Journal of Natural Sciences Research www.iiste.org
ISSN 2224-3186 (Paper) ISSN 2225-0921 (Online)
Vol.6, No.11, 2016

The Effect of Serial Correlation in Estimating Dynamic Panel data Models

Olubusoye, Olusanya E.
Department of Statistics University of Ibadan, Ibadan, Nigeria

Olajide, Johnson T. *
Mathematics & Statistics Department, The Polytechnic Ibadan, P.M.B. 22, UI post office, Ibadan, Nigeria

Abstract
There are several methods of estimating dynamic panel data models in the context of both micro-economic and macro-economic data. This paper investigates the performance of five different estimators of dynamic panel data models (the random effect model). A Monte Carlo experiment was conducted when individual, N is large and time dimension, T is finite and the error component model is assumed to be serially correlated. The bias and Root Mean Square Error criterion were used to access the performance of different estimators under consideration. We find that the Anderson-Hsiao using lagged differences as instrument (AH(d)) performs better when the time dimension is small (T=5), Anderson-Hsiao using lagged levels as instrument (AH(l)) performs better when T is moderate(T=10) and the first step Arellano-Bond estimator (ABGMM1) outperforms all other estimators when T increases to 20, this confirms the work of Kiviet (1995) and Judson-Owen(1996) that no estimator has been found to be appropriate choice in all circumstances. For a dynamic panel data with large time dimension we suggest that the first step Arellano-Bond Estimator (ABGMM1) Estimator is appropriate. The result shows that the bias of the first step Arellano-Bond estimator (ABGMM1) estimate is severe with small time dimension and the ordinary Least Square (OLS) and Least Square Dummy Variable (LSDV) are also bias when T is small. It was discovered that the effect of serial correlation is negligible irrespective of the order.
Keywords: Autocorrelation, Dynamic Panel data, Econometric models, Generalized Method of Moment (GMM), Moving Average.

1. Introduction

Panel data models are used extensively both in micro and macro-economic empirical research. Application of dynamic panel data model is widely of interest in the field of science, economics and social sciences which includes Euler equations for household consumption, empirical model of economic growth etc.

According to Baltagi (2008 pp. 147), the dynamic specification has two basic problems associated with it; autocorrelation due to the presence of lagged dependent variable among the regressors and individual effects characterizing the heterogeneity among individuals. These problems lead to certain estimation issues which are dealt with by different estimation techniques.

The discussion of dynamic panel data was opened by Balestra and Nerlove (1966). In that paper, the authors proposed to estimate the model with unobserved component using the Generalized Least Squares (GLS) estimator. However, GLS or ML-Random Effects (RE) estimators are not consistent if the unobserved individual effects are correlated with the exogenous variables. In the latter case the Fixed Effects (FE) specification is preferred.

There are many studies on the properties of dynamic panel data estimators, most are geared towards the performance of the estimators using the conventional OLS, LSDV and some GMM estimators with micro-economic data sets with large cross-section but small time dimension this includes: Arellano and Bond (1991), Kiviet (1995), Judson Owen (1996), Andreas Behr (200) Haris and Matyas (2010) but to mention few.

A number of works on the testing for serial correlation in the disturbances of error terms in dynamic panel data models they are: Baltagi and Li (1997), Hosung Jung (2005), Hujer, R., Rodgues J.M and Zeiss Christopher (2005) using several test of AR(1) and MA(1).

Similarly, among the notable works on the problem of serial correlation in panel data are Lillard and Willis (1978), Bhargava, Franzini, and Narendranathan (1982) Burke, Godfrey and Termayne (1990), Baltagi and Li (1991, 1994, 1995) Galbraith and Zinde-Wash (1992,1995).The error component model was extended to take into account first-order serial correlation in the remainder disturbances by Lillard and Willis (1978) for the random effects model and by Bhargava, Franzini, and Narendranathan (1982) for the fixed effects model. Both studies considered the first order Autoregressive [AR(1)] specification on the remainder disturbances. Nicholls, Pagan, and Terrell (1975), while considering first order moving average MA(1), find MA(1) is a viable alternative to AR(1). Baltagi and Li (1991) give a transformation which may be applied to certain autocorrelated disturbances in an error components model to yield spherical disturbances. They derive the transformations for first order Autoregressive AR(1) and second order Autoregressive [AR(2)] cases but little work has been done on dynamic panel data model.

This study is similar to the work of Harris and Matyas (2010) in the basic designs of experiment. However, there are differences, first we modify the parameter values by varying it to be mild, moderate and severe, two we increase the sample size, N and T especially we consider N to be large and T finite, three we take a subset of the estimation methods considered in their paper. On the final note, we extend the experiment by incorporating different degrees of serial correlation of the disturbances to observe their effect on the estimators. Also the values of parameters of the serial correlation (AR and MA) is assumes to take a low, moderate and value close to one. Monte Carlo experiments were performed to compare the relative efficiency of various estimators of a dynamic panel data models when the disturbances v_{it} follow an AR(1), AR(2), MA(1) or MA(2) processes. We consider a similar problem for the DPD error component regression with autocorrelated remainder disturbances. Monte Carlo experiments were performed to compare small sample properties of five alternative estimators, when the remainder disturbances are generated by different generating schemes. The estimators are Ordinary Least Squares (OLS), Least Square Dummy Variable (LSDV), The Anderson-Hsiao estimator using lagged levels as instrument(AH(l)), The Anderson-Hsiao estimator using lagged differences as instrument (AH(d)) and First step Arellano-Bond estimator GMM (ABGMM1).

2 The model

2.1 Dynamic Panel models

All panel data models are dynamic, in so far as they exploit the longitudinal nature of panel data. Dynamic models include a lagged dependent variable on the right-hand side of the equation. A widely used modeling approach is:

$$y_{it} = \delta y_{i,t-1} + x'_{it}\beta + u_{it} \qquad i = 1, \ldots, N \quad t = 1, \ldots, T \tag{1}$$

with i denoting households, individuals, firms, countries, etc and t denoting time. The i subscript, therefore denotes the cross-section dimension whereas t denotes the time-series dimension. y_{it} is the dependent variable, $y_{i,t-1}$ is the lagged dependent variable , δ is a scalar, x'_{it} is the row vector of explanatory variable, dimension k , β is unknown parameter vector of k explanatory variables and u_{it} is the disturbance term. We assume that the u_{it} follow a one way error component model.

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

where μ_i denotes the unobserved individual specific effect and v_{it} denotes the remainder disturbance, $\mu_i \sim IID(0, \sigma^2_\mu)$ and $v_{it} \sim IID(0, \sigma^2_v)$ independent of each other and among themselves

2.2 The fixed Effects Dynamic Panel Model

It is assumed that the variable of interest y_{it} is a linear function of the individual's previous realization of this variable, and of their contemporaneous personal characteristics x_{it} with unknown coefficient, δ and β , respectively:

$$y_{it} = \delta y_{i,t-1} + x'_{it}\beta + \mu_i + v_{it} , \tag{3}$$

where: μ_i are the individual effects (constant for each i) and v_{it} are the usual white noise disturbance terms. In matrix form:

$$\underline{y}_{it} = D\underline{\mu}_i + \delta \underline{y}_{i,t-1} + X\beta + \underline{v}_{it} \tag{4}$$

Where $D = I_N \otimes \underline{l}_T$ *and* l_T *is the* $T \times 1$ *unit vector.*

The usual method of estimating equation (4), i.e. when there is no Lagged Dependent Variable, consists of estimating equation directly by OLS (the Least Squares Dummy Variable Estimator- LSDV), which also leads to the well known Within estimator. However, given the short time series component typical of panel data sets, the OLS and Within estimators are well known to be biased and inconsistent as $N \to \infty$ with finite T (see Nickel (1981) and Sevestre and Trognon (1985) for a theoretical approach, and Nerlove (1967,1971) for a simulation based only).

2.3 The Random Effects Dynamic Panel Model

Under the random effects specification, the μ_i terms of (3) are treated as independent random drawings from a particular distribution and the disturbance term becomes "composite", $u_{it} = \mu_i + v_{it}$. As with the fixed effects specification, the traditional estimators (Within and GLS) of the static random effects panel model are semi-inconsistent in the dynamic setting (Sevestre and Trognon ,1985).

Again semi-consistent estimators for the dynamic random effects model rely on certain maintained hypothesis, which are violated by the inclusion of a lagged dependent variable. The assumptions concerning the equation's disturbances imply that variance-covariance matrix of the composite disturbance term will be

$$\Omega_v = V(v) = I_N \otimes E(vv') = I_N \otimes \sum\nolimits_v \ , \tag{5}$$

$$\sum\nolimits_v = \sigma_\mu^2 J_T + \sigma_u^2 I_T = \sigma_v^2 \begin{bmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \rho \\ \rho & \cdots & \rho & 1 \end{bmatrix},$$

Where ρ is the intra-class correlation coefficient and $\rho = \dfrac{\sigma_\mu^2}{(\sigma_\mu^2 + \sigma_u^2)}$.

For the research work we are to assume a random effect of the dynamic panel data model.

3. Methodology

Here is the brief discussion on the estimators considers in the work

3.1 Ordinary Least Square (OLS) Estimator

In the static case in which all the explanatory variables are exogenous and are uncorrelated with the effects, we can ignore the error-component structure and apply the OLS method. The OLS estimator, although less efficient, is still unbiased and consistent. But this is no longer true for dynamic error-component models. The correlation between the lagged dependent variable and individual-specific effects would seriously bias the OLS estimator.

OLS, the simplest of all estimators considered, is applied to the equation in the level form. Since the initial values of y_{it} are known, OLS can use in actual estimation all of the cross-sections.

The OLS estimator is given as:

$$\hat{\delta}^{OLS} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}.y_{i,t-1}}{\sum_{i=1}^{N}\sum_{t=1}^{T} y_{i,t-1}^2} = \delta + \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}(\alpha_i + u_{it})y_{i.t-1}}{\sum_{i=1}^{N}\sum_{t=1}^{T} y_{i,t-1}^2} \tag{6}$$

3.2 Least Square Dummy Variable (LSDV)

Consider now the *least squares dummy variable* (LSDV) estimator, also known as the *fixed-effects* or *within-group* estimator. We assume that the explanatory variables in x_{it} are strictly exogenous. Estimates of $(\delta \ and \ \beta)$ are obtained by applying OLS to the model expressed in deviations from time means:

$$y_{it} - \bar{y}_i = \delta(y_{it-1} - \bar{y}_{i-1}) + (x'_{it} - \bar{x}_{i,t-1})\beta + (v_{it} - \bar{v}_i), \qquad t \in \{1, \cdots, T\}$$

Where $\bar{y}_i = \sum_{i=1}^{T} y_{it}/T$, $\bar{y}_{i,-1} = \sum_{i=1}^{T} y_{i,t-1}/T$, and $u_{it} = \sum_{i=1}^{T} u_{it}/T$. This transformation wipes out the unobserved individual effects, eliminating one possible source of inconsistency

The LSDV estimators for δ is

$$\hat{\delta}^{LSDV} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \bar{y}_i)(y_{i,t-1} - \bar{y}_{i.-1})}{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{i,t-1} - \bar{y}_{i.-1})^2}$$

$$= \delta + \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{i,t-1} - \bar{y}_{i.-1})(u_{it} - \bar{u}_i)\big/NT}{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{i,t-1} - \bar{y}_{i.-1})^2\big/NT} \tag{7}$$

3.3 The Anderson-Hsiao estimator

Anderson and Hsiao (1981) proposed an instrumental-variable (IV) estimator that is consistent for fixed T and $N \to\infty$. The estimator suggested by Anderson and Hsiao (1982) is based on the differenced form of the original equation (3)

$$y_{it} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (x'_{it} - x'_{i,t-1})\beta + v_{it} - v_{i,t-1} \quad (8)$$

which cancels the individual fixed effects assumed to possibly correlate with the exogenous variables $(E(X'_{it}\mu_i \neq 0)$.

When the dimension of the panel is $N \times T$, the Anderson-Hsiao we employ is

$$\hat{\gamma}^{AH} = (Z'X)^{-1}Z'Y \quad (9)$$

We add the symbol L or D to indicate the use of levels or differences as instruments $(\hat{\gamma}^{AH,L}, \hat{\gamma}^{AH,D})$.

3.4 The Arellano-Bond estimator

The AH estimator is consistent but not efficient because it does not use all the available moment conditions. Arellano and Bond (1991) propose a generalized method of moments (GMM) estimator that also relies on first-differencing the model. The estimator is similar to the estimator suggested by Anderson and Hsiao but exploits additional moment restrictions, which enlarges the set of instruments.

The dynamic equation to be estimated in levels is

$$y_{it} = \delta y_{i,t-1} + X'_{it}\beta + \mu_i + v_{it} \quad (10)$$

where differencing eliminates the individual effects μ_i:

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

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

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

where the instruments $y_{i,1}, x'_{i2}$ *and* x'_{i1} are available. Because the differencing operation introduces first order autocorrelation into the error term, the first-step estimator makes use of a covariance matrix taking this autocorrelation into account.

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

$$G = (I_N \otimes G'_T) \quad and \quad G_T = F_T F'_T = \begin{bmatrix} 2 & -1 & & 0 \\ -1 & 2 & \ddots & \\ & \ddots & \ddots & -1 \\ 0 & & -1 & 2 \end{bmatrix}$$

Where

The two-step GMM estimator uses the residuals of the first-step estimation to estimate the covariance matrix as suggested by White (1980):

$$\hat{V} = \sum_{i=1}^{N} W'F_T \hat{v}_i \hat{v}'_i F_T' W_i$$

The resulting estimator finally is

$$\hat{\gamma}^{ABGMM} = (XW\hat{V}^{-1}W'X)^{-1} X'W\hat{V}^{-1}W'y \quad (11)$$

4. Monte Carlo study

We study different estimators in the Monte Carlo experiment, the Ordinary Least Square (OLS), Least Square Dummy variable(LSDV), Anderson and Hsiao using lagged levels as instrument (AH(l), The Anderson-Hsiao using differences as instrument and First step Arellano –Bond GMM (ABGMM1) and compare them under different circumstances. The data generating process closely follows Nerlove (1971). The simulation is based on the following model:

$$y_{it} = \delta y_{i,t-1} + X'_{it}\beta + u_{it}$$

$X_{it} = \lambda x_{i,t-1} + \varepsilon_{it}$ where ε_{it} is uniformly distributed on the interval $(-0.5, 0.5)$ For the random effect specification we generate $u_{it} = \mu_i + v_{it}$ where $\mu_i \sim N(0, 1)$ and classical error term v_{it} is generated either by

AR(1) process: $v_{it} = \rho v_{i,t-1} + \omega_{it}$, with $\omega_{it} \sim IIN(0, \sigma_{\omega}^{2})$,

AR(2) process: $v_{it} = \rho_1 v_{i,t-1} + \rho_2 v_{i,t-2} + \omega_{it}$, with $\omega_{it} \sim IIN(0, \sigma_{\omega}^{2})$,

MA(1) process: $v_{it} = \theta v_{i,t-1} + \omega_{it}$, with $\omega_{it} \sim IIN(0, \sigma_{\omega}^{2})$ or

MA(2) process: $v_{it} = \theta_1 \omega_{i,t-1} + \theta_2 \omega_{i,t-2} + \omega_{it}$, with $\omega_{it} \sim IIN(0, \sigma_{\omega}^{2})$.

Where σ_{ω}^{2} is normalized to 1.

The value of the serial correlation parameters $\rho \text{ and } \theta$ are varied as $\rho = 0.2, \ 0.5, \ 0.8$ $\theta = 0.2, \ 0.5, \ 0.8$, δ and λ alternates between 0.1, 0.5 and 0.9 , $\beta = 1$ and $\gamma = (\delta, \beta)'$.

In the experiment, we consider N=50, 100 and T=5, 10, 20. 500 replications are performed since GMM estimator is quite computationally intensive and time consuming. We examine the bias of different estimators under consideration to determine how their magnitudes vary with the characteristics of the dataset. Also, The Root Mean Square Error (RMSE) criterion is used to assess the efficiency of the estimators.

5. Results

Table 1-4 present the bias and RMSE for estimate of the autoregressive coefficient, δ for the case of N=50, T= 5, 10, 20. Table 5 report the bias and RMSE for AH(d) estimator when it follows different error component process. Tables 6-9 show the bias and RMSE of the parameter of lagged dependent variable of all possible combinations of N and T when λ takes the values of 0.1, 0.5 and 0.9 for only AR(1) and MA(1) to save space.

The results in table 1 indicates that AH(d) outperforms other methods of estimation under consideration when T=5 while the ABGMM1 estimator performs worst in term of producing higher bias and RMSE. The bias and RMSE of the estimate using OLS and LSDV are constant for the various value of T even when the autoregressive parameter is varied. For T=10, AH(l) performs best in terms of RMSE with a very small bias followed by LSDV while ABGMM1 still perform worse but the estimator seem to show the serious improvement (larger percentage reduction in average RMSE and bias as it increases). When T=20, ABGMM1 shows a sharp changes as it outperforms other estimator when T is large it follow closely by AH(d), though it does not produce a superior estimate in terms of average bias. Using a ABGMM1 estimator with small instruments produces a smaller expected bias in most cases, but using the full set of instruments almost always increases the efficiency of the estimate (Judson and Owen, 1996). Here, the LSDV have the least performance with a small reduction in terms of RMSE and bias. As the time dimension T increases AH(l) perform equally well . It was also observed that AH (l) and AH(d) estimates improve in performance as the serial correlation ρ increases. For ABGMM1 estimator it deteriorates in performance as the serial correlation increases. The performance is constant for OLS and LSDV even when ρ increases given that the two estimators ignore the serial correlation in the remainder term.

Table 2 gives similar results as that of table 1, The performance in the AR(1) process is similar to the AR(2) process, but there is slight improvement in the performance of ABGMM1 When the serial correlation is of the higher order i.e AR(2) compared with AR(1) in term of RMSE but the bias of AR(2) is more than that of AR(2) . AH(d) still perform better when T=5 and AH(l) perform better at T=10 and 20. As T increases ABGMM1 also improve better in performance in both RMSE and bias.

Table 3 and 4 shows the performance of different estimators when the serial correlation follows MA(1) or MA(2) process. The result is similar to that of AR(1) and AR(2) in tables 1 and2 respectively. AH(d) estimator perform better than other estimators when T is small (T=5), AH(l) performs better when T is moderate (T=10), while ABGMM1 estimator outperforms others as T increases to 20. ABGMM1 estimator performs badly when T is small but as T increases to 10 there is a drastic improvement in both the RMSE and bias of the estimate. For AH(l) ,AH(d) and ABGMM1 their performances are fair when the serial correlation assumes MA(2) process than MA(1) process (though there is little difference).

Table 5 shows the results to bias and RMSE of the estimate of δ for AH(d) estimator when the serial correlation follows AR(1), AR(2), MA(1) or MA(2) process. The results at different scenario shows that when the autoregressive of order 1 (AR(1)) is better than AR(2) though their differences are minimal. When following the Moving Average process, MA(2) is better than MA(1).

Similarly results were obtained when the number of individual units is 100 at different combination of N and T except that their bias and RMSE reduces compared to when the number of individual units is 50 (the result can be given on the request from the authors).

The result in tables 6-9 show that for OLS estimator as value of λ increases the bias and RMSE deteriorates but for other estimators considered it improves as λ increases. It was also observed that the ABGMM1 has a larger bias and RMSE when the value of $\lambda = 0.1$ compared to when it is 0.5 or 0.9 especially when time dimension, T is small. Similar results were obtained irrespective of the number of individual and pattern of serial correlation process. All the estimators improves in performance as the sample size increases this confirms the asymptotic properties of sample size.

6. Conclusion

In general, the result of the Monte Carlo experiment shows that AH(d) outperforms other estimator when T is small, AH(l) is better when T is moderate(T=10) and ABGMM1 perform better when T is getting larger(T=20) at various level of serial correlation under consideration . Also, it was observed that as T increases there is an improvement in the performance of ABGMM1 due to the increase in the instruments, this implies that ABGMM1 will be better when T is large. The OLS and LSDV are constant at various level of T even when the Autoregressive and Moving Average parameters δ and θ are varied in terms of bias and RMSE.

The bias of most of the estimators reduces as the value of T increases especially the ABGMM1 estimator. The effect of making the serial correlation, v_{it} to follow AR(1), AR(2), MA(1) or MA(2) are negligible in the performances of the estimators.

Also, the result revealed that the bias and RMSE of OLS deteriorates as the value of λ increases while other estimators improves with increase in the value of λ. The GMM estimator proposed by Arellano-Bond(1991) has a larger bias and RMSE when the value of the autoregressive parameter of exogenous variable, λ is mild and when the time dimension is small (i.e. T=5). It was noted that as the sample sizes increases the performances of all the estimators improves.

Table 1: The RMSE and Bias of estimate with respect to δ at N=50, λ=0.1 True model is AR(1)

AR(1)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
T	Δ	P	RMSE	Bias	RMSE	bias	RMSE	bias	RMSE	bias	RMSE	bias
5	0.1	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062771	0.007446	0.059643	0.005909	9.028333	-3.69962
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062758	0.007408	0.059635	0.005901	10.44749	-5.63274
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.06274	0.007373	0.059628	0.005894	11.44526	-6.45764
	0.5	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062759	0.007451	0.059643	0.005909	9.028333	-3.69962
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.06275	0.007418	0.059635	0.005901	10.44749	-5.63274
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062737	0.007387	0.059628	0.005894	11.44526	-6.45764
	0.9	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062747	0.007456	0.059643	0.005909	9.028333	-3.69962
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062742	0.007427	0.059635	0.005901	10.44749	-5.63274
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062735	0.0074	0.059628	0.005894	11.44526	-6.45764
10	0.1	0.2	0.048386	0.004411	0.046233	0.000345	0.042131	-0.0056	0.047527	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042133	-0.0056	0.047528	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042134	-0.0056	0.04753	-0.00491	0.073993	0.007844
	0.5	0.2	0.048386	0.004411	0.046233	0.000345	0.042129	-0.00559	0.047527	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042131	-0.00559	0.047528	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042132	-0.00559	0.04753	-0.00491	0.073993	0.007844
	0.9	0.2	0.048386	0.004411	0.046233	0.000345	0.042127	-0.00559	0.047527	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042128	-0.00559	0.047528	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.04213	-0.00559	0.04753	-0.00491	0.073993	0.007844
20	0.1	0.2	0.032644	0.001599	0.033381	0.004305	0.031256	-0.00306	0.03293	-0.00313	0.022775	0.018235
		0.5	0.032644	0.001599	0.031147	-0.00196	0.031708	-0.00223	0.032804	-0.00228	0.021301	0.021262
		0.8	0.032644	0.001599	0.032536	0.002453	0.03206	-0.00086	0.031064	-0.00366	0.024192	0.020222
	0.5	0.2	0.032644	0.001599	0.032874	0.004217	0.029745	-0.00335	0.03499	-0.00339	0.026919	0.014908
		0.5	0.032644	0.001599	0.032835	0.004264	0.031344	-0.00413	0.033387	-0.00268	0.022772	0.020233
		0.8	0.032644	0.001599	0.033168	0.003927	0.030974	-0.00341	0.033547	-0.00379	0.023453	0.020957
	0.9	0.2	0.032644	0.001599	0.033074	0.002324	0.033035	-0.00017	0.030843	-0.00501	0.022095	0.019508
		0.5	0.032644	0.001599	0.033285	0.001504	0.032091	-0.00091	0.030739	-0.0043	0.023589	0.019079
		0.8	0.032644	0.001599	0.033643	0.002047	0.032095	-0.00096	0.030613	-0.00403	0.024142	0.019842

Table 2: The RMSE and Bias of estimate with respect to δ at N=50, λ=0.1. True Model is AR(2)

AR(2)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
T	Δ	P	RMSE	Bias	RMSE	bias	RMSE	bias	RMSE	bias	RMSE	Bias
5	0.1	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062674	0.007475	0.059653	0.005938	8.59908	-4.51107
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062668	0.00746	0.05965	0.005937	9.927795	-6.18696
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062662	0.00744	0.059647	0.005934	11.0135	-7.2032
	0.5	0.2	0.073378	-0.00313	0.061595	-0.00497	0.06267	0.007466	0.059654	0.005938	8.59908	-4.51107
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062666	0.007452	0.05965	0.005937	9.927795	-6.18696
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062664	0.007436	0.059647	0.005934	11.0135	-7.2032
	0.9	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062665	0.007457	0.059654	0.005938	8.59908	-4.51107
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062664	0.007445	0.05965	0.005937	9.927795	-6.18696
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062666	0.007431	0.059647	0.005934	11.0135	-7.2032
10	0.1	0.2	0.048386	0.004411	0.046233	0.000345	0.042136	-0.0056	0.047531	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042136	-0.0056	0.047532	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042137	-0.0056	0.047533	-0.00491	0.073993	0.007844
	0.5	0.2	0.048386	0.004411	0.046233	0.000345	0.042133	-0.0056	0.047531	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042134	-0.0056	0.047532	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042135	-0.0056	0.047533	-0.00491	0.073993	0.007844
	0.9	0.2	0.048386	0.004411	0.046233	0.000345	0.042131	-0.00559	0.047531	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042132	-0.00559	0.047532	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042133	-0.00559	0.047533	-0.00491	0.073993	0.007844
20	0.1	0.2	0.032644	0.001599	0.034468	0.006371	0.029066	-0.00339	0.034352	-0.00368	0.030234	0.013783
		0.5	0.032644	0.001599	0.027814	-0.00623	0.035954	-0.00305	0.028295	-0.0017	0.04041	-0.00059
		0.8	0.032644	0.001599	0.031147	-0.00196	0.031709	-0.00224	0.032804	-0.00228	0.029434	0.018052
	0.5	0.2	0.032644	0.001599	0.034501	0.00607	0.029116	-0.00342	0.035024	-0.00403	0.029314	0.01551
		0.5	0.032644	0.001599	0.032874	0.004328	0.030992	-0.00348	0.03375	-0.00318	0.030873	0.015157
		0.8	0.032644	0.001599	0.032958	0.004524	0.0312	-0.00253	0.033617	-0.00201	0.030568	0.015236
	0.9	0.2	0.032644	0.001599	0.034501	0.00607	0.029117	-0.00342	0.035024	-0.00403	0.030391	0.014257
		0.5	0.032644	0.001599	0.033152	0.002881	0.029027	-0.00337	0.035341	-0.00352	0.037143	0.011974
		0.8	0.032644	0.001599	0.03305	0.0024	0.028731	-0.00507	0.035497	-0.00344	0.033985	0.015612

Table 3: The RMSE and Bias of estimate with respect to δ at N=50, λ=0.1. True Model is MA(1)

MA(1)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
T	Δ	ρ	RMSE	Bias	RMSE	bias	RMSE	Bias	RMSE	bias	RMSE	Bias
5	0.1	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062769	0.007467	0.059646	0.005915	8.143542	-2.00429
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.06276	0.007466	0.059645	0.005916	8.081237	-1.97864
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062751	0.007464	0.059643	0.005918	8.032053	-1.92207
	0.5	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062756	0.007469	0.059646	0.005915	8.143542	-2.00429
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062747	0.007467	0.059645	0.005916	8.081237	-1.97864
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062738	0.007465	0.059643	0.005918	8.032053	-1.92207
	0.9	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062742	0.00747	0.059646	0.005915	8.143542	-2.00429
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062733	0.007467	0.059645	0.005916	8.081237	-1.97864
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062725	0.007464	0.059643	0.005918	8.032053	-1.92207
10	0.1	0.2	0.048386	0.004411	0.046233	0.000345	0.04213	-0.0056	0.047526	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.04213	-0.0056	0.047526	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.04213	-0.0056	0.047525	-0.00491	0.073993	0.007844
	0.5	0.2	0.048386	0.004411	0.046233	0.000345	0.042128	-0.00559	0.047526	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042128	-0.00559	0.047526	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042128	-0.00559	0.047525	-0.00491	0.073993	0.007844
	0.9	0.2	0.048386	0.004411	0.046233	0.000345	0.042126	-0.00559	0.047526	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042126	-0.00559	0.047526	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042125	-0.00559	0.047525	-0.00491	0.073993	0.007844
20	0.1	0.2	0.032644	0.001599	0.032689	0.001586	0.030242	-0.00574	0.035201	-0.00045	0.021055	0.018388
		0.5	0.032644	0.001599	0.033438	0.00325	0.028908	-0.00365	0.035493	-0.00389	0.021694	0.014905
		0.8	0.032644	0.001599	0.032958	0.004524	0.031198	-0.00253	0.033616	-0.00201	0.020277	0.0155
	0.5	0.2	0.032644	0.001599	0.033168	0.003927	0.030973	-0.00341	0.033547	-0.00379	0.020351	0.015713
		0.5	0.032644	0.001599	0.033168	0.003927	0.030974	-0.00341	0.033547	-0.00379	0.021081	0.016427
		0.8	0.032644	0.001599	0.032958	0.004524	0.0312	-0.00253	0.033616	-0.00201	0.02153	0.015573
	0.9	0.2	0.032644	0.001599	0.033643	0.002047	0.032095	-0.00096	0.030612	-0.00403	0.019415	0.019379
		0.5	0.032644	0.001599	0.033001	0.002638	0.031566	-0.00247	0.031765	-0.0023	0.02146	0.015651
		0.8	0.032644	0.001599	0.033643	0.002047	0.032095	-0.00096	0.030612	-0.00403	0.020277	0.0155

Table 4: The RMSE and Bias of estimate with respect to δ at N=50, λ=0.1. True Model is MA(2)

MA(2)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
T	Δ	P	RMSE	Bias	RMSE	bias	RMSE	Bias	RMSE	bias	RMSE	Bias
5	0.1	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062738	0.007461	0.059642	0.005919	7.987977	-1.79924
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062728	0.007458	0.059641	0.00592	7.97179	-1.67299
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062719	0.007455	0.05964	0.005921	7.970587	-1.51942
	0.5	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062708	0.007452	0.05964	0.005921	7.970587	-1.51942
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062717	0.007456	0.059641	0.00592	7.97179	-1.67299
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062708	0.007452	0.05964	0.005921	7.970587	-1.51942
	0.9	0.2	0.073378	-0.00313	0.061595	-0.00497	0.062713	0.007458	0.059642	0.005919	7.987977	-1.79924
		0.5	0.073378	-0.00313	0.061595	-0.00497	0.062705	0.007454	0.059641	0.00592	7.97179	-1.67299
		0.8	0.073378	-0.00313	0.061595	-0.00497	0.062697	0.007448	0.05964	0.005921	7.970587	-1.51942
10	0.1	0.2	0.048386	0.004411	0.046233	0.000345	0.042129	-0.0056	0.047525	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042129	-0.0056	0.047525	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042129	-0.0056	0.047525	-0.00491	0.073993	0.007844
	0.5	0.2	0.048386	0.004411	0.046233	0.000345	0.042127	-0.00559	0.047525	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042127	-0.00559	0.047525	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042127	-0.00559	0.047525	-0.00491	0.073993	0.007844
	0.9	0.2	0.048386	0.004411	0.046233	0.000345	0.042125	-0.00559	0.047525	-0.00491	0.073993	0.007844
		0.5	0.048386	0.004411	0.046233	0.000345	0.042125	-0.00559	0.047525	-0.00491	0.073993	0.007844
		0.8	0.048386	0.004411	0.046233	0.000345	0.042125	-0.00559	0.047525	-0.00491	0.073993	0.007844
20	0.1	0.2	0.032644	0.001599	0.032906	0.004222	0.030959	-0.00338	0.033778	-0.00328	0.01916	0.014106
		0.5	0.032644	0.001599	0.028879	-0.00288	0.035403	-0.0036	0.029772	-0.00322	0.018454	0.013647
		0.8	0.032644	0.001599	0.032835	0.004264	0.031342	-0.00413	0.033387	-0.00268	0.017711	0.012411
	0.5	0.2	0.032644	0.001599	0.031382	-0.00303	0.033115	-0.00247	0.031766	-0.00137	0.018166	0.015199
		0.5	0.032644	0.001599	0.033643	0.002047	0.032093	-0.00096	0.030612	-0.00403	0.017525	0.014396
		0.8	0.032644	0.001599	0.033643	0.002047	0.032093	-0.00096	0.030612	-0.00403	0.016717	0.013449
	0.9	0.2	0.032644	0.001599	0.033423	0.003093	0.033303	0.001591	0.029247	-0.00747	0.016163	0.016124
		0.5	0.032644	0.001599	0.033487	0.002528	0.033747	0.001283	0.028563	-0.00694	0.016184	0.016144
		0.8	0.032644	0.001599	0.033168	0.003927	0.030976	-0.00341	0.033546	-0.00379	0.016497	0.013286

Table 5: AH(d) RMSE and Bias of estimate with respect to δ at N=50, λ=0.1. {AR(1), AR(2), MA(1) and MA(2) errors}

			AR(1)		AR(2)		MA(1)		MA(2)	
T	δ	P	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias
5	0.1	0.2	0.059643	0.005909	0.059653	0.005938	0.059646	0.005915	0.059642	0.005919
		0.5	0.059635	0.005901	0.05965	0.005937	0.059645	0.005916	0.059641	0.00592
		0.8	0.059628	0.005894	0.059647	0.005934	0.059643	0.005918	0.05964	0.005921
	0.5	0.2	0.059643	0.005909	0.059654	0.005938	0.059646	0.005915	0.05964	0.005921
		0.5	0.059635	0.005901	0.05965	0.005937	0.059645	0.005916	0.059641	0.00592
		0.8	0.059628	0.005894	0.059647	0.005934	0.059643	0.005918	0.05964	0.005921
	0.9	0.2	0.059643	0.005909	0.059654	0.005938	0.059646	0.005915	0.059642	0.005919
		0.5	0.059635	0.005901	0.05965	0.005937	0.059645	0.005916	0.059641	0.00592
		0.8	0.059628	0.005894	0.059647	0.005934	0.059643	0.005918	0.05964	0.005921
10	0.1	0.2	0.047527	-0.00491	0.047531	-0.00491	0.047526	-0.00491	0.047525	-0.00491
		0.5	0.047528	-0.00491	0.047532	-0.00491	0.047526	-0.00491	0.047525	-0.00491
		0.8	0.04753	-0.00491	0.047533	-0.00491	0.047525	-0.00491	0.047525	-0.00491
	0.5	0.2	0.047527	-0.00491	0.047531	-0.00491	0.047526	-0.00491	0.047525	-0.00491
		0.5	0.047528	-0.00491	0.047532	-0.00491	0.047526	-0.00491	0.047525	-0.00491
		0.8	0.04753	-0.00491	0.047533	-0.00491	0.047525	-0.00491	0.047525	-0.00491
	0.9	0.2	0.047527	-0.00491	0.047531	-0.00491	0.047526	-0.00491	0.047525	-0.00491
		0.5	0.047528	-0.00491	0.047532	-0.00491	0.047526	-0.00491	0.047525	-0.00491
		0.8	0.04753	-0.00491	0.047533	-0.00491	0.047525	-0.00491	0.047525	-0.00491
20	0.1	0.2	0.03293	-0.00313	0.034352	-0.00368	0.035201	-0.00045	0.033778	-0.00328
		0.5	0.032804	-0.00228	0.028295	-0.0017	0.035493	-0.00389	0.029772	-0.00322
		0.8	0.031064	-0.00366	0.032804	-0.00228	0.033616	-0.00201	0.033387	-0.00268
	0.5	0.2	0.03499	-0.00339	0.035024	-0.00403	0.033547	-0.00379	0.031766	-0.00137
		0.5	0.033387	-0.00268	0.03375	-0.00318	0.033547	-0.00379	0.030612	-0.00403
		0.8	0.033547	-0.00379	0.033617	-0.00201	0.033616	-0.00201	0.030612	-0.00403
	0.9	0.2	0.030843	-0.00501	0.035024	-0.00403	0.030612	-0.00403	0.029247	-0.00747
		0.5	0.030739	-0.0043	0.035341	-0.00352	0.031765	-0.0023	0.028563	-0.00694
		0.8	0.030613	-0.00403	0.035497	-0.00344	0.030612	-0.00403	0.033546	-0.00379

Table 6: The RMSE and Bias of estimate with respect to δ when δ =0.1 , ρ=0.2. True Model is AR(1)

AR(1)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
N	T	λ	RMSE	Bias	RMSE	bias	RMSE	bias	RMSE	bias	RMSE	bias
50	5	0.1	0.0734	-0.0031	0.0616	-0.004968	0.0628	0.007446	0.05964	0.00591	9.02833	-3.6996
		0.5	0.1087	-0.0076	0.0615	-0.004967	0.0627	0.007422	0.05961	0.00588	1.75235	-0.8214
		0.9	0.1174	-0.0084	0.0615	-0.004966	0.0627	0.007417	0.0596	0.00586	0.94524	-0.4838
	10	0.1	0.0484	0.00441	0.0462	0.000345	0.0421	-0.0056	0.04753	-0.0049	0.07399	0.00784
		0.5	0.0725	0.01116	0.0462	0.000344	0.0421	-0.00562	0.04752	-0.0049	0.07349	0.00894
		0.9	0.0835	0.01252	0.0462	0.000343	0.0421	-0.00561	0.04752	-0.0049	0.07193	0.00967
	20	0.1	0.0326	0.0016	0.0334	0.004305	0.0313	-0.00306	0.03293	-0.0031	0.02277	0.01824
		0.5	0.0501	0.0007	0.0337	0.004112	0.0303	-0.00189	0.03362	-0.002	0.02164	0.01889
		0.9	0.0835	0.01252	0.0462	0.000343	0.0421	-0.00561	0.04752	-0.0049	0.07193	0.00967
100	5	0.1	0.045	0.00216	0.0481	-1.44E-05	0.0445	-0.00574	0.0484	-0.00506	9.97346	6.57738
		0.5	0.0671	-0.0005	0.0516	-1.07E-05	0.0407	-0.0061	0.04661	-0.0044	2.91687	1.31446
		0.9	0.0783	0.00108	0.0481	-2.18E-05	0.0445	-0.00576	0.04839	-0.005	1.19035	0.83821
	10	0.1	0.0324	0.00068	0.028	-0.001669	0.0282	-0.0013	0.03487	0.00311	0.05488	-0.0028
		0.5	0.0475	0.00423	0.028	-0.001668	0.0282	-0.00131	0.03486	0.00313	0.05292	-0.002
		0.9	0.0543	0.00683	0.028	-0.001664	0.0282	-0.00131	0.03486	0.00313	0.05049	-0.0012
	20	0.1	0.022	0.00301	0.0227	0.001905	0.0219	0.001905	0.02187	0.00082	0.03009	9.99E-05
		0.5	0.0332	0.00469	0.023	0.001327	0.022	0.001852	0.02093	0.00111	0.02938	0.00026
		0.9	0.0396	0.00447	0.0217	0.002261	0.0222	0.002261	0.02148	-0.0029	0.02833	0.00044

Table 7: The RMSE and Bias of estimate with respect to δ when δ =0.9 , ρ=0.8. True Model is AR(1)

AR(1)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
N	T	λ	RMSE	Bias	RMSE	bias	RMSE	bias	RMSE	bias	RMSE	bias
50	5	0.1	0.0734	-0.0031	0.0616	-0.004968	0.0627	0.0074	0.05963	0.00589	11.4453	-6.4576
		0.5	0.1087	-0.0076	0.0615	-0.004973	0.0627	0.00738	0.05957	0.00584	2.313	-1.4754
		0.9	0.1174	-0.0084	0.0615	-0.004973	0.0627	0.007385	0.05956	0.00581	1.28376	-0.8805
	10	0.1	0.0484	0.00441	0.0462	0.000345	0.0421	-0.00559	0.04753	-0.0049	0.07399	0.00784
		0.5	0.0725	0.01116	0.0462	0.000344	0.0421	-0.00561	0.04752	-0.0049	0.07349	0.00894
		0.9	0.0835	0.01252	0.0462	0.000343	0.0421	-0.00561	0.04753	-0.0049	0.07193	0.00967
	20	0.1	0.0326	0.0016	0.0336	0.002047	0.0321	-0.00096	0.03061	-0.004	0.02414	0.01984
		0.5	0.0501	0.0007	0.0336	0.003403	0.0329	0.000196	0.02932	-0.006	0.02289	0.01829
		0.9	0.0578	-0.0014	0.0327	0.001974	0.0318	-0.00064	0.03105	-0.0034	0.0203	0.01735
100	5	0.1	0.045	0.00216	0.0481	-1.43E-05	0.0445	-0.00574	0.0484	-0.00506	9.94916	6.59152
		0.5	0.0665	0.00118	0.0481	-1.97E-05	0.0445	-0.00575	0.0484	-0.005	2.07666	1.42704
		0.9	0.0783	0.00108	0.0481	-2.19E-05	0.0445	-0.00576	0.04839	-0.005	1.19475	0.84621
	10	0.1	0.0324	0.00068	0.028	-0.001669	0.0282	-0.0013	0.03487	0.00311	0.05488	-0.0028
		0.5	0.0475	0.00423	0.028	-0.001668	0.0282	-0.0013	0.03486	0.00312	0.05292	-0.002
		0.9	0.0543	0.00683	0.028	-0.001664	0.0282	-0.0013	0.03486	0.00313	0.05049	-0.0012
	20	0.1	0.022	0.00301	0.023	0.001327	0.0219	0.001327	0.02093	0.00111	0.03009	9.99E-05
		0.5	0.0332	0.00469	0.0226	-0.000193	0.0235	-0.00019	0.02017	0.00328	0.02955	-0.0039
		0.9	0.0396	0.00447	0.0225	0.001528	0.021	0.001528	0.02224	-0.0019	0.02833	0.00044

Table 8: The RMSE and Bias of estimate with respect to δ when δ =0.1 , θ=0.2 True Model is MA(1)

MA(1)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
N	T	λ	RMSE	Bias	RMSE	bias	RMSE	bias	RMSE	bias	RMSE	bias
50	5	0.1	0.0734	-0.0031	0.0616	-0.004967	0.0628	0.007467	0.05965	0.00591	8.14354	-2.0043
		0.5	0.1087	-0.0076	0.0615	-0.004966	0.0627	0.007444	0.05962	0.0059	1.56075	-0.4781
		0.9	0.1174	-0.0084	0.0615	-0.004964	0.0627	0.007437	0.05961	0.00588	0.83503	-0.2958
	10	0.1	0.0484	0.00441	0.0462	0.000345	0.0421	-0.0056	0.04753	-0.0049	0.07399	0.00784
		0.5	0.0725	0.01116	0.0462	0.000345	0.0421	-0.00562	0.04752	-0.0049	0.07349	0.00894
		0.9	0.0835	0.01252	0.0462	0.000343	0.0421	-0.00562	0.04752	-0.0049	0.07193	0.00967
	20	0.1	0.0326	0.0016	0.0327	0.001586	0.0302	-0.00574	0.0352	-0.0004	0.02106	0.01839
		0.5	0.0501	0.0007	0.0329	0.004222	0.0309	-0.00339	0.03378	-0.0033	0.02254	-0.0002
		0.9	0.0578	-0.0014	0.0319	-0.000593	0.0318	-0.00243	0.03243	-0.0025	0.01875	0.01868
100	5	0.1	0.0433	0.00136	0.0516	-1.07E-06	0.0407	-0.00608	0.04668	-0.0044	16.839	10.3364
		0.5	0.0671	-0.0005	0.0516	-1.07E-05	0.0407	-0.0061	0.04661	-0.0044	2.91687	1.31446
		0.9	0.0778	-0.0004	0.0516	-1.79E-05	0.0407	-0.0061	0.0466	-0.0044	1.4298	0.3648
	10	0.1	0.0324	0.00068	0.028	-0.001669	0.0282	-0.00131	0.03487	0.00311	0.05488	-0.0028
		0.5	0.0475	0.00423	0.028	-0.001668	0.0282	-0.00131	0.03486	0.00313	0.05292	-0.002
		0.9	0.0543	0.00683	0.028	-0.001664	0.0282	-0.00131	0.03486	0.00313	0.05049	-0.0012
	20	0.1	0.022	0.00301	0.023	0.001858	0.0217	0.001474	0.02173	0.00135	0.03107	-0.0146
		0.5	0.0332	0.00469	0.023	0.001327	0.022	0.001852	0.02093	0.00111	0.02938	0.00026
		0.9	0.0396	0.00447	0.0247	0.001831	0.0198	0.004238	0.02222	-0.0023	0.02833	0.00044

Table 9: The RMSE and Bias of estimate with respect to δ when δ =0.9 , θ=0.8 True Model is MA(1)

MA(1)			OLS		LSDV		AH(l)		AH(d)		ABGMM1	
N	T	λ	RMSE	Bias	RMSE	bias	RMSE	bias	RMSE	bias	RMSE	bias
50	5	0.1	0.0734	-0.0031	0.0616	-0.004967	0.0627	0.007464	0.05964	0.00592	8.03205	-1.9221
		0.5	0.1087	-0.0076	0.0615	-0.004966	0.0627	0.007443	0.05962	0.00591	1.53896	-0.4598
		0.9	0.1174	-0.0084	0.0615	-0.004964	0.0627	0.007437	0.05961	0.00589	0.82317	-0.2848
	10	0.1	0.0484	0.00441	0.0462	0.000345	0.0421	-0.00559	0.04753	-0.0049	0.07399	0.00784
		0.5	0.0725	0.01116	0.0462	0.000345	0.0421	-0.00561	0.04752	-0.0049	0.07349	0.00894
		0.9	0.0835	0.01252	0.0462	0.000343	0.0421	-0.00561	0.04752	-0.0049	0.07193	0.00967
	20	0.1	0.0326	0.0016	0.0336	0.002047	0.0321	-0.00096	0.03061	-0.004	0.02028	0.0155
		0.5	0.0501	0.0007	0.0329	0.004328	0.031	-0.00349	0.03375	-0.0032	0.02063	0.01587
		0.9	0.0578	-0.0014	0.0329	0.003035	0.0317	-0.0027	0.03175	-0.0023	0.0216	0.01697
100	5	0.1	0.0433	0.00136	0.0516	3.73E-07	0.0407	-0.00609	0.04669	-0.0044	17.5865	11.5782
		0.5	0.0671	-0.0005	0.0516	-9.13E-06	0.0407	-0.0061	0.04662	-0.0044	3.01919	1.51332
		0.9	0.0833	-0.0027	0.0481	-9.03E-06	0.0445	-0.00577	0.04839	-0.005	1.19705	0.872
	10	0.1	0.0324	0.00068	0.028	-0.001669	0.0282	-0.0013	0.03487	0.00311	0.05488	-0.0028
		0.5	0.0475	0.00423	0.028	-0.001668	0.0282	-0.00131	0.03486	0.00313	0.05292	-0.002
		0.9	0.0543	0.00683	0.028	-0.001664	0.0282	-0.00131	0.03486	0.00313	0.05049	-0.0012
	20	0.1	0.022	0.00301	0.0241	0.002893	0.021	0.002734	0.02264	-0.0017	0.03009	9.99E-05
		0.5	0.0332	0.00469	0.0234	0.002342	0.0202	0.003277	0.02233	-0.0008	0.02938	0.00026
		0.9	0.0396	0.00447	0.0231	0.001634	0.0203	-1.93E-05	0.022	-0.0003	0.02833	0.00044

References

Anderson, T.W and C. Hsiao (1981). Estimation of Dynamic Models with Error Components, Journal of American Statistical of Econometrics 76, 598-606.

Arellano, M and S. Bond (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, Review of Economic Studies 58, 277-297.

Balestra, P. and Nerlove, M. (1966). Pooling Cross-section and Time-Series Data in the Estimation of Dynamic Model, Econometrica, Vol.34, pp. 585-612.

Baltagi, Badi H. (2008). Econometric Analysis of Panel Data, John Wiley & Sons, Ltd. (4th edition),U.S.A.

Baltagi, B. H and Li (1997). Monte Carlo Results on Pure and Pretest Estimators of an Error Component Model with Autocorrelated Disturbances, Annales D'econnmie et Statistique-No 48- 1997.

Behr Andreas (2003). A comparison of Dynamic Panel Data Estimators: Monte Carlo Evidence an Application to the Investment Function, Economic Research Centre of the Deutsche Bundesbank.

Bhargava, A.L, Franzini and W. Narendranathan (1982). Serial correlation and fixed effects model, Review of Economic Studies 49, 533-549.

Burke, S.P, L.G. Godfrey and A.R. Termmaye (1990). Testing AR(1) against MA(1) Disturbances in the Linear Regression Model: An Alternative Procedure, Review of Economic Studies 57, 135-145.

Galbraith, J.W. and V. Zinde-Walsh (1995). Transforming the Error-Component Model for Estimation with General ARMA disturbances, Journal of Econometrics 66,349-355.

Harris, M. and Matyas, L. (2010). A Comparative Analysis of Different Estimators for Dynamic Panel Data Models, The Melbourne Institute of Applied Economic and Social Research, University of Melbourne, Australia.

Hosung Jung(2005). A Test for Autocorrelation in Dynamic Panel Data Models, Institute of Economic Research Hitotsubashi University, Kunitachi, Tokyo, Japan.

Hsiao, C (2005). Analysis of Panel Data, Cambridge University Press (2nd edition), New York.

Hujer Reinhard, Paulo J.M and Zeiss Chritopher (2005). Serial Correlation in Dynamic Panel Data Models with Weankly Exogenous Regressors and Fixed Effects,Working paper 9

Judson, R.A and Owen, A.L (1996). Estimating Dynamic Panel Data Models: A Practical Guide for Macroeconomists , Journal of Econometrics

Kiviet, Jan F(1995). On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamic Panel Data Models, Journal of Econometrics, 68, 53-78

Lillard, L.A. and R.J. Willis (1978). Dynamic Aspect of Earning Mobility, Econometrica 46, 985-1012.

Nicholls, D.F., Pagan, A.R., and R.D. Terrell (1975). The Estimation and Use of Models with Moving Average Disturbances Term: A Survey, International Economic Review, 16, 113-134.

Sevestre, P. and Trognon, A. (1985). A Note on Autoregressive Error Component Models, Journal of Econometrics, Vol. 29, pp. 231-245.

Stephen Bond (2002). Dynamic Panel Data Models, Institute for Fiscal Studies Working Paper Series No.CWP09/02, London