identify the maximum (optimal) number of such conditions ([13], [14], [15] and [16]).

This study is on the estimation of dynamic panel model with autocorrelated disturbance term using GMM estimators from a panel of large number of individual units, observed for a finite time dimension. We want to evaluate the performance of GMM estimators of a one-way random effect error component model using a Monte Carlo Simulation. The bias (absolute) and Root Mean Square Error (RMSE) were used as criteria to assess the performance of the estimators.

II. Materials and Methods

In this study we consider the simple dynamic panel data model:

$$y_{ij} = \delta y_{i,t=1} + \beta X'_{it} + \mu_i + v_{it}\,; \quad i = 1, \cdots, N, \quad t = 1, \cdots, T \quad (1)$$

where y_{it} is the dependent variable, δ is the autoregressive parameter of the lagged dependent variable, X'_{it} is the row vector of exogenous variable, β is the parameter of the exogenous variable, μ_i is the unobserved individual specific effect and v_{it} is the error term which varies over the cross-section and time. The disturbance term, v_{it} in equation (1) is assumed to follow the following autocorrelation processes:

$$AR(1): v_{it} = \rho v_{i,t-1} + \omega_{it} \quad (2)$$

$$MA(1): v_{it} = \omega_{it} + \theta\omega_{i,t-1} \quad (3)$$

$$ARMA(1,1): v_{it} = \rho v_{i,t-1} + \omega_{it} + \theta\omega_{i,t-1} \quad (4)$$

Where ω_{it} is iid with zero mean and for σ^2_ω.

The design of our Monte Carlo experiments follows closely [17]. The model for y_{it} is given in (1). X_{it} was generated with $X_{it} = \lambda x_{i,t-1} + \varepsilon_{it}$ where $\varepsilon_{it} \sim U(-0.5,\ 0.5)$. For random effect specification, $\mu_i \sim N(0,\ \sigma^2_\mu)$. Our parameter choices are as follows: σ^2_μ and σ^2_ε is normalized to 1; $\beta = 1$; $\lambda,\ \rho\ and\ \theta$ are set at intermediate of 0.5 and δ alternate between 0.1 and 0.9. In the simulation, we choose T=5, 20 and N= 50, 200 with 500 replications.

A good number of DPD estimators have been proposed and thoroughly characterized in the literature. The classical OLS and within Group (WG) estimators, among the estimation methods. for DPD, provide consistent estimate for static models. In DPD models, [11] showed that the WG estimator of the coefficient of the lagged dependent variable parameter is downward biased and the bias only disappear as the number of time periods grows larger. Therefore [16] proposed GMM estimator that uses all the available lags at each period as instruments for the equations in first or second differences, this is known as the one or two step Arellano-Bond GMM estimator (ABGMM1 or ABGMM2). [15] revisit the importance of exploiting the initial condition in generating efficient estimators of the DPD model when T is small. They further proposed the now called system GMM estimator which uses both the lags and of the level and first difference as instruments.

The following DPD GMM estimators are considered: Arellano-Bond GMM, one step (ABGMM); Arellano-Bond GMM, two step (ABGMM2); Blundell-Bond GMM, first step (SYS1) and Blundell-Bond GMM, two step (SYS2).

III. Analysis And Results

Tables 1 and 2 below show the simulation results of average bias (absolute) and RMSE of δ and β when N = 50 and 200 when the design of autocorrelation assumes AR(1) and MA(1) only to save space.

Table 1: Simulation results N=50, ρ=θ=0.5, λ=0.1, δ=0.9 for AR and MA models

	δ			
	T=5		T=20	
Estimators	ARMSE	Abias	ARMSE	Abias
			AR(1)	
ABGMM1	10.447	5.6327	**0.0213**	0.0213
ABGMM2	10.925	0.2626	0.3621	0.3613
SYS1	**0.322**	0.2725	0.389	0.3226
SYS2	0.4012	0.3284	0.1386	0.0725
			MA(1)	
ABGMM1	8.1435	2.0043	**0.0217**	0.0149
ABGMM2	10.782	4.4495	0.2806	0.2656
SYS1	**0.3018**	0.2512	0.3847	0.3118
SYS2	0.3747	0.304	0.1431	0.1347
		β		
		AR(1)		
ABGMM1	6.2356	1.4578	**0.0352**	0.0338
ABGMM2	6.5716	1.5972	0.3263	0.3256
SYS1	**0.9067**	0.0307	0.303	0.1181
SYS2	1.0006	0.6108	3.6897	2.731
		MA(1)		
ABGMM1	5.689	0.6658	**0.0389**	0.0328
ABGMM2	5.9577	0.6194	0.2867	0.2752
SYS1	**0.9162**	0.1385	0.2681	0.0729
SYS2	0.9653	0.5355	1.5448	0.9011

Table 2 Simulation results N=200, ρ=0.5, λ=0.1, δ=0.1 for AR and MA models

	δ			
	T=5		T=20	
Estimators	ARMSE	Abias	ARMSE	Abias
		AR(1)		
ABGMM1	15.696	14.355	**0.0168**	0.0007
ABGMM2	6.9559	1.717	0.0221	0.0092
SYS1	**0.3444**	0.2064	0.0226	0.0022
SYS2	0.3856	0.2384	0.0241	0.0123
		MA(1)		
ABGMM1	15.404	14.077	**0.0168**	0.0007
ABGMM2	6.7977	1.1382	0.0221	0.008
SYS1	**0.3206**	0.1919	0.0226	0.0022
SYS2	0.3771	0.2401	0.0205	0.0044
		β		
		AR(1)		
ABGMM1	9.0097	8.0016	**0.0199**	0.0035
ABGMM2	4.5413	2.5645	0.0212	0.003
SYS1	**0.6436**	0.4153	0.2082	0.009
SYS2	0.6958	0.5026	0.2168	0.0372
		MA(1)		
ABGMM1	8.8544	7.8502	**0.0199**	0.0035
ABGMM2	4.329	2.2628	0.0203	0.0006
SYS1	**0.6273**	0.3971	0.2082	0.009
SYS2	0.7115	0.5171	0.2217	0.0499

Table 1 show that SYS1 performed better when T=5 and ABGMM1 outperformed others when T=20 with minimum RMSE of 0.3018 and 0.02169, respectively in estimating δ. Also, in estimating β, SYS1 has better performance when T is 5 while ABGMM1 performed better when T=20 with minimum RMSE of 0.9067 and 0.0332, respectively.

The results show similar pattern when N=200 (as shown in Table 2) with that of Table 1. It was discovered that the bias and RMSE of ABGMM estimators are higher when T=5 compared with when T=20, this may be as a result of number of instruments used [18]. It was also observed that most of the estimators are nearly unbias especially when T is 20 and λ is 0.1 (see Table 2).

IV. Conclusion

In this study, we considered three experiments with four GMM estimators using dynamic panel data model in the presence of autocorrelation. Our Monte Carlo results reveal the following: There are little or no difference in performance of the estimators in terms of bias and RMSE with respect to alternative generating scheme of v_{it}, the system-GMM1 is appropriate for small T while ABGMM1 is better for longer time period. ABGMM estimators performed poorly in terms of RMSE and bias when value of T and λ is small. Our results conform to a notable asymptotic property as N and T increase.

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